SOCIAL NETWORK STRUCTURE AND HEALTH IN THE SECOND HALF OF LIFE

Inauguraldissertation
zur
Erlangung des Doktorgrades
der
Wirtschafts- und Sozialwissenschaftlichen Fakultät
der
Universität zu Köln

2025

vorgelegt von
Amelie Reiner, M.Sc. M.Sc.
aus
München

SOCIAL NETWORK STRUCTURE AND HEALTH IN THE SECOND HALF OF LIFE

Referentin: Prof. Dr. Lea Ellwardt, Universität zu Köln

Korreferent: Prof. Dr. Karsten Hank, Universität zu Köln

Tag der Promotion:

Acknowledgements

In crafting this dissertation, I've had the privilege of the guidance of many who played pivotal roles in my academic journey. Their contributions and support (instrumental *and* emotional!) deserve recognition, and I am grateful for the lasting imprint they have left.

First and foremost, I would like to thank my advisors Lea Ellwardt and Karsten Hank. They accompanied me on this journey in a way one could hardly wish for better – always supportive and with an impressive level of expertise. I am deeply grateful to Lea Ellwardt for her excellent academic mentorship, her ongoing motivation, and her trust. She has been not only an inspiring mentor but also a truly outstanding supervisor. Working on the project under her guidance brought me great joy – not least because of the collegial, friendly, and respectful atmosphere she fostered. I would also like to thank Karsten Hank for his continuous academic support and constructive feedback throughout the past three years. I am very grateful for the opportunity to work at his chair, where I gained valuable teaching experience and became part of not just one, but two wonderful teams at the Department of Sociology (DSS) at the University of Cologne.

My heartfelt thanks also go to my co-authors Paula Steinhoff, Elena De Gioannis, Mark Wittek, Lea Ellwardt, and James Moody. Without your invaluable collaboration and intellectual contributions, this dissertation would not have been possible in its current form. A special thank-you goes to my co-author Jim – I am especially grateful for the opportunity to spend a research stay at Duke University and to benefit from his extensive expertise. My sincere thanks also go to Lea Ellwardt and the Deutsche Forschungsgemeinschaft for the financial support that made this possible.

The heart of my PhD journey was undoubtedly the *Jeckenstudie*. My special thanks go to all gatekeepers and respondents – thank you for placing your trust in the study and for your remarkable commitment across multiple waves of data collection. I would also like to thank the project team, without whose dedication and commitment none of this would have been possible. Lea – thank you for your trust in us, for striking the perfect balance between freedom and guidance, and for giving us the space to grow independently. Paula – thank you for being my methodologically qualitative twin, always ready with advice, openness, and reliability. Barbara Harms, Anna Leuwer, and Maya Wermeyer also played a key role in shaping this project – not only enriching it with their contributions but also making it a joyful experience. I'm very grateful for the memories we created together – from team meetings and chair trips to our quirky advent calendar ceremonies and our very own *Jeckenstudie* merchandise!

I am equally grateful to my wonderful colleagues at the DSS. Daily lunches at the Mensa, stimulating academic exchanges, and a collegial atmosphere made my everyday work life even more enjoyable. I would particularly like to thank Heike Krüger, who – due to her similar research focus, more or less voluntarily – followed the progress of my papers across various conferences and was always open to questions. In addition, I would like to thank Katya Sytkina, Stefan Mauritz, Vanessa Wittemann and Susanne Böller for sharing the highs and lows of this PhD journey with me. Thanks also go to Barbara Harms, Petra Altendorf, Joël Binckli, André Ernst, and the Geschäftszimmer for their consistent administrative support.

A big thank-you goes out to the PhDlies in their prime (although some of them are already PostDocs in their prime) – Bettina Hünteler, Lisa Jessee, Lina Tobler, and Paula Steinhoff. I am so grateful not only for the academic exchange we shared but also for your friendship and all the lovely evenings spent together over good food. A very special thank-you goes to Paula, who – as my office mate, co-author, and project colleague – supported me through the ups and downs of not only my academic journey but also my personal life. Thank you for your incredible support, your always-open ear, being a great travel buddy and the many musical hours in the office, at karaoke bars and London musicals! Work would have been only half as fun without you, and I am deeply thankful for our friendship.

I also want to thank all the weak ties and those beyond that I cannot name here due to recall bias – you provided me with unanticipated gains and non-redundant information that added great value to this dissertation.

Further, I want to thank my all friends from Cologne and Munich. Special thanks go to my closest friends Sunny, Sara, Sello, Isa, Coco, and Sascha. Your unconditional support, love, and presence over the past three years gave me the strength and balance I needed to complete this dissertation.

Finally, particular thanks to my extended family for their continuous encouragement! Dad, thank you for your support and enthusiasm which made me even more certain and excited to take this path. Mum, Felix, thank you for always believing in me and holding me up when I needed it most. Your unwavering support meant everything.

Content

CHAPTER 1. INTRODUCTION

1.1 Background and aim of the dissertation

As inherently social beings, most individuals engage in daily interactions with others. From birth, people are embedded in social contexts: they are born into families, grow up in neighborhoods, attend school with peers, join social clubs, and work alongside colleagues. Those with whom an individual has regular interactions—family members, friends, neighbors, colleagues, and so on—form what is known as a personal social network. A social network is traditionally defined as "the web of social relationships that surround an individual and the characteristics of those ties" (Berkman et al., 2000, p. 847). These networks evolve across the life course and tend to shrink in older adulthood, especially after retirement. Importantly, networks are not formed at random: People make active choices about those with whom we engage and maintain relationships. At the same time, those with whom they interact are equally making their own choices. As a result, the personal networks and their structure emerges not solely from an individual's decisions, but from the intersecting choices of many.

Building and maintaining social connections takes time and effort, constituting a conscious investment. Yet, people pursue these relationships because they offer joy, emotional support, and a sense of belonging, all of which are essential for health and well-being. A growing body of research shows that both individual relationships and the broader structure of their social environment play a vital role in health outcomes. While communicable diseases have long been linked to social contact, social networks were also found to be crucial for non-communicable health outcomes. They can reduce the risk of cognitive decline (Kuiper et al., 2016), dementia (Kuiper et al., 2015), depression (Reiner et al., 2025; Reiner & Steinhoff, 2024), and even premature death (Holt-Lunstad et al., 2010). At the same time, this relationship is reciprocal: poor health also influences one's social network. Health limitations may reduce opportunities for participation, prompt social withdrawal, or cause others to distance themselves—all of which may ultimately shrink a person's network (Copeland et al., 2023; Haas et al., 2010; Link, 1987). Forming the largest demographic group in Western societies, middle-aged and older adults are particularly at risk, as they face a naturally shrinking network over the life course and an increasing risk of age-related illnesses and chronic conditions (Wrzus et al., 2013). Therefore, this dissertation investigates the overarching research question: *What is the relationship between social network structure and health in the second half of life?*

Before addressing this question, it is important to clarify how social networks are conceptualized in the literature and which dimensions are most relevant for health. Prior research and reviews on social networks and health offer various definitions and measurement strategies (Ayalon & Levkovich, 2019; Siette et al., 2015), generally distinguishing between functional and structural aspects of social relationships (House, 1987; Santini et al., 2015). Functional aspects refer to the qualitative nature and potential of social relationships, including social support, relationship quality, relationship satisfaction, and loneliness (Kuiper et al., 2016; Santini et al., 2015). In contrast, structural aspects refer to the setup of the social environment in which relationships are embedded, including network size and composition, as well as contact frequency (Santini et al., 2015). Given that structural aspects precede functional ones and are particularly useful for understanding the connection between social networks and critical health outcomes (Holt-Lunstad et al., 2010; Kuiper et al., 2015, 2016), which is why this dissertation focuses predominantly on structural aspects of social networks.

As a central mental health outcome, depression is a major mental health concern among older adults, affecting approximately 5.7% of people over 60 worldwide (World Health Organization, 2023). Europe has a slightly higher prevalence, with 8.5% of those aged 65 and older affected, and 8% specifically in Germany (Eurostat, 2022). Research shows a significant association between social networks and depression, with more socially integrated older adults experiencing lower levels of depression than less socially integrated older adults (Schwarzbach et al., 2014; Tengku Mohd et al., 2019). Previous reviews have restricted their scope to specific geographic areas (Iran: Harandi et al., 2017; Middle-Eastern countries: Tajvar et al., 2013; Asian countries: Tengku Mohd et al., 2019; Western countries: Gariépy et al., 2016), while Schwarzbach et al. (2014) conducted a comprehensive review over a decade ago. Given the substantial growth in research within the past decade, there is a renewed need to conduct a systematic, transnational review and quantification of evidence on the association between social networks and depression among older adults.

Although the relationship between social networks and general health is reciprocal, most research has addressed the influence of social networks on health outcomes, overlooking the reverse effect—how health shapes social networks—as well as the dynamic interdependence between the two (for a review, see Reiner & Steinhoff, 2024). Moreover, while Berkman et al.'s (2000, p. 847) definition of social networks explicitly includes the characteristics of network ties, most studies do not fully integrating both network members' characteristics and network structure when examining the interdependence between social networks and health. This dissertation attends to these factors, understanding that an individual's network members directly and indirectly influence their health and the structure of their personal network shapes social interactions, as well as access to resources and support. Beyond an individual's immediate ties, their broader network structure also plays a critical role (Cohen, 2004; Smith & Christakis, 2008), as weaker or more casual ties to others may provide access to non-redundant resources (Granovetter, 1973).

A key mechanism linking social networks to health is the mobilization of social support, particularly in the context of non-communicable diseases. Social support encompasses a range of resources—including advice, information, emotional support, and affirmation—that individuals draw upon to navigate health challenges (Abbott et al., 2012; Schafer, 2013). Communication is central to this process: through everyday conversations, people routinely share health concerns, seek advice, and influence each other's health decisions (Berkman et al., 2000; Smith & Christakis, 2008). Beyond actual interactions, it is also the perceived availability of support—such as the belief that advice is accessible if needed—that has been shown to be more predictive of positive health outcomes than support that is actually received (Uchino, 2009; Wills & Shinar, 2000), reflecting the latent potential within social networks (Thoits, 2011). Importantly, such health-related exchanges are not limited to close ties; individuals may intentionally seek advice from knowledgeable acquaintances or encounter useful information in more casual interactions (Perry & Pescosolido, 2010; Small, 2009, 2013). A growing body of research emphasizes the role of these health advice partners in shaping health behaviors, access to resources, and emotional support (Perry & Pescosolido, 2010; Schafer, 2013). Despite their importance, the structure of health advice networks remains underexplored in the literature, particularly in contexts exceeding the immediate social circle. Moreover, not only communicable diseases, but also non-communicable health-related outcomes, including obesity, loneliness, depression, and happiness tend to diffuse throughout entire networks via social contagion (Cacioppo et al., 2009; Christakis & Fowler, 2007; Fowler & Christakis, 2008; Rosenquist et al., 2011). Importantly, individuals do not passively absorb network influence: they actively shape and select their networks based on shared behaviors and characteristics, a process known as homophily or preferential attachment (McPherson et al., 2001). Much of the existing literature considers these dynamics at the individual level. As Kawachi and Berkman (2001) emphasize, social ties are embedded within larger social structures, and it is important to consider this broader, layered context to understand how social networks and health are connected.

Critically, network structures follow inherent patterns which influence social dynamics, including shared or reciprocal relationships or the tendency to form close-knit groups. Failing to account for these network structural tendencies might lead to misinterpreting network effects, as observed patterns could emerge from structural network constraints rather than genuine individual-level processes. This limitation is particularly relevant given that existing research on preferential attachment to those with similar health status has primarily examined institutional settings—such as schools, workplaces, and retirement homes (Crosnoe et al., 2008; Schaefer et al., 2011; Schafer, 2016; Van Zalk et al., 2010a)—where social ties form within structurally constrained environments. These settings shape network formation through mechanisms of sorting and implicit compulsion, under which individuals have limited agency in selecting social ties and thus often form connections based on similarities to others within a predefined pool (McPherson et al., 2001). However, these scope conditions remain underspecified in the literature, limiting our understanding of how social networks and health interact beyond institutional constraints. Examining this relationship without considering network structure and the mechanisms that drive tie formation risks biased conclusions, potentially obscuring the pathways through which health and social networks influence each other (Christakis & Fowler, 2011; Valente, 2010).

In this dissertation, I contribute to the scholarly understanding of the relationship between social network structure and health in the second half of life by fulfilling two primary aims: *first*, I (a) synthesize (Study 1) and (b) quantify (Study 2) the vast body of scientific evidence on the relationship between structural social network aspects and depression; *second*, I employ a holistic methodological approach to examine the social network structure in relation to health while considering network member characteristics, and network structural factors. Looking beyond immediate social ties, this analysis focuses on voluntary associations as a broader social context. Specifically, I examine (a) the structure of health advice networks (Study 3) and (b) the reciprocal relationship of social networks and health among adults in the second half of life in a fully voluntary context (Study 4). As social network structure and dynamics tend to differ by health condition, I distinguish between mental and physical health (Study 3), as well as self-rated health (Study 4). To explore the first aim, this dissertation draws on self-collected data following a systematic literature search with strict inclusion and exclusion criteria. For the second aim, I use cross-sectional and longitudinal quantitative whole-network data from the *Jeckenstudie*.

In the following section, I outline my theoretical framework and research approach. In the fourth section, I summarize the four studies that are part of this dissertation. Finally, I conclude by highlighting the key findings, contributions, limitations, and scientific and policy implications. Chapters 2, 3, 4, and 5 present the four empirical studies.

1.2 Theoretical framework

In general, the relationship between social networks and health is dynamic and reciprocal. On the one hand, social relationships affect health through direct and indirect pathways. On the other hand, declining health also affects the extent of social relationships through mechanisms of social avoidance or withdrawal. Here I present the main theoretical assumptions underlying this thesis first by introducing the primary pathways through which social relationships impact health outcomes and, second, by examining how declining health can in turn reshape social networks. Third, I highlight the importance of embedding these individual-level processes within broader contextual and structural perspectives. Finally, I describe common dynamics within social networks in relation to health.

1.2.1 Causal pathways of social networks on health

Two causal models describe the pathways through which social networks influence health: the Main Effect Model and the Stress-Buffering Model. The former proposes that social relationships are beneficial regardless of individual stress level, while the latter posits that social ties are related to well-being for individuals under stress. The two models are not mutually exclusive but rather complementary, offering insights into how different dimensions of social relationships influence health. Structural aspects are suggested to be primarily aligned with the main effect model, while functional aspects (e.g., social support) operate through a stress-buffering mechanism (Cohen, 2004; Kawachi & Berkman, 2001).

The *Main Effect Model* (Cohen & Wills, 1985) posits that social relationships influence both physical and mental health through a range of direct and indirect pathways. Directly, social ties can influence biological systems, such as the endocrine, immune, and cardiovascular systems, by promoting oxytocin release and reducing sympathetic nervous system arousal through positive social interactions, which in turn reduce inflammation and produce calming, immune-enhancing effects (Heinrichs et al., 2003; Uchino, 2006). Indirectly, they shape health via social influence, access to information, and resources, and psychological states that promote health-related behaviors.

Social networks impact health in several ways. First, social influence within networks exerts normative pressure on individuals, encouraging or discouraging certain health behaviors. Second, networks act as channels for health-related information, which may be particularly valuable during illness episodes, as emphasized by the *Network Episode Model* that highlights the activation of social ties in response to health events (Pescosolido, 1991, 1992). Third, social resources or support plays a protective role by buffering individuals against health risks (e.g., by providing healthy food) and through informal caregiving. Fourth, social integration fosters a generalized sense of positive psychological affect through social recognition and a sense of belonging, which may directly benefit health or indirectly enhance motivation for self-care (Cohen & Syme, 1987). While physical health is influenced through these behavioral and biological mechanisms, mental health is also shaped by psychological states and social influence. Additionally, research suggests that social networks may directly affect neuroendocrine responses, further linking social integration to mental health outcomes (Cohen et al., 2000; Uchino, 2006).

The *Stress-Buffering Model* (Cohen & Wills, 1985) posits that social relationships are particularly beneficial for well-being under conditions of stress. In this framework, social support is hypothesized to prevent or mitigate the negative effects of stressful events on health in two keyways. First, the perceived availability of support might alter cognitive appraisal, making a situation seem less threatening and thereby averting negative emotional and behavioral responses. Second, perceived support can reduce emotional distress and attenuate physiological and behavioral responses to stress, while received instrumental support may directly address or alleviate the stressor itself.

1.2.2 Causal pathways of health on social networks

While the majority of the literature has examined the impact of social networks on health outcomes, the reverse direction of this relationship—namely, the influence of health on social networks—has received comparatively less attention (for a review on depression, see Reiner & Steinhoff, 2024). However, this perspective is equally important. Individuals in poor health tend to have smaller and more constrained social networks than their healthier counterparts (Reiner & Steinhoff, 2024). This pattern can be partially attributed to the stigma surrounding poor health, which often manifests in social avoidance or self-imposed withdrawal (Link & Phelan, 2001).

Social *avoidance* of individuals in poor health, particularly when the condition is visible or socially stigmatized, may occur for two primary reasons. First, individuals in poor health may be perceived as less desirable social partners due to reduced capacity for regular participation in social activities (Galenkamp & Deeg, 2016). Second, others may fear that association with stigmatized individuals could negatively affect their own social reputation (Crosnoe et al., 2008; Haas et al., 2010).

In addition to avoidance by others, individuals experiencing poor health may actively *withdraw* from social life. On the one hand, poor health may have implications on the ability to engage in social activities or the capacity to maintain or expand their social network. Physical health limitations, such as chronic illnesses or disabilities limiting mobility, can directly impair the ability to engage socially. Similarly, mental health conditions can diminish motivation, energy, and interest in social interaction; for instance, symptoms of depression often include social withdrawal and loss of interest in previously valued activities (National Institute of Mental

Health, 2024). On the other hand, individuals experiencing health problems may withdraw from social settings to conceal their condition. Anticipating stigma or adverse social reactions, they may choose to distance themselves from others as a form of self-protection (Link & Phelan, 2001). According to the *Cognitive Theory of Depression* (Beck, 1967, 1979), distorted thought patterns—characterized by a negative view of the self, social environment, and future—can lead individuals to overlook or dismiss positive social experiences. This cognitive bias fosters dissatisfaction with social relationships, increases the potential for conflict, and may ultimately lead to dissolution of relationships, further reinforcing social withdrawal. In line with this, the *Behavioral Theory of Depression* (Lewinsohn, 1974) suggests that reduced positive reinforcement from social interactions can trigger a downward spiral of withdrawal and deepening depressive symptoms.

From a life course perspective, older adults are especially vulnerable to these dynamics. With advancing age, age-related illnesses constrain opportunities for social participation (Griffith et al., 2017), causing social networks to naturally shrink (Wrzus et al., 2013). These changes often interact cumulatively, reinforcing a vicious cycle of mutual decline.

1.2.3 Contextual and structural dimensions of social ties and health

To this point, the relationship between social networks and health has been considered primarily at the level of the individual. However, as Berkman et al. (2000) emphasize, interpersonal ties are embedded within a broader constellation of meso- and macrosocial structures. Understanding health outcomes through social relationships requires attention to the nested, multi-layered structure of these ties, encompassing macro-level socio-structural conditions, meso-level network structures, and micro-level psychosocial mechanisms.

At the *macro level*, socio-structural conditions, such as culture, socioeconomic factors, politics and social change, shape the broader environment in which social networks form and evolve. These forces attenuate the *meso-level* dimensions of social networks, including their overall structure and the specific characteristics of social ties, which in turn shape opportunities for *micro-level* psychosocial processes, such as social support, social influence, interpersonal engagement, and access to resources. To reiterate, these processes influence health through behavioral, psychological, and physiological pathways. This dissertation focuses on the meso and micro levels, examining how the structure and context of social networks influence individual health outcomes. By integrating contextual and structural dimensions of social ties, this research expands beyond individualistic frameworks to capture the dynamic interplay between social networks and health.

To understand this interplay more fully, it is important to consider the range and layering of social relationships. These range from intimate connections (e.g., marital partners), to more extended personal networks (e.g., friends and close relatives), and further outward to weaker ties embedded in civic, religious, and voluntary associations (Berkman, 1995; Lin et al., 1999). While the majority of health-related research has traditionally focused on the role of close ties (e.g., family members, spouses, close friends) in shaping health outcomes (House, 1987; Thoits, 2011), there is also an increasing recognition of the value of weaker ties. Following Granovetter (1973), weak ties are particularly beneficial in obtaining non-redundant information, such as that which is crucial for responding to acute health crises. Moreover, Small et al. (2024) find that individuals may even avoid confiding in close ties when faced with certain situations. In addition, early research primarily emphasized the supportive functions of close relationships, but there is a growing understanding that social support is only one pathway through which networks influence health. Focusing exclusively on strong ties and individual-level effects risk overlooking the structural context—how ties are arranged and embedded in broader social configurations—that influences both the availability and function of these ties.

Importantly, these outer layers of weak ties, although not necessarily characterized by close interpersonal exchange, contribute to a sense of social identity and belonging, which sociological theorists have long linked to psychological well-being (Durkheim, 1951). This broader framework resonates with the concept of *social capital* (Kawachi et al., 1997; Kawachi & Berkman, 2001), which foregrounds the role of community-level structures, such as civic engagement, social trust, and voluntary participation, in shaping individual health. Supporting this, Small (2009) highlights that social contexts beyond family or close friends can serve as unexpected sources of social capital, potentially offering valuable resources in health-related challenges. Thus, a comprehensive understanding of the link between social relationships and health requires the consideration of both network structure and context, moving beyond individualistic frameworks.

1.2.4 Network structure and health: selection and influence

Building on the broader perspective that social relationships and health must be contextualized within structural network contexts, existing research identifies network segregation as a consistent structural feature of close relationships (McPherson et al., 2001). Segregation often occurs along multiple social dimensions such as education, gender, and age. Wimmer and Lewis (2010) conceptualize network segregation as the result of multiple interrelated processes: the opportunity structure for tie formation, endogenous network dynamics, and individual preferences for similarity (i.e., homophily). Homophily has been found to occur among individuals with shared occupational statuses, gender, ethnicity, beliefs and values (McPherson et al., 2001) and helps determine from whom individuals seek support. Similarity fosters easier communication, greater trust and predictability, and fewer interpersonal conflicts (McPherson et al., 2001; Suitor & Keeton, 1997). Similarity is also psychologically rewarding as agreement in opinions and behaviors can validate one's own views (Lazarsfeld & Merton, 1954) while such confirmation reduces psychological discomfort, making homophilous relationships more satisfying (Festinger, 1957). Importantly, health has emerged as a salient axis of homophily in social networks across diverse contexts—including among adolescents in schools (Crosnoe et al., 2008; Schaefer et al., 2011), employees in workplaces (Chancellor et al., 2017), older adults in retirement communities (Schafer, 2016), and residents of low-income senior housing (Flatt et al., 2012).

Two key mechanisms account for the emergence of homophily: selection and influence (McPherson et al., 2001). These processes are not mutually exclusive; rather, they operate concurrently to shape the composition and impact of social relationships. *Selection* refers to the formation of social ties based on shared attributes, personal preferences, or contextual factors. Individuals with similar health statuses tend to form connections, especially in contexts where health differences are socially salient or stigmatized. For example, adolescents experiencing depression were found to face peer rejection and consequently tend to form friendships with others facing similar mental health challenges (Hogue & Steinberg, 1995; Schaefer et al., 2011). Similarly, adolescents with obesity were found to be more likely to befriend peers with comparable weight statuses (Crosnoe et al., 2008). Among older adults, homophilous ties frequently form around shared health status, as studies have shown in retirement settings (Schafer, 2016). In later life, health status may become an increasingly important determinant for social tie formation as both individuals and their peers face mounting health-related challenges (Wrzus et al., 2013).

In contrast, *influence* describes the dynamic through which ongoing social network interactions shape individuals' health outcomes and behaviors. Particularly in the context of health, sociologists often frame the process of network influence through the lens of *Social Contagion Theory* (Christakis & Fowler, 2013). This theory posits that individuals are influenced by their social contacts, who are themselves embedded within broader relational structures. Empirical studies have demonstrated contagion effects for communicable diseases, such as sexually transmitted diseases (Chapman et al., 2022; Moody, 2002) and, more recently, Covid-19 (Marqués-Sánchez et al., 2023), but also across a range of non-communicable health outcomes, including obesity, depression, loneliness, and happiness (Cacioppo et al., 2009; Christakis & Fowler, 2007; Fowler & Christakis, 2008; Rosenquist et al., 2011). Whereas influence effects of physical health are largely understood to operate through the transmission of health-related behaviors (Christakis & Fowler, 2007), peer influence in the domain of mental health is predominantly explained through the mechanism of emotional contagion (Block & Burnett Heyes, 2022; Chancellor et al., 2017; Hatfield et al., 1993) and co-rumination (Van Zalk et al., 2010a, 2010b).

Taken together, these theoretical perspectives emphasize the need for an analytical approach that allows for both the reciprocal nature and the contextual and structural embeddedness of the social networks–health relationship. Considering the cumulative disadvantages and reinforcing cycle of declining health and shrinking social networks in the second half of life, it is particularly important to investigate these dynamics among middle-aged and older adults. The following chapter outlines the research approach adopted to empirically investigate the dynamic interplay between social network structure and health in the second half of life.

1.3 Research approach

I use a two-pronged research design in my investigation of social network structures and health in later life: first, I conduct both a systematic review and a meta-analysis to synthesize and quantify the global body of research on the reciprocal association between social networks and depression among older adults. Second, I analyze cross-sectional and longitudinal complete network data collected in carnival clubs in North Rhine-Westphalia, as part of the *Jeckenstudie*. In the following, I detail each methodological approach and highlight how they contribute to understanding the complex interrelations between network structure and health in the second half of life.

1.3.1 Systematic literature review and meta-analysis

A systematic literature review is a rigorous and structured method for synthesizing research evidence. Unlike narrative reviews, which offer broad but often selective overviews (McKenzie et al., 2019), or scoping reviews, which use less strict criteria to map qualitative and quantitative evidence on emerging topics (Munn et al., 2018), systematic reviews focus on answering a specific question, usually within a well-researched area. Systematic reviews minimize bias, enhance reliability, and ensure transparency and replicability by following a predefined protocol, as well as strict inclusion and exclusion criteria (Lasserson et al., 2019). To achieve my first research aim, I selected a systematic review to synthesize and critically evaluate the growing body of scientific evidence regarding the association between social networks and depression among older adults.

While systematic literature reviews synthesize existing research, they remain largely descriptive, often leaving uncertainty about the magnitude and consistency of associations across studies. In contrast, meta-analyses statistically combine results from multiple studies, providing a clearer estimate of the relationship in question and resolving inconsistencies in previous findings (Deeks et al., 2019). This method also enables researchers to address gaps in systematic reviews by examining variations across study populations, geographical contexts, and methodological approaches. Additionally, statistical techniques help detect potential publication bias, further enhancing the reliability of conclusions (Deeks et al., 2019). Conducting a meta-analysis allowed me to better understand the strength and consistency of the association between social networks and depression in older adults.

1.3.2 The importance of (longitudinal) complete network studies

Network approaches

There are two primary research approaches for studying social networks: the egocentric approach and the sociometric network approach. The *egocentric approach* focuses on individually bounded networks by identifying an individual's (ego) function-specific connections with immediate contacts (alters). These networks typically elicit unique personal networks consisting primarily of core network members, such as family, friends, and confidants (Marin, 2004; McCarty et al., 2019). A key advantage of the egocentric approach is its flexibility: it does not require a confined community space and can leverage survey-based sampling techniques. Many large-scale aging surveys, such as the German Aging Survey (DEAS), the Survey of Health, Ageing and Retirement in Europe (SHARE) and the US-American National Social Life, Health, and Aging Project (NSHAP), include modules assessing an ego's relationships with alters (Cornwell et al., 2009; Litwin et al., 2013). This approach is particularly useful for studying the functional aspects of social networks (e.g., support exchange) in representative study samples but is limited in assessing network member characteristics and network structure (McCarty et al., 2019).

Regarding network member characteristics, a key critique of the egocentric approach revolves around the uncertainty of individuals' knowledge about their alters. Some researchers argue that it is not the actual attitudes or behaviors of alters that matter, but how ego perceives them, as this perception can influence ego's attitudes and behaviors (Bearman & Parigi, 2004; Krackhardt, 1987; Marsden, 1990). Others suggest that when people are unsure about an alter's preferences or attitudes, they tend to project their own (Eveland et al., 2018; White & Watkins, 2000). Additionally, selective disclosure of network members based on social desirability can contribute to an experience of network homogeneity (Cowan & Baldassarri, 2018). Health is a particular sensitive topic, which may lead to limited disclosure by alter and awareness by ego, affecting the reliability of the health information they indicate about alter.

When assessing network structure via an egocentric network approach requires eliciting information on relationships between network members (alter-alter ties). However, this is particularly burdensome for respondents and compromises reliability (Golinelli et al., 2010; McCarty et al., 2007, 2019), prompting many large-scale studies to avoid collecting this data. Accurate data collection is also inhibited by egos' knowledge on details of alter-alter relationships, which is likely even more limited than their understanding of network member characteristics (McCarty et al., 2019). Crucially, egocentric network approaches can only capture ties about which ego is aware and chooses to report, meaning that potentially valuable social connections remain undetected, such as individuals in the ego's social environment who could serve as resources but with whom a relationship has yet to be established.

By contrast, the *sociometric approach* focuses on the relationships, interactions, or roles among all members within a defined social group, such as schools, workplaces or organizations (McCarty et al., 2019; Stark, 2018). It examines "small social settings with clear boundaries to identify all members of the underlying network" (Stark, 2018, p. 242). Through information on all network members and their individual relationships to others, this approach captures the entire network structure of a given social setting, enabling the analysis of direct and indirect relationships within a bound setting as well as structural factors that shape networks. It also allows for examining network dynamics (e.g., selection and influence mechanisms) when studied longitudinally. Unlike the egocentric approach, the sociometric approach focuses solely on ties within a defined group and excludes non-members. This approach has the advantage of being more reliable for assessing both network member characteristics and structure, as it directly captures both aspects (McCarty et al., 2019). Much sociometric research has been conducted in institutional settings (e.g., schools, workplaces), where social ties form within structurally constrained environments (Crosnoe et al., 2008; Schaefer et al., 2011; Schafer, 2016; Van Zalk et al., 2010a). These settings provide clear network boundaries that are crucial for eliciting sociometric data. However, they also shape network formation through sorting mechanisms and implicit compulsion, wherein individuals have limited agency in selecting their social ties, often forming homophilous connections within a predefined pool (McPherson et al., 2001). These setting constraints remain understudied, limiting our understanding of how social networks and health interact in contexts beyond institutional constraints.

Much of the existing socio-gerontological literature examines the relationship between social networks and health using egocentric networks while largely neglecting sociometric ones

(Ayalon & Levkovich, 2019), due to laborious data collection and challenges in defining clear network boundaries outside institutional settings. Moreover, the few sociometric studies conducted in aging research have primarily focused on institutionalized older adults, such as those in retirement and nursing homes or special care units (for a review, see Ayalon & Levkovich, 2019). However, these settings are already selective regarding a population's health, often including individuals in poor health who have a heightened need for support. This selection bias has implications for studying social network dynamics and health among adults in their second half of life, as the context itself influences network formation. I chose the sociometric research approach, as its advantages serve the research aim of this dissertation is on the network structure and network dynamics of people in their second half of life.

Research context: Jeckenstudie

To achieve my research aim, I collected longitudinal sociometric survey data within the project *Jeckenstudie*, funded by the German Research Foundation (DFG; PI: Prof. Dr. Lea Ellwardt). This survey comprises a three-wave panel study of members of three carnival clubs in a region in North Rhine-Westphalia, Germany. Carnival clubs play a central role in organizing cultural festivities during the carnival season, a lively and traditional celebration marked by parades, music, costumes, and parties leading up to Lent in the Christian calendar. Beyond the festivities, they engage members in year-round social activities, including summer festivals, monthly informal gatherings, and charity events. Carnival clubs are a setting for members to engage in formal social participation—specifically volunteering, defined as non-mandatory, unpaid work for an organization or community (Donnelly & Hinterlong, 2010).

Carnival clubs offer a compelling setting for studying community-based social networks among middle-aged and older adults for multiple reasons: their membership skews toward individuals in their second half of life, and the formal nature of participation provides clearly defined network boundaries, making them well-suited for sociometric analysis. Moreover, they remained active despite the social distancing restrictions imposed during the early years of the Covid-19 pandemic, demonstrating their resilience as social institutions—a crucial factor making them viable research setting at the start of this research project in 2022, shortly after most pandemic-related restrictions were lifted. Carnival clubs have relatively low health-related participation barriers or eligibility criteria.[1] Unlike sports clubs or retirement homes, the population in these carnival clubs is less health-selective. In fact, the self-rated health characteristics of their members closely resemble those of the broader German population (Robert Koch-Institut, 2018), indicating that these clubs do not disproportionately attract healthier individuals. This

[1] Two of the three carnival clubs selected for this study do not allow women to become members.

inclusivity minimizes selection bias when investigating health-related network structure and the interplay between health and social networks. Furthermore, these clubs offer a setting for informal social interactions within a diverse social environment beyond family, workplace, and neighborhood structures (cf. Granovetter, 1973).

Qualitative interviews conducted by Steinhoff et al. (2024) reveal that the primary motivation for joining carnival clubs is not participation in the festival itself but the sense of belonging they foster: members value the ease of social connection, as maintaining relationships requires little active effort. The following quotations illustrate the strategic use of carnival clubs to initiate and maintain social engagement (Steinhoff et al., 2024, p. 5):

> *“Because I basically had these two centres of life, it was simply difficult to build a normal, let’s say, social organisation around myself, i.e. a circle of friends, etc. [...] And basically that was one of the main arguments at the time, to look at it, to do it and say, yes, I have a circle of friends that is organized in a secondary way, so to speak.” (69 years, retired, male)*

> *“I don’t have that much interest in carnival. I have a great interest in the club. And that I walk through the streets and know people. [...] It’s also nice to have an extended circle of acquaintances. And socialising is something I enjoy.” (58 years, working, male)*

For retirees, carnival club participation serves as a proactive strategy for finding purpose and mitigating the loss of roles and status that can accompany exiting the workforce. Engagement in these clubs enhances members’ feelings of being useful and necessary, which are essential to well-being (Steinhoff et al., 2024).

Research design: Jeckenstudie

The longitudinal sociometric data collection derives from the larger multi-method project *Jeckenstudie*, which employs both qualitative and quantitative research approaches—namely, the collection of cross-sectional qualitative egocentric network data (e.g., Steinhoff et al., 2024) and longitudinal quantitative sociometric network data. As previously outlined, the latter provides the foundation for addressing my second research aim, as it offers the most suitable means of capturing the structural and temporal dynamics central to my research question. For this reason, I exclusively outline the quantitative research design below.

This study’s longitudinal data collection comprised three waves with an interval of six months to allow for sufficient change within the social networks and health characteristics. Research staff initially recruited professional contacts and further used snowball sampling to gain access to three carnival clubs. We restricted eligibility to active members only to ensure that every member had a nonzero chance of meeting and talking to every other member. After debriefing the club's gatekeeper before data collection, we excluded five members from study participation due to permanent inactivity, residence in institutional settings or distant locations. This led to a target baseline sample of 143 individuals, distributed across three clubs with 45 to 53 members each. No participants belonged to more than one of the selected clubs, resulting in three entirely non-overlapping networks.

Board members informed club members in advance of each wave of data collection, after which we invited participants to complete an online survey. The clubs' transition to online communication prompted by the Covid-19 pandemic, as well as participants' general familiarity with digital devices, enabled the use of a digital questionnaire. Where needed, research staff provided support via home visits, including two cases in which we gathered data via a Computer Assisted Personal Interview. The average time for survey completion was approximately 25.8 minutes.

Achieving high response rates is critical for conducting full-network social network analyses. To promote participation, this study offered a club-level incentive: each club could receive up to 500€, depending on its members' collective response rate. For instance, an 80% response rate would yield 400€. Additionally, we invited clubs to submit customized survey questions on topics of interest to them, which were appended to the end of the research questionnaire. We provided the club boards with summary reports of the responses to these additional questions, presented at an aggregated level to ensure the anonymity of club participants.

Data collection took place between November 2022 and March 2024 across three waves at intervals of six months. The study sample comprised 148 unique individuals, with a mean response rate of 81.2% across clubs and waves. While two clubs were involved in all three waves, the third club participated in only two waves. Two clubs were male-only, and in the third, 43% of participants were men. Participants' average age at baseline ranged from 53 to 58 years, with an overall age span of 21 to 86 years. The majority (96%) was born in present-day Germany. Educational attainment, classified using the CASMIN system (Federal Institute for Vocational Education and Training, 2024), showed that 19% of respondents had low education, 42% medium, and 39% high. Most respondents (73%) were employed, and 17% lived alone, while the rest shared their household with partners, children, parents, or others.

Ethical approval was granted by the University of Cologne's ethics committee (reference: 220036LE). The study adhered strictly to data protection standards and obtained informed consent from all participants.

1.4 Summary of the four studies

In this section, I comprehensively summarize the four studies included in this cumulative dissertation (see Table 1-1 for an overview of each study). Each study contributes to my overall research aim of analyzing the relationship between social network structure and health in the second half of life. I achieve this aim by fulfilling two primary objectives: (1) synthesizing and quantifying the scientific evidence on the relationship between structural social network aspects and depression and (2) examining the social network structure in relation to health while considering network member characteristics and network structural factors. The first two studies focus on the first objective, and the last two address the second objective. In the first study, I systematically review and synthesize existing research; in the second, I apply a meta-analytical approach to quantify the results of the first study. In the third study, I examine the structure of health advice networks among middle-aged and older adults while comparing them to the structure of more commonly studied networks of close ties by using cross-sectional data from the *Jeckenstudie*. In the fourth study, I draw on longitudinal data from the *Jeckenstudie* to explore health and network dynamics in later life within the fully voluntary setting of carnival clubs.

By synthesizing and quantifying research evidence as well as using advanced social network analysis methods, these studies collectively advance scholarly understanding of the relationship of social network structure and health in the second half of life. Following the summary, I discuss the key insights derived from the four studies and propose directions for future research and policy implications based on these findings.

Table 1-1 Overview of the dissertation studies

	Study 1	Study 2	Study 3	Study 4
Title	The association of social networks and depression in community-dwelling older adults: a systematic review	Social networks and their association with depression in community-dwelling older adults: a meta-analysis	Who would ask whom for health advice? The structural anatomy of health advice networks among middle-aged and older adults	Moving beyond constrained settings: Health and network dynamics among middle-aged and older adults in voluntary clubs
Research Question(s)	How do structural aspects of social networks impact depression outcomes in community-dwelling older adults, and vice versa?	a) What is the overall magnitude of the association between structural network aspects—namely, network size, network scales, and contact frequency—and depression in older adults? b) How does the effect of these structural network aspects on depression differ by gender? c) Which type of social network—mixed, family, or friends—has the strongest influence on depression outcomes in older adults?	What are the self-organizing principles of health advice networks of middle-aged and older adults in comparison to close relationship networks?	How does health status shape social networks in fully voluntary settings, and vice versa?
Dependent Variable(s)	a) Depression b) Structural aspects of social networks: composition, contact frequency, density, geographic proximity, homogeneity, scales, size	Effect size of social network aspects on depression	a) Health advice networks b) Close relationship networks	a) Close relationship networks b) Health: self-rated health, mental health, physical health
Core Independent Variable(s)	a) Structural aspects of social networks: composition, contact frequency, density, geographic proximity, homogeneity, scales, size b) Depression	a) Network indicator (network size, network scales, and contact frequency) b) Gender c) Type of alters (family, friends, neighbor, mixed)	a) Transitive closure b) Same gender c) Same age-group d) Same education e) Physical health: received nominations f) Mental health: received nominations	a) Health similarity b) Received nominations c) Given nominations d) Average health of close ties

	Study 1	Study 2	Study 3	Study 4
			g) Physical health: given nominations h) Mental health: given nominations i) Same physical health j) Same mental health	
Data	Self-collected: systematic search in seven electronic databases (APA PsycINFO, ProQuest, PSYINDEX, PubMed, Scopus, SocINDEX, and Web of Science)	Self-collected: systematic search in seven electronic databases (APA PsycINFO, ProQuest, PSYINDEX, PubMed, Scopus, SocINDEX, and Web of Science)	Self-collected: *Jeckenstudie*, survey wave 2, three clubs	Self-collected: *Jeckenstudie*, survey wave 1 to 3, two clubs
Statistical Method	Descriptive tables, count statistics	Bivariate and multivariate meta-regression	Exponential random graph models	Stochastic actor-oriented models
Co-author(s)	Paula Steinhoff	Elena De Gioannis & Paula Steinhoff	Mark Wittek & Lea Ellwardt	James Moody
Publication Status	Published in *Systematic Reviews* (2024, DOI: 10.1186/s13643-024-02581-6)	Published in *Aging & Mental Health* (2025, DOI: 10.1080/13607863.2025.2468892)	Revised and Resubmit at *Network Science*	Submitted to and under review at *Network Science*

1.4.1 Study 1: The association of social networks and depression in community-dwelling older adults: a systematic review

The first study synthesizes the evidence on the reciprocal relationship between structural aspects of social networks and depression in community-dwelling older adults. To address the gaps left by outdated and geographically limited prior literature reviews, this study analyzes existing research across geographically diverse regions to provide a comprehensive overview.

Seven electronic databases (APA PsycINFO, ProQuest, PSYINDEX, PubMed, Scopus, SocINDEX, and Web of Science) were searched from inception to July 11, 2023, applying strict inclusion and exclusion criteria. Inclusion criteria required that eligible studies had to focus on community-dwelling adults aged 40 and above, with a mean age of at least 60 years. Studies were required to include reference to the term "social network" in the abstract, use an acceptable definition of depression, apply multivariate analyses adjusting for confounders, be peer-reviewed, and written in English. We excluded studies focusing on patient or institutionalized populations, online networks, or retrospective accounts of networks, e.g., from young adulthood. We also excluded editorials, protocols, conference papers, comments, reviews, qualitative research, grey literature, case studies, and intervention studies. Our search strategy was informed by prior reviews and combined terms related to "depression," "social networks," and "older adults"; we assessed study quality using the Newcastle-Ottawa Scale.

Our final results include a total of 127 studies, identifying seven structural network domains: composition, contact frequency, density, geographic proximity, homogeneity, scales, and size. Most studies examined the association of depression and network size, composition, contact frequency, and scales but rarely addressed density, homogeneity, and proximity and thus yielded inconclusive findings. Most articles examined the causal relationship direction of structural network aspect on depression, typically cross-sectionally. Larger, more diverse networks and higher network scale scores were generally associated with lower levels of depression. However, findings on contact frequency were inconsistent. Also, no clear advantage was found for either family or friend networks, challenging previous assumptions about the primacy of family support. Gender differences in associations were minimal and inconsistent.

A minority of studies explored the reverse direction—how depression affects social networks. The studies revealed that depression reduces network size and alters composition, though evidence for its effect on contact frequency or density was inconsistent. Only five studies examined reciprocal effects, though none provided conclusive evidence of bidirectionality.

Contrary to earlier reviews, this study does not support the conclusion that functional aspects of social networks are more strongly associated with depression than structural ones.

Studies that examined both structural and functional aspects of social networks showed no consensus on their relative importance.

Given the limited longitudinal evidence and the underexplored domains of density, homogeneity, and proximity, causal inferences remain limited. The review underscores the need for future longitudinal research to clarify reciprocal pathways and guide interventions. Importantly, this systematic review highlights implications for social gerontology, suggesting that fostering larger, more diverse social networks may help buffer depression among older adults.

1.4.2 Study 2: Social networks and their association with depression in community-dwelling older adults: a meta-analysis

Building on the findings of the preceding systematic review (see Study 1), the second study aimed to systematically assess and quantify the strength of the association between structural aspects of social networks and depression outcomes in older adults. While prior reviews have been largely descriptive, this study addresses key uncertainties in the literature by providing a meta-analytic quantification. Due to limited statistical evidence on the reverse direction—how depression influences social networks—this study focuses exclusively on how social networks relate to depression. Three research questions guide the analyses of the study: (1) What is the overall magnitude of the association between structural network aspects and depression in older adults? (2) How does the effect of these structural network aspects on depression differ by gender? (3) Which type of social network—mixed, family, or friends—has the strongest influence on depression outcomes in older adults?

To ensure statistical comparability across studies, we included only studies examining the association of network size, scales, or contact frequency with depression. We excluded indicators such as proximity, density, homogeneity, and composition due to inconsistent measurement and limited use, which hinder statistical synthesis. Of the 127 studies from the prior review, 62 studies met the criteria for meta-analysis.

Using a random-effects meta-analytic approach, the study combined standardized beta coefficients for continuous depression outcomes ($N = 221$) and log odds for binary outcomes ($N = 42$) and assessed study quality, heterogeneity, and risk of bias.

Separate random-effects meta-analyses were conducted for continuous and binary depression outcomes. The overall association was small but statistically significant in both cases ($\beta = -0.078$; log odds $= -0.31$), indicating that larger networks, more frequent contact, and higher network scale scores are associated with lower depression levels. Network scales showed the greatest buffering effect for depression, followed by network size and contact frequency. However, the effect of network scales was only marginally significant in multivariate models.

Although the analysis revealed no significant gender differences, the study lacked sufficient statistical power to conduct subgroup analyses, limiting firm conclusions. Regarding network type, mixed and family networks have comparable associations with depression, but family ties have a greater buffering effect on depression than friend networks.

Although high heterogeneity was present, it was not fully explained by study characteristics and did not appear to undermine the robustness of results. Some evidence of publication bias warrants caution, particularly in studies using binary depression outcomes. Continuous measures offered more nuanced insights, as binary classifications may be an oversimplified measure of depressive symptoms.

In conclusion, although the overall association between structural social network characteristics and depression is modest, its consistency across indicators underscores the relevance of this association in understanding mental health in older adults. Future research should prioritize more nuanced subgroup analyses, particularly by gender and network type, and further explore the longitudinal impact of social networks on depression.

1.4.3 Study 3: Who would ask whom for health advice? The structural anatomy of health advice networks among middle-aged and older adults

The third study aimed to examine the self-organizing principles of health advice networks through a comparison to those of close relationships among middle-aged and older adults. Prior research has emphasized the role of close ties in health advice (Perry & Pescosolido, 2010, 2015) while largely overlooked health advice seeking beyond close relationships—despite their potential to provide novel, nonredundant information (Granovetter, 1973). Rather than focusing on actual health advice exchanged, this study emphasizes the perceived availability of advice—who individuals believe they could consult— which captures the latent potential of social networks to influence health behavior in times of need. Moreover, most studies lack complete network data, limiting the understanding of structural patterns that shape health-related advice opportunities. To help close this gap, this study examines health advice networks among middle-aged and older adults within the unique context of voluntary associations, specifically carnival clubs in Germany. As spaces tend to be less health-selective and feature formally bounded memberships with a high proportion of middle-aged and older adults, carnival clubs offer an ideal context to explore health advice networks beyond an individual's immediate social circle.

Using the cross-sectional data from second wave of the *Jeckenstudie*, which contains all the relevant information required for this study, our analysis includes data for 143 individuals (mean age = 53.9 years) across three carnival clubs to examine health advice networks and close tie networks in relation to health and socio-demographic variables. Anticipating that processes tend to differ by health status, we distinguish between mental and physical health.

Our analyses demonstrate that networks of health advice and close relationships overlap by only 34%. Applying recent advances in Exponential Random Graph Models (ERGMs), we reveal that the structural patterns of health advice networks differ markedly from those of close relationship networks. Notably, health advice networks display lower transitivity, indicating a broader and less clustered structure, which is likely driven by the functional specificity of social interactions. We also observed stronger homophily in health advice networks regarding gender and age, suggesting that shared characteristics facilitate the exchange of sensitive health information. Interestingly, individuals in poor physical health were less likely to perceive others as health advisors but more likely to be nominated as close ties compared to those in good health. In contrast, we found that mental health status did not significantly affect engagement in either health advice or close relationship networks. These patterns suggest that voluntary associations may offer unanticipated benefits by fostering inclusive spaces where individuals, regardless of their health status, can engage socially with both close and distant confidants without fear of marginalization.

These findings highlight the value of voluntary associations as informal, yet structured, social environments that may foster access to diverse health information and support, even beyond close-knit ties. Despite their primary purposes, such associations may serve as unexpected conduits for social capital. Taken together, our study underscores the need to understand how health advice is embedded within broader social contexts, as well as how the structures of these contexts shape individuals' opportunities to obtain health advice. Future research would benefit from longitudinal approaches to more effectively capture the dynamics of health status and advice seeking behavior over time.

1.4.4 Study 4: Moving beyond constrained settings: Health and network dynamics among middle-aged and older adults in voluntary clubs

The aim of this fourth empirical study is to examine whether assumptions about network dynamics and health generally hold among middle-aged and older adults in a fully voluntary setting. Prior research has examined health and network dynamics in constrained settings, such as schools, workplaces or other institutional contexts (Chancellor et al., 2017; Crosnoe et al., 2008; Flatt et al., 2012; Schaefer et al., 2011; Schafer, 2016; Van Zalk et al., 2010a). However, existing research has failed to specify how the inherent constraints of these environments shape previously identified social mechanisms of homophilous sorting and network formation. Therefore, this study examines the reciprocal relationship between health and social networks in a fully voluntary context in which members often self-select into groups.

Using three-wave longitudinal whole network data from two carnival clubs in Germany (n = 102; wave 1 to wave 3, *Jeckenstudie*) and Stochastic Actor-Oriented Models (SAOMs), we analyze close relationship networks in two carnival clubs, distinguishing selection from influence effects across self-rated, mental, and physical health measures.

Our findings diverge from those observed in more constrained settings: specifically, we found no evidence of health influence, suggesting that health does not spread through these networks within the observed time frame. Selection effects were limited and specific: while our analysis reveals some social avoidance of individuals with poor physical health, there was no broad evidence of health-based homophily. Notably, individuals in poorer health, particularly with poor mental health, were more likely to nominate others as close ties, suggesting active social engagement rather than withdrawal. This may reflect a compensatory strategy to maintain social connectedness and mitigate health-related challenges.

These results challenge prevailing assumptions about health-based network dynamics, particularly assumptions about social withdrawal and health contagion, and underscore the importance of voluntary settings as inclusive environments that sustain social participation regardless of health status. Thus, we argue that theories of health and network dynamics must consider the role of setting constraints, as our findings suggest that such dynamics may be stronger in environments where participation is not self-selected and structures are constrained.

Future research should explore health-network processes across a spectrum of contexts, varying by boundedness, to refine theoretical scope conditions. Longer observation periods and larger samples would help determine whether influence effects emerge over time or are attributable to specificities of settings.

1.5 Conclusions

1.5.1 Summary of the key findings and contributions

This dissertation explored the interrelationship between social network structure and health in the second half of life through two primary objectives. First, I synthesized and quantified the vast body of scientific evidence on the relationship between structural social network aspects and depression. Second, I followed a more holistic methodological approach by examining the social network structure in relation to health while considering network member characteristics, and network structural factors. Here, I specifically examined the structure of health advice networks and further, focused on the reciprocal relationship of social networks and health among adults in the second half of life in a fully voluntary context, specifically carnival clubs. By combining systematic evidence synthesis and quantification with advanced empirical analyses in a fully voluntary social setting consisting of primarily people in the second half of life, this dissertation contributes to the literature in three keyways.

First, structural characteristics of social networks play a significant, albeit moderate, role in shaping depression outcomes in later life. Synthesizing (see Study 1) and quantifying (see Study 2) the vast body of research evidence on the association of social networks and depression among older adults, I found the following. While the relationship is reciprocal, most studies follow the Main Effect Model (Kawachi & Berkman, 2001), in which depression is considered an outcome of social network characteristics, yet the reverse dynamic—how depression affects social networks—lacks robust empirical evidence despite theoretical recognition. Even less evidence exists regarding the conjoint reciprocal examination of the relationship at interest. Key findings show that larger network size, higher contact frequency and especially higher network scale scores were associated with lower levels of depression. These patterns held across various regions and study designs, suggesting a robust relationship between structural aspects of social networks and depression in later life. Gender differences in the association between social networks and depression were minimal and inconsistent. Further, network scales combining functional and structural aspects of social relationships tend to exhibit a greater buffering effect on depression outcomes than network size or contact frequency. This tentative trend is consistent with the Main Effect Model (Kawachi & Berkman, 2001), which posits that the psychological benefits of social networks stem not just from their size but also from their functional roles, such as providing emotional support. Additionally, family or mixed networks tend to show a stronger protective effect against depression than friend-only networks. This tentative evidence concurs with existing research highlighting diverse views on the relative contributions of family and friends to mental health in later life. Some scholars underscore the distinct advantages of family ties, often referring to their long-term stability and greater likelihood of providing instrumental and emotional support (Antonucci et al., 2011; Litwin, 2011). In contrast, other studies suggest friendships, particularly those characterized by high quality and low conflict, to be equally or even more beneficial for the emotional well-being of older adults (Huxhold et al., 2014).

Second, health advice networks of middle-aged and older adults extend beyond close ties and are shaped by structural patterns that differ from those governing close relationship networks. Consistent with prior research (Small, 2013), a notable proportion of ties are exclusively characterized by health advice, without the presence of a close relationship (see Study 3). Compared to close relationship networks, health advice networks exhibit lower transitive closure, denoting broader, more open structures that facilitate the flow of novel and diverse information. This finding reinforces the idea that social interaction is function-specific and goal-directed (Perry & Pescosolido, 2010; Small, 2013), with individuals identifying health advisors outside their immediate social circle. These findings align with the argument that (in)formal social environments such as voluntary clubs like those included in this study can serve as an unexpected source of valuable resources (Martin et al., 2001; Small, 2009). Additionally, we found that individual health status and homophily in sociodemographic characteristics are associated with variations in the tendency to perceive others as health advisors. Shared gender and age increase the likelihood of identifying someone as health advisor, likely serving as a proxy for shared experiences and sensitive health topics. Importantly, the integration into health advice networks differs by health status. Compared to those in good health, individuals with poor mental health were not more likely to nominate or be nominated as health advisor, while those with poor physical health were significantly less likely to nominate others as health advisor. This suggests that obtaining health advice when in poor health is not that common in the contexts of voluntary associations, perhaps arising from fear of stigmatization that visible illnesses carry (Link & Phelan, 2001). However, our findings suggest that while individuals may identify potential health advisors selectively, these nominations extend beyond close relationships.

Third, the network structure and network dynamics in relation to health in fully voluntary settings differ from those in more constrained settings. The structure of close relationship networks, as well as the ways in which health shapes social dynamics, diverge from patterns found in constrained settings. Contrary to the theoretical assumptions about stigma surrounding poor health (Link & Phelan, 2001) and previous findings that show individuals in poor health to be less popular as friends (Crosnoe et al., 2008; Galenkamp & Deeg, 2016; Haas et al., 2010; Schafer, 2016), the results of this dissertation indicate individuals with poor physical health are more likely to be nominated as close ties compared to those with good physical health when examining network structure cross-sectionally (see Study 3). This suggests that, in voluntary settings, the formation of close relationships may not be determined by poor health. However, longitudinal analyses (see Study 4) reveal a more nuanced picture: while some evidence shows that declining physical health can lead to social avoidance by others, this effect appears to be tentative and weaker than in studies conducted in more constrained environments (Crosnoe et al., 2008; Haas et al., 2010). Thus, relational dynamics of avoidance can still occur, even though individuals in poor physical health might receive more nominations as close ties, indicating the coexistence of social integration and subtle exclusion in this voluntary setting. Additionally, we found suggestive evidence for the reverse relational dynamic of social withdrawal of people with poor mental and self-rated health: rather than withdrawing, they were more active in forming close ties than their healthier peers. In line with the Network Episode Model (Pescosolido, 1991, 1992), this may indicate that, in voluntary contexts, social ties are used as a source of support or compensation, rather than socially withdrawing out of fear of anticipated stigma. Further, our findings show only limited evidence for health-based homophily and no indication of health-related social influence over time, which challenges existing theoretical assumptions on network structure and dynamics in relation to health, which have largely been developed and tested in constrained settings (Chancellor et al., 2017; Christakis & Fowler, 2013; Crosnoe et al., 2008; Schafer, 2016). Together, these findings suggest that the scope conditions of health-related relational processes are shaped by the broader social context, particularly by the degree of voluntariness in social participation. While exclusionary processes such as avoidance may still occur in voluntary settings, they appear less pronounced than in more constrained environments. As such, these settings may serve as relatively inclusive social spaces for middle-aged and older adults, where individuals can participate and build relationships without fear of marginalization due to their health status.

1.5.2 Limitations

Despite the unique contributions of this dissertation, it has some limitations. Note that each chapter of this dissertation discusses distinct limitations, which are reiterated in the respective discussion sections for each study. In this section, I outline four broader limitations of my dissertation.

First, while my focus is on individuals in the second half of life, I exclusively examine community-dwelling adults, which excludes institutionalized individuals who represent a small but important population of older adults—4.4% of people aged 65 and older in Germany (Statistisches Bundesamt, 2025). This distinct subgroup is characterized by heightened support needs and increased health challenges that in turn impact the interrelation between social networks and health. Furthermore, the institutional context itself significantly influences network structure and relational processes relevant to health outcomes (Abbott & Pachucki, 2017; Casey et al., 2016; Schafer, 2016). To enhance analytical clarity, I deliberately concentrate my analysis on community-dwelling middle-aged and older adults. Nonetheless, it is important to acknowledge that the associations between social network characteristics and health may differ in institutional contexts, and thus the findings of this dissertation are not necessarily generalizable to institutionalized populations.

Second, my dissertation focuses exclusively on the structural dimensions of social networks, intentionally leaving aside their functional aspects, such as social support. Along with the suggestive findings of my meta-analysis presented in Study 2, prior research indicates that functional characteristics could be at least equally as relevant for understanding health outcomes (Schwarzbach et al., 2014). However, my research here is driven by specific theoretical considerations, as structural features are the foundation upon which functional processes emerge (Kawachi & Berkman, 2001). From this perspective, structural characteristics can be understood as opportunity structures that shape the flow of resources, such as health-related information. By analyzing network structure, I contribute to scholarly understanding of the conditions which enable beneficial relational processes. Nevertheless, I acknowledge that structural analysis alone does not permit conclusions about the actual presence, quality, or accessibility of social support, or other functional aspects of social relationships. As such, this approach cannot capture whether ties are supportive, ambivalent, or even strained. Given that difficult or ambivalent ties are more commonly found within kin networks (Fingerman et al., 2004; Offer & Fischer, 2018), and my research focuses on a voluntary, mainly non-familial context, their potential influence is likely limited.

Third, a key limitation shared by Studies 3 and 4 that is common to many social network studies is their reliance on a specific social setting (Ellwardt et al., 2012; Schafer, 2016; Vörös et al., 2021; Yap & Harrigan, 2015), which limits the generalizability of our findings. Although the health status of the study population in Studies 3 and 4 is largely comparable to that of the broader population, the context in which data were collected—namely, carnival clubs—may introduce a selection bias. Individuals who voluntarily participate in such clubs are likely to exhibit higher levels of sociability and social integration than the general population. This may result in structurally richer or more cohesive networks, potentially amplifying the observed associations between network characteristics and health. Consequently, while the setting provides a meaningful lens into socially engaged network structures, the findings must be understood as context-bound and cannot be generalized to socially non-participating individuals or beyond the scope of this particular case study.

Fourth, Studies 3 and 4 do not capture ties outside the observed networks, including close personal relationships (e.g., spouses, children, close friends), as well as other health advisors. This is a notable limitation, as previous egocentric research highlights the importance of close ties, such that health advice networks often center around core supporters (Perry & Pescosolido, 2010). Additionally, close ties have a profound impact on individual health, both directly—through social support—and indirectly, by their health as well as influencing behaviors and perceptions related to health. Nevertheless, I argue that studying community-based networks beyond individuals' immediate personal circle yields distinct and valuable insights. First, empirical evidence from this dissertation indicates that health advice ties overlap with close personal ties in only 34% of cases, suggesting that health-related conversations frequently extend beyond the intimate sphere. Second, while sociometric approaches necessarily constrain the study population, they offer critical advantages: they allow for the direct observation of network structure, integration of network member characteristics, and identification of mechanisms such as selection and influence—factors that are central to understanding how social ties affect health. These features also make sociometric designs particularly powerful for developing targeted and effective social interventions.

Fifth, my dissertation relies entirely on survey data, potentially introducing bias due to unreported existing social ties. In comparison to the general population, this recall bias is likely more pronounced among this study population of middle-aged and older adults (Bell et al., 2007). Furthermore, individuals with poor mental health might also underreport their networks due to cognitive bias (Beck, 1967, 1979). While observational studies, or those using devices to track face-to-face interactions, can mitigate recall bias, they neglect the functional dimensions of relationships (e.g., health advice networks or close ties) that our research aims to capture. Moreover, the complexity and resource demands of real-time tracking fell outside the project timeframe, which aimed to capture changes in health—a process that requires a longer duration over years. Consequently, we opted to elicit social networks via survey data.

1.5.3 Implications and avenues for future research

The findings of this dissertation carry important implications for future research regarding social networks and health in the second half of life. *First*, the synthesis of existing evidence highlights a substantial gap in understanding the causal influence of depression on social network aspects. An even more pronounced gap concerns the reciprocal relationship between social networks and depression, which continues to limit causal inference. In general, existing research has largely overlooked how structural characteristics such as network density, geographic proximity, and homogeneity intersect to influence depression among older adults. To strengthen the evidence base, future studies should conduct more nuanced subgroup analyses, particularly with respect to gender and types of social ties, as well as prioritize longitudinal designs that can clarify causality. Finally, harmonizing cutoff thresholds in studies using binary depression measures would enhance comparability and reduce measurement variability, thereby improving the reliability of findings across studies.

Second, my findings underscore the need to account for network structure, network member characteristics, and ties beyond the immediate social circle when examining the relationship between social ties and health in later life. Study 3 demonstrates that health advice extends close relationships and is likely to be exchanged through more distant or peripheral ties. Such exchanges appear to be function-specific and goal-oriented, sometimes even occurring between weak ties or strangers (Perry & Pescosolido, 2010; Small, 2013). Traditional egocentric approaches that rely on name generators tend to overlook these types of connections, yet they may play a vital role in health-related support. Future research should aim to elicit these overlooked ties and integrate information on network structure and member characteristics. Examining structural features also helps identify opportunity structures for support exchanges, such as the flow of health advice. Moreover, network member attributes significantly influence both the potential for advice exchange and the likelihood of tie formation. As such, advancing research on social networks and health requires a broader lens in large-scale studies—one that moves beyond the intimate social circle to consider how wider social contexts and individual characteristics shape support dynamics.

Third, it is crucial to consider the nature of the study setting in which the interrelation between social networks and health is studied. The results of Studies 3 and 4 suggest that network dynamics in relation to health might differ depending on the degree of contextual constraint. In institutional contexts, network formation is often shaped by structural limitations and implicit compulsion, as individuals have limited choice over their social ties and tend to form homophilous relationships within a fixed pool (McPherson et al., 2001). In contrast, fully voluntary settings such as carnival clubs allow for greater agency in tie selection, resulting in different patterns of network dynamics and structure. Importantly, carnival clubs serve as an illustrative and underutilized case of voluntary, community-based engagement. Although this study centers on a specific context, the mechanisms uncovered are likely relevant across a wide range of voluntary associations. In Germany, approximately 24.2 million people are active in clubs or associations (Priemer et al., 2019); in the U.S., nearly 76 million adults—28.3% of the population—volunteered through an organization in 2023 (AmeriCorps, 2024). Such widespread engagement underscores the broader significance of voluntary contexts for research on social networks, health, and aging, especially given that older adults often use formal volunteering as a strategy to maintain social connections and mitigate loneliness (Donnelly & Hinterlong, 2010; Jongenelis et al., 2022). In light of their long-term, self-selected, and meaningful nature, voluntary associations offer a promising context for advancing network theory and informing public health strategies. Hence, future research would benefit from comparative study of contexts with varying levels of structural constraint, as well as investigation of other voluntary associations. Following Berkman et al.'s (2000) framework, such comparative studies are particularly useful for capturing the nuanced ways that diverse social environments shape network dynamics and health.

1.5.4 Policy implications

The findings of this dissertation underscore the importance of strengthening social networks to support health in the second half of life. This is particularly relevant for policymakers, as middle-aged and older adults represent the largest demographic population group in Western societies and face both age-related health challenges and a shrinking social network over the life course (Wrzus et al., 2013). By reviewing and synthesizing the scientific evidence, I have identified larger, more diverse social networks with frequent contact as particularly beneficial for health outcomes, notably depression, among older adults. My findings emphasize the importance of strengthening personal networks of older adults to mitigate worsening health. Such efforts can occur on two levels: reinforcing existing ties and facilitating access to new social connections through inclusive community settings.

My research shows that carnival clubs, characterized as local, social communities that impose no formal health-related participation barriers and offer a particularly beneficial social context. On one hand, they provide access to diverse, non-redundant health-related information beyond one's immediate social circle; on the other, they offer a social context in which individuals are socially integrated regardless of health status, a contrast to findings in more constrained settings. While subtle signs of avoidance may occur, people in poor health remain embedded in the network, and I found no evidence of social withdrawal as health declined. As such, my findings highlight the importance of fostering open and accessible community environments where middle-aged and older adults can develop diverse and supportive social ties, free from the risk of exclusion due to health limitations. Putnam (2001) underscores the importance of civic involvement for social trust and community bonds. Inclusive community-based settings that do not restrict participation based on health, such as those examined in this research, have the potential to reduce social divides and play a meaningful role in advancing public health and strengthening social cohesion in aging societies.

On this basis, policy efforts should focus on three key areas. *First*, local associations and voluntary clubs, particularly those that foster diverse contacts, should receive financially subsidies. *Second*, civic infrastructure must be strengthened, especially in aging regions, by creating and maintaining accessible community spaces. This includes practical measures such as subsidized transportation to enable participation even as mobility and physical health decline. *Third*, while health professionals can play a role in encouraging engagement, maintaining the voluntary nature of participation is essential. Based on my findings, it is precisely this intrinsic voluntariness that enhances the benefits of participation, distinguishing these spaces from more formalized interventions like *social prescribing* (NHS England, n.d.).

1.6 Status of the studies and contributions of co-authors

The first study, titled “The association of social networks and depression in community-dwelling older adults: a systematic review” was published 2024 in *Systematic Reviews* (DOI: 10.1186/s13643-024-02581-6). As first author, I developed the design of the study, screened the articles, led the analysis and interpretation of the data, and wrote the manuscript. Paula Steinhoff (University of Cologne) contributed to the conceptualization of the study, participated in screening the articles, supported the analysis and interpretation of the data, and reviewed and edited the manuscript.

The second study, titled “Social networks and their association with depression in community-dwelling older adults: a meta-analysis” was published 2025 in *Aging & Mental Health* (DOI: 10.1080/13607863.2025.2468892). As first author, I developed the study design, screened the articles, extracted the data, and wrote the introduction, theoretical background, as well as parts of the methods and results sections of the manuscript. Further, I wrote the discussion section of the manuscript. Elena De Gioannis (University of Milan) extracted the data, conducted the statistical analyses, contributed to the methods section, wrote the results section, and reviewed and edited the manuscript. Paula Steinhoff (University of Cologne) screened the articles and contributed to the review and editing of the manuscript.

The third study, titled “Who would ask whom for health advice? The structural anatomy of health advice networks among middle-aged and older adults” is currently undergoing revision following a revise-and-resubmit decision from *Network Science*. As first author, I developed the research question, designed the methodology, prepared the data, conducted the empirical analyses, and wrote the manuscript. Mark Wittek (Central European University) contributed to the conceptualization of the study, helped writing the introduction, provided methodological suggestions, and edited the manuscript. Lea Ellwardt (University of Cologne) contributed to the conceptualization of the study and edited the manuscript.

The fourth study, titled “Moving beyond constrained settings: Health and network dynamics among middle-aged and older adults in voluntary clubs” is currently under review at *Network Science.* As first author, I developed the research question, designed the methodology, prepared the data, conducted the empirical analyses, and wrote the manuscript. James Moody (Duke University) contributed to the conceptual framing of the study, supported data visualization, and provided feedback on the manuscript.

1.7 References

Abbott, K. M., Bettger, J. P., Hanlon, A., & Hirschman, K. B. (2012). Factors associated with health discussion network size and composition among elderly recipients of long-term services and supports. *Health Communication*, *27*(8), 784–793. https://doi.org/10.1080/10410236.2011.640975

Abbott, K. M., & Pachucki, M. C. (2017). Associations between social network characteristics, cognitive function, and quality of life among residents in a dementia special care unit: A pilot study. *Dementia*, *16*(8), 1004–1019. https://doi.org/10.1177/1471301216630907

AmeriCorps. (2024). *More than 75.7 million people volunteered in America, AmeriCorps Reports*. AmeriCorps. https://americorps.gov/newsroom/press-release/more-757-million-people-volunteered-america-americorps-reports

Antonucci, T. C., Birditt, K. S., Sherman, C. W., & Trinh, S. (2011). Stability and change in the intergenerational family: A convoy approach. *Ageing and Society*, *31*(7), 1084–1106. https://doi.org/10.1017/S0144686X1000098X

Ayalon, L., & Levkovich, I. (2019). A systematic review of research on social networks of older adults. *The Gerontologist*, *59*(3), e164–e176. https://doi.org/10.1093/geront/gnx218

Bearman, P., & Parigi, P. (2004). Cloning headless frogs and other important matters: Conversation topics and network structure. *Social Forces, 83*(2), 535–557. https://doi.org/10.1353/sof.2005.0001

Beck, A. T. (1967). *Depression.* Harper and Row.

Beck, A. T. (1979). *Cognitive therapy and the emotional disorders*. Penguin Publishing Group.

Bell, D. C., Belli-McQueen, B., & Haider, A. (2007). Partner naming and forgetting: Recall of network members. *Social Networks*, *29*(2), 279–299. https://doi.org/10.1016/j.socnet.2006.12.004

Berkman, L. F. (1995). The role of social relations in health promotion. *Psychosomatic Medicine*, *57*(3), 245–254. https://doi.org/10.1097/00006842-199505000-00006

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social Science & Medicine*, *51*(6), 843–857. https://doi.org/10.1016/S0277-9536(00)00065-4

Block, P., & Burnett Heyes, S. (2022). Sharing the load: Contagion and tolerance of mood in social networks. *Emotion*, *22*(6), 1193–1207. https://doi.org/10.1037/emo0000952

Cacioppo, J. T., Fowler, J. H., & Christakis, N. A. (2009). Alone in the crowd: The structure and spread of loneliness in a large social network. *Journal of Personality and Social Psychology*, *97*(6), 977–991. https://doi.org/10.1037/a0016076

Casey, A.-N. S., Low, L.-F., Jeon, Y.-H., & Brodaty, H. (2016). Residents perceptions of friendship and positive social networks within a nursing home. *The Gerontologist*, *56*(5), 855–867. https://doi.org/10.1093/geront/gnv146

Chancellor, J., Layous, K., Margolis, S., & Lyubomirsky, S. (2017). Clustering by well-being in workplace social networks: Homophily and social contagion. *Emotion*, *17*(8), 1166–1180. https://doi.org/10.1037/emo0000311

Chapman, A., Verdery, A. M., & Moody, J. (2022). Analytic advances in social networks and health in the twenty-first century. *Journal of Health and Social Behavior*, *63*(2), 191–209. https://doi.org/10.1177/00221465221086532

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, *357*(4), 370–379. https://doi.org/10.1056/NEJMsa066082

Christakis, N. A., & Fowler, J. H. (2011). *Connected: The surprising power of our social networks and how they shape our lives* (First ebook edition). Little, Brown Spark.

Christakis, N. A., & Fowler, J. H. (2013). Social contagion theory: Examining dynamic social networks and human behavior. *Statistics in Medicine*, *32*(4), 556–577. https://doi.org/10.1002/sim.5408

Cohen, S. (2004). Social relationships and health. *American Psychologist*, *59*(8), 676–684. https://doi.org/10.1037/0003-066X.59.8.676

Cohen, S., & Syme, S. L. (1987). Issues in the study and application of social support. In S. Cohen & S. L. Syme (Eds.), *Social support and health* (2. print, pp. 3–22). Academic Press.

Cohen, S., Underwood, L. G., Gottlieb, B. H., & Fetzer Institute (Eds.). (2000). *Social support measurement and intervention: A guide for health and social scientists*. Oxford University Press.

Cohen, S., & Wills, T. A. (1985). Stress, social support, and the buffering hypothesis. *Psychological Bulletin*, *98*(2), 310–357. https://doi.org/10.1037/0033-2909.98.2.310

Copeland, M., Kamis, C., & West, J. S. (2023). To make and keep friends: The role of health status in adolescent network tie formation and persistence. *Social Networks*, *74*, 216–223. https://doi.org/10.1016/j.socnet.2023.04.005

Cornwell, B., Schumm, L. P., Laumann, E. O., & Graber, J. (2009). Social networks in the NSHAP study: rationale, measurement, and preliminary findings. *The Journals of Gerontology Series B*, *64B*(Supplement 1), i47–i55. https://doi.org/10.1093/geronb/gbp042

Cowan, S. K., & Baldassarri, D. (2018). "It could turn ugly": Selective disclosure of attitudes in political discussion networks. *Social Networks*, *52*, 1–17. https://doi.org/10.1016/j.socnet.2017.04.002

Crosnoe, R., Frank, K., & Mueller, A. S. (2008). Gender, body size and social relations in American high schools. *Social Forces*, *86*(3), 1189–1216. https://doi.org/10.1353/sof.0.0004

Donnelly, E. A., & Hinterlong, J. E. (2010). Changes in social participation and volunteer activity among recently widowed older adults. *The Gerontologist*, *50*(2), 158–169. https://doi.org/10.1093/geront/gnp103

Durkheim, E. (1951). *Suicide* (2nd ed.). Routledge. https://doi.org/10.4324/9780203994320

Ellwardt, L., Steglich, C., & Wittek, R. (2012). The co-evolution of gossip and friendship in workplace social networks. *Social Networks*, *34*(4), 623–633. https://doi.org/10.1016/j.socnet.2012.07.002

Eurostat. (2022). *Persons reporting a chronic disease, by disease, sex, age and educational attainment level* [Dataset]. Eurostat. https://doi.org/10.2908/HLTH_EHIS_CD1E

Eveland, W. P., Appiah, O., & Beck, P. A. (2018). Americans are more exposed to difference than we think: Capturing hidden exposure to political and racial difference. *Social Networks*, *52*, 192–200. https://doi.org/10.1016/j.socnet.2017.08.002

Federal Institute for Vocational Education and Training. (2024). *Comparative Analysis of Social Mobility in Industrial Nations (CASMIN)*. https://metadaten.bibb.de/en/classification/detail/16

Festinger, L. (1957). *A theory of cognitive dissonance*. Stanford University Press.

Fingerman, K. L., Hay, E. L., & Birditt, K. S. (2004). The best of ties, the worst of ties: Close, problematic, and ambivalent social relationships. *Journal of Marriage and Family*, *66*(3), 792–808. https://doi.org/10.1111/j.0022-2445.2004.00053.x

Flatt, J. D., Agimi, Y., & Albert, S. M. (2012). Homophily and health behavior in social networks of older adults. *Family & Community Health*, *35*(4), 312–321. https://doi.org/10.1097/FCH.0b013e3182666650

Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ*, *337*, a2338. https://doi.org/10.1136/bmj.a2338

Galenkamp, H., & Deeg, D. J. H. (2016). Increasing social participation of older people: Are there different barriers for those in poor health? Introduction to the special section. *European Journal of Ageing*, *13*(2), 87–90. https://doi.org/10.1007/s10433-016-0379-y

Gariépy, G., Honkaniemi, H., & Quesnel-Vallée, A. (2016). Social support and protection from depression: Systematic review of current findings in Western countries. *British Journal of Psychiatry*, *209*(4), 284–293. https://doi.org/10.1192/bjp.bp.115.169094

Golinelli, D., Ryan, G., Green, H. D., Kennedy, D. P., Tucker, J. S., & Wenzel, S. L. (2010). Sampling to reduce respondent burden in personal network studies and its effect on estimates of structural measures. *Field Methods*, *22*(3), 217–230. https://doi.org/10.1177/1525822X10370796

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380.

Griffith, L. E., Raina, P., Levasseur, M., Sohel, N., Payette, H., Tuokko, H., Van Den Heuvel, E., Wister, A., Gilsing, A., & Patterson, C. (2017). Functional disability and social participation restriction associated with chronic conditions in middle-aged and older adults. *Journal of Epidemiology and Community Health*, *71*(4), 381–389. https://doi.org/10.1136/jech-2016-207982

Haas, S. A., Schaefer, D. R., & Kornienko, O. (2010). Health and the structure of adolescent social networks. *Journal of Health and Social Behavior*, *51*(4), 424–439. https://doi.org/10.1177/0022146510386791

Harandi, T. F., Mohammad Taghinasab, M., & Dehghan Nayeri, T. (2017). The correlation of social support with mental health: A meta-analysis. *Electronic Physician*, *9*(9), 5212–5222. https://doi.org/10.19082/5212

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1993). Emotional contagion. *Current Directions in Psychological Science*, *2*(3), 96–100. https://doi.org/10.1111/1467-8721.ep10770953

Heinrichs, M., Baumgartner, T., Kirschbaum, C., & Ehlert, U. (2003). Social support and oxytocin interact to suppress cortisol and subjective responses to psychosocial stress. *Biological Psychiatry*, *54*(12), 1389–1398. https://doi.org/10.1016/S0006-3223(03)00465-7

Hogue, A., & Steinberg, L. (1995). Homophily of internalized distress in adolescent peer groups. *Developmental Psychology*, *31*(6), 897–906.

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *PLoS Medicine*, *7*(7), e1000316. https://doi.org/10.1371/journal.pmed.1000316

House, J. S. (1987). Social support and social structure. *Sociological Forum*, *2*(1), 135–146. https://doi.org/10.1007/BF01107897

Huxhold, O., Miche, M., & Schuz, B. (2014). Benefits of having friends in older ages: Differential effects of informal social activities on well-being in middle-aged and older adults. *The Journals of Gerontology: Series B*, *69*(3), 366–375. https://doi.org/10.1093/geronb/gbt029

Jongenelis, M. I., Jackson, B., Newton, R. U., & Pettigrew, S. (2022). Longitudinal associations between formal volunteering and well-being among retired older people: Follow-up results from a randomized controlled trial. *Aging & Mental Health*, *26*(2), 368–375. https://doi.org/10.1080/13607863.2021.1884845

Kawachi, I., & Berkman, L. F. (2001). Social ties and mental health. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, *78*(3), 458–467. https://doi.org/10.1093/jurban/78.3.458

Kawachi, I., Kennedy, B. P., Lochner, K., & Prothrow-Stith, D. (1997). Social capital, income inequality, and mortality. *American Journal of Public Health*, *87*(9), 1491–1498. https://doi.org/10.2105/AJPH.87.9.1491

Krackhardt, D. (1987). Cognitive social structures. *Social Networks*, *9*(2), 109–134. https://doi.org/10.1016/0378-8733(87)90009-8

Kuiper, J. S., Zuidersma, M., Oude Voshaar, R. C., Zuidema, S. U., van den Heuvel, E. R., Stolk, R. P., & Smidt, N. (2015). Social relationships and risk of dementia: A systematic review and meta-analysis of longitudinal cohort studies. *Ageing Research Reviews*, *22*, 39–57. https://doi.org/10.1016/j.arr.2015.04.006

Kuiper, J. S., Zuidersma, M., Zuidema, S. U., Burgerhof, J. G. M., Stolk, R. P., Oude Voshaar, R. C., & Smidt, N. (2016). Social relationships and cognitive decline: A systematic review and meta-analysis of longitudinal cohort studies. *International Journal of Epidemiology*, 1169–1206. https://doi.org/10.1093/ije/dyw089

Lasserson, T. J., Thomas, J., & Higgins, J. P. (2019). Starting a review. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), *Cochrane handbook for systematic reviews of interventions* (1st ed., pp. 1–12). Wiley. https://doi.org/10.1002/9781119536604.ch1

Lazarsfeld, P. F., & Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. In M. Berger & T. Abel (Eds.), *Freedom and control in modern society* (pp. 18–66). Van Nostrand.

Lewinsohn, P. M. (1974). A behavioral approach to depression. In R. J. Friedman & M. M. Katz (Eds.), *The psychology of depression: Contemporary theory and research* (pp. 157–185). John Wiley & Sons.

Lin, N., Ye, X., & Ensel, W. M. (1999). Social support and depressed mood: A structural analysis. *Journal of Health and Social Behavior*, *40*(4), 344–359. https://doi.org/10.2307/2676330

Link, B. G. (1987). Understanding labeling effects in the area of mental disorders: An assessment of the effects of expectations of rejection. *American Sociological Review*, *52*(1), 96–112. https://doi.org/10.2307/2095395

Link, B. G., & Phelan, J. C. (2001). Conceptualizing stigma. *Annual Review of Sociology*, *27*(1), 363–385. https://doi.org/10.1146/annurev.soc.27.1.363

Litwin, H. (2011). The association between social network relationships and depressive symptoms among older Americans: What matters most? *International Psychogeriatrics*, *23*(6), 930–940. https://doi.org/10.1017/S1041610211000251

Litwin, H., Stoeckel, K., Roll, A., Shiovitz-Ezra, S., & Kotte, M. (2013). Social Network Measurement in SHARE Wave Four. In F. Malter & A. Börsch-Supan (Eds.), *SHARE Wave 4: Innovations & Methodology* (pp. 18–37). MEA, Max Planck Institute for Social Law and Social Policy.

Marin, A. (2004). Are respondents more likely to list alters with certain characteristics? *Social Networks*, *26*(4), 289–307. https://doi.org/10.1016/j.socnet.2004.06.001

Marqués-Sánchez, P., Martínez-Fernández, M. C., Leirós-Rodríguez, R., Rodríguez-Nogueira, Ó., Fernández-Martínez, E., & Benítez-Andrades, J. A. (2023). Leadership and contagion by COVID-19 among residence hall students: A social network analysis approach. *Social Networks*, *73*, 80–88. https://doi.org/10.1016/j.socnet.2023.01.001

Marsden, P. V. (1990). Network data and measurement. *Annual Review of Sociology*, *16*(1), 435–463. https://doi.org/10.1146/annurev.so.16.080190.002251

Martin, J. L., Yeung, K.-T., & Zablocki, B. D. (2001). The Urban Communes Data Set. *Connections, 24*(2), 54–58.

McCarty, C., Killworth, P. D., & Rennell, J. (2007). Impact of methods for reducing respondent burden on personal network structural measures. *Social Networks*, *29*(2), 300–315. https://doi.org/10.1016/j.socnet.2006.12.005

McCarty, C., Lubbers, M. J., Vacca, R., & Molina, J. L. (2019). *Conducting personal network research: A practical guide*. The Guilford Press.

McKenzie, J. E., Brennan, S. E., Ryan, R. E., Thomson, H. J., Johnston, R. V., & Thomas, J. (2019). Defining the criteria for including studies and how they will be grouped for the synthesis. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), *Cochrane handbook for systematic reviews of interventions* (1st ed., pp. 33–65). Wiley. https://doi.org/10.1002/9781119536604.ch3

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Moody, J. (2002). The importance of relationship timing for diffusion. *Social Forces*, *81*(1), 25–56. https://doi.org/10.1353/sof.2002.0056

Munn, Z., Peters, M. D. J., Stern, C., Tufanaru, C., McArthur, A., & Aromataris, E. (2018). Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Medical Research Methodology*, *18*(1), 143. https://doi.org/10.1186/s12874-018-0611-x

National Institute of Mental Health. (2024). *Depression (NIH Publication No. 24-MH-8079)*. U.S. Department of Health and Human Services, National Institutes of Health. https://www.nimh.nih.gov/health/publications/depression

NHS England. (n.d.). *Social prescribing*. Retrieved April 17, 2025, from https://www.england.nhs.uk/personalisedcare/social-prescribing/

Offer, S., & Fischer, C. S. (2018). Difficult people: Who is perceived to be demanding in personal networks and why are they there? *American Sociological Review*, *83*(1), 111–142. https://doi.org/10.1177/0003122417737951

Perry, B. L., & Pescosolido, B. A. (2010). Functional specificity in discussion networks: The influence of general and problem-specific networks on health outcomes. *Social Networks*, *32*(4), 345–357. https://doi.org/10.1016/j.socnet.2010.06.005

Perry, B. L., & Pescosolido, B. A. (2015). Social network activation: The role of health discussion partners in recovery from mental illness. *Social Science & Medicine*, *125*, 116–128. https://doi.org/10.1016/j.socscimed.2013.12.033

Pescosolido, B. A. (1991). Illness careers and network ties: A conceptual model of utilization and compliance. In G. L. Albrecht & J. A. Levy (Eds.), *Advances in medical sociology* (pp. 161–184). JAI Press.

Pescosolido, B. A. (1992). Beyond rational choice: The social dynamics of how people seek help. *American Journal of Sociology*, *97*(4), 1096–1138. https://doi.org/10.1086/229863

Priemer, J., Bischoff, A., Hohendanner, C., Krebstakies, R., Rump, B., & Schmitt, W. (2019). Organisierte Zivilgesellschaft. In H. Krimmer (Ed.), *Datenreport Zivilgesellschaft* (1st ed, pp. 7–54). Springer Fachmedien Wiesbaden.

Putnam, R. D. (2001). *Bowling alone: The collapse and revival of American community*. Simon & Schuster.

Reiner, A., De Gioannis, E., & Steinhoff, P. (2025). Social networks and their association with depression in community-dwelling older adults: A meta-analysis. *Aging & Mental Health*, 1–22. https://doi.org/10.1080/13607863.2025.2468892

Reiner, A., & Steinhoff, P. (2024). The association of social networks and depression in community-dwelling older adults: A systematic review. *Systematic Reviews*, *13*(1), 161. https://doi.org/10.1186/s13643-024-02581-6

Robert Koch-Institut. (2018). *The subjective health of adults in Germany*. https://doi.org/10.17886/RKI-GBE-2018-073

Rosenquist, J. N., Fowler, J. H., & Christakis, N. A. (2011). Social network determinants of depression. *Molecular Psychiatry*, *16*(3), 273–281. https://doi.org/10.1038/mp.2010.13

Santini, Z. I., Koyanagi, A., Tyrovoloas, S., Mason, C., & Haro, J. M. (2015). The association between social relationships and depression: A systematic review. *Journal of Affective Disorders, 175*, 53–65. https://doi.org/10.1016/j.jad.2014.12.049

Schaefer, D. R., Kornienko, O., & Fox, A. M. (2011). Misery does not love company: Network selection mechanisms and depression homophily. *American Sociological Review*, *76*(5), 764–785. https://doi.org/10.1177/0003122411420813

Schafer, M. H. (2013). Discussion networks, physician visits, and non-conventional medicine: Probing the relational correlates of health care utilization. *Social Science & Medicine*, *87*, 176–184. https://doi.org/10.1016/j.socscimed.2013.03.031

Schafer, M. H. (2016). Health as status? Network relations and social structure in an American retirement community. *Ageing and Society*, *36*(1), 79–105. https://doi.org/10.1017/S0144686X14000993

Schwarzbach, M., Luppa, M., Forstmeier, S., König, H.-H., & Riedel-Heller, S. G. (2014). Social relations and depression in late life-A systematic review. *International Journal of Geriatric Psychiatry*, *29*(1), 1–21. https://doi.org/10.1002/gps.3971

Siette, J., Gulea, C., & Priebe, S. (2015). Assessing social networks in patients with psychotic disorders: A systematic review of instruments. *PLOS ONE*, *10*(12), e0145250. https://doi.org/10.1371/journal.pone.0145250

Small, M. L. (2009). *Unanticipated gains: Origins of network inequality in everyday life*. Oxford University Press.

Small, M. L. (2013). Weak ties and the core discussion network: Why people regularly discuss important matters with unimportant alters. *Social Networks*, *35*(3), 470–483. https://doi.org/10.1016/j.socnet.2013.05.004

Small, M. L., Brant, K., & Fekete, M. (2024). The avoidance of strong ties. *American Sociological Review*, *89*(4), 615–649. https://doi.org/10.1177/00031224241263602

Smith, K. P., & Christakis, N. A. (2008). Social networks and health. *Annual Review of Sociology*, *34*(1), 405–429. https://doi.org/10.1146/annurev.soc.34.040507.134601

Stark, T. H. (2018). Collecting social network data. In D. L. Vannette & J. A. Krosnick (Eds.), *The Palgrave handbook of survey research* (pp. 241–254). Springer International Publishing. https://doi.org/10.1007/978-3-319-54395-6_31

Statistisches Bundesamt. (2025). *Pflege*. Statistisches Bundesamt. https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Gesundheit/Pflege/_inhalt.html

Steinhoff, P., Ellwardt, L., & Wermeyer, M. (2024). Well-being in middle-aged and older adults who volunteer: A qualitative network analysis. *Aging & Mental Health*, *29*(2), 343–351. https://doi.org/10.1080/13607863.2024.2393250

Suitor, J., & Keeton, S. (1997). Once a friend, always a friend? Effects of homophily on women's support networks across a decade. *Social Networks*, *19*(1), 51–62. https://doi.org/10.1016/S0378-8733(96)00290-0

Tajvar, M., Fletcher, A., Grundy, E., & Arab, M. (2013). Social support and health of older people in Middle Eastern countries: A systematic review. *Australasian Journal on Ageing*, *32*(2), 71–78. https://doi.org/10.1111/j.1741-6612.2012.00639.x

Tengku Mohd, T. A. M., Yunus, R. M., Hairi, F., Hairi, N. N., & Choo, W. Y. (2019). Social support and depression among community dwelling older adults in Asia: A systematic review. *BMJ Open*, *9*(7), e026667. https://doi.org/10.1136/bmjopen-2018-026667

Thoits, P. A. (2011). Mechanisms linking social ties and support to physical and mental health. *Journal of Health and Social Behavior*, *52*(2), 145–161. https://doi.org/10.1177/0022146510395592

Uchino, B. N. (2006). Social support and health: A review of physiological processes potentially underlying links to disease outcomes. *Journal of Behavioral Medicine*, *29*(4), 377–387. https://doi.org/10.1007/s10865-006-9056-5

Uchino, B. N. (2009). Understanding the links between social support and physical health: A life-span perspective with emphasis on the separability of perceived and received support. *Perspectives on Psychological Science*, *4*(3), 236–255. https://doi.org/10.1111/j.1745-6924.2009.01122.x

Valente, T. W. (2010). *Social networks and health: Models, methods, and applications*. Oxford University Press.

Van Zalk, M. H. W., Kerr, M., Branje, S. J. T., Stattin, H., & Meeus, W. H. J. (2010a). It takes three: Selection, influence, and de-selection processes of depression in adolescent friendship networks. *Developmental Psychology*, *46*(4), 927–938. https://doi.org/10.1037/a0019661

Van Zalk, M. H. W., Kerr, M., Branje, S. J. T., Stattin, H., & Meeus, W. H. J. (2010b). Peer contagion and adolescent depression: The role of failure anticipation. *Journal of*

Clinical Child & Adolescent Psychology, *39*(6), 837–848. https://doi.org/10.1080/15374416.2010.517164

Vörös, A., Boda, Z., Elmer, T., Hoffman, M., Mepham, K., Raabe, I. J., & Stadtfeld, C. (2021). The Swiss StudentLife Study: Investigating the emergence of an undergraduate community through dynamic, multidimensional social network data. *Social Networks*, *65*, 71–84. https://doi.org/10.1016/j.socnet.2020.11.006

White, K., & Watkins, S. C. (2000). Accuracy, stability and reciprocity in informal conversational networks in rural Kenya. *Social Networks*, *22*(4), 337–355. https://doi.org/10.1016/S0378-8733(00)00030-7

Wills, T. A., & Shinar, O. (2000). Measuring perceived and received social support. In S. Cohen, L. G. Underwood, & B. H. Gottlieb (Eds.), *Social support measurement and intervention* (pp. 86–135). Oxford University Press. https://doi.org/10.1093/med:psych/9780195126709.003.0004

Wimmer, A., & Lewis, K. (2010). Beyond and below racial homophily: Erg models of a friendship network documented on Facebook. *American Journal of Sociology*, *116*(2), 583–642. https://doi.org/10.1086/653658

World Health Organization. (2023). *Depressive disorder (depression)*. https://www.who.int/news-room/fact-sheets/detail/depression

Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: A meta-analysis. *Psychological Bulletin*, *139*(1), 53–80. https://doi.org/10.1037/a0028601

Yap, J., & Harrigan, N. (2015). Why does everybody hate me? Balance, status, and homophily: The triumvirate of signed tie formation. *Social Networks*, *40*, 103–122. https://doi.org/10.1016/j.socnet.2014.08.002

During the preparation of this work, I used Cambridge Proofreading and ChatGPT in order to refine the manuscript's language and readability. After using this tool/service, I reviewed and edited the content as needed and take full responsibility for the content of the publication.

CHAPTER 2. THE ASSOCIATION OF SOCIAL NETWORKS AND DEPRESSION IN COMMUNITY-DWELLING OLDER ADULTS: A SYSTEMATIC REVIEW

Amelie Reiner & Paula Steinhoff

Abstract

Background & Objective: Depression is a globally prevalent mental condition, particularly among older adults. Previous research has identified that social networks have a buffering effect on depression. Existing systematic reviews have either limited their research to specific geographic areas or provided evidence from over a decade ago. The vast body of recent literature particularly from the last decade emphasizes the need for a comprehensive review. This systematic review aims to analyze the association of structural aspects of social networks and depression in older adults.

Methods: The electronic databases APA PsycINFO, ProQuest, PSYINDEX, PubMed, Scopus, SocINDEX, and Web of Science were searched from date of data base inception until 11 July 2023. Studies were eligible for inclusion if they reported on community-dwelling older adults (defined as a mean age of at least 60 years old), had an acceptable definition for depression, referred to the term social network in the abstract, and were published in English. Quality was appraised using the Newcastle Ottawa Scale for cross-sectional and longitudinal studies. Outcome data were extracted independently from each study and analyzed by direction of the relationship, social network domain and cross-sectional or longitudinal study design.

Results: In total, 127 studies were included. The study categorizes structural network aspects into seven domains and finds that larger and more diverse networks, along with closer social ties, help mitigate depression. The literature on the relationships between depression and network density, homogeneity, and geographical proximity is scarce and inconclusive.

Discussion and Implications: Despite inconsistent findings, this review highlights the importance of quantifying complex social relations of older adults. Limitations of this review include publication and language bias as well as the exclusion of qualitative research. Further research should use longitudinal approaches to further investigate the reciprocal relationship between social networks and depression. Following this review, interventions should promote the integration of older adults in larger and more diverse social settings.

Other: This work was supported by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Grant [454899704]. This systematic review was pre-registered. The review-protocol can be accessed at https://doi.org/10.17605/OSF.IO/6QDPK.

Keywords: social network, mental health, depression, older adults, systematic review

2.1 Background and Objective

Depression is a mental condition that is particularly prevalent among older adults (World Health Organization, 2021). Scholars have identified a significant association between social networks and depression, with socially integrated older adults showing lower levels of depression than less socially integrated older adults (Mohd et al., 2019; Schwarzbach et al., 2014). As older adults face a decreasing number of social relationships and a shrinking social network over their life course (Wrzus et al., 2013), this growing population is at risk for depression. Systematizing and quantifying the social networks of older adults is vital to understanding their relationship with depression. The prevalence of depression will increase in the future. Understanding the aspects of social networks that are particularly important for preventing depressive symptomatology in older adults will allow appropriate social gerontological interventions.

Previous systematic reviews have generated important insights into the relationship between social networks and mental health. Across several geographical areas, various social network measures have been found to be significantly associated with mental health in older adults (Middle Eastern countries: Tajvar et al., 2013; Iran: Harandi et al., 2017), and specifically depression (Asia: Mohd et al., 2019; Western countries: Gariépy et al., 2016). However, only one systematic review has addressed the relationship between social networks and depression among older adults without restricting its evidence to a geographical area (Schwarzbach et al., 2014). While Schwarzbach et al.'s (2014) review has been helpful, new evidence about the social relations of older adults and depression outcomes must be reviewed because a significant amount has emerged over the last decade.

Additionally, previous studies and literature reviews have loosely applied the concept of social networks and engaged with different definitions and measures of social networks (Ayalon & Levkovich, 2019; Siette et al., 2015). A social network is traditionally defined as the quantifiable ties binding individuals, families, communities, or businesses (i.e., nodes) together through a shared need, aim, or interest (Berkman et al., 2000; Cohen et al., 2000). The nature of one's social network was found to have a significant influence on an individual's life expectancy, mortality rate, quality of life, and health-related behaviors (Ayalon & Levkovich, 2019).

Generally, the literature has distinguished between the quantitative/ structural and qualitative/ functional aspects of social relationships (Cohen, 2004; Santini, Koyanagi, Tyrovoloas, et al., 2015). Qualitative aspects refer to the social network's function, including the potential of social relationships, such as social support, the perceived quality of support provided, relationship satisfaction, loneliness and social isolation (Kuiper et al., 2016; Santini, Koyanagi, Tyrovoloas, et al., 2015). In contrast, quantitative aspects refer to the network's structure, including its size, composition, and the frequency of contact between network members. Recently, it has become increasingly clear that quantifying social networks, which provides an objective measure of the structure of relationships, is particularly suited for understanding their association with critical health outcomes, such as cognitive decline (Kuiper et al., 2016), dementia (Kuiper et al., 2015), and mortality (Holt-Lunstad et al., 2010). As structural aspects of social networks are causally prior to functional aspects, this review exclusively focuses on their structural aspects while examining their relationship with depression in older adults.

The relationship between social networks and depression can be considered reciprocal. The main effect model (Kawachi & Berkman, 2001) states that social networks positively affect psychological state through mechanisms such as social recognition, a sense of belonging, and normative guidance for health-promoting behavior. Conversely, depression may affect the extent of social networks by causing social withdrawal and decreased social participation. Older adults who experience depression in later life often struggle with maintaining larger and more diverse personal networks and experience disruptions in their contact with social network members (Blazer, 2003). Existing research has predominantly focused on the effect of social networks on depression. Conversely, the reversed effect of depression on social networks has been largely neglected (Bui, 2020; Domènech-Abella et al., 2019).

This systematic review, therefore, aims to synthesize the evidence about the relationship between structural aspects of social networks and depression in community-dwelling older adults. It addresses two research questions: (1) How do structural aspects of social networks impact depression outcomes in community-dwelling older adults? (2) How does depression impact structural aspects of social networks of community-dwelling older adults? It strives to provide a comprehensive picture by gathering cross-sectional as well as longitudinal evidence and by focusing on the reciprocal relationship between social networks and depression in older adults.

2.2 Methods

This systematic review was pre-registered. The review-protocol can be accessed at https://doi.org/10.17605/OSF.IO/6QDPK. In addition, we followed PRISMA guidelines for the reporting of this systematic review (Page et al., 2021; see Appendix, Table A2-1).

1.1.1 Eligibility criteria

We expected to include peer-reviewed articles on the association of structural social network characteristics and depression among community-dwelling older adults. Following the World Health Organization (WHO; World Health Organization, n.d.), we define older adults as those, being 60 years and older. To counteract possible regional selection bias induced by language knowledge, we focused on English publications only. We did not exclude studies based on publication year or geographic area.

Related previous systematic reviews informed the inclusion and exclusion criteria (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini, Koyanagi, Tyrovoloas, et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018). Articles were included if the population of interest consisted of community-dwelling adults, specifically those older than 40 years, with a study mean age of at least 60 years. We opted for a minimum age in order to include relevant age studies from the age of 40 (e.g., the German DEAS), but focused on older adults by deciding that the mean age of the study participants must be at least 60 years, following the definition of older adults. The exposure or outcome focused on social networks, explicitly mentioned in the abstract of the studies. Further exposure or outcome of interest was depression, with an acceptable definition involving diagnostic criteria or a cut-off point on a depression rating scale. The association between social networks and depression had to be reported using a multivariate analysis adjusting for any confounders (the specifics of the included confounders are evaluated in the quality assessment). Only peer-reviewed journal articles published in English were considered for inclusion. Articles were excluded if they focused on patient groups or included institutionalized individuals, unless the analyses separated community-dwelling and institutionalized participants. Additionally, studies were excluded if they referred to recalled social network characteristics from the past, such as youth and adolescence, to measure present depression outcomes, or if they exclusively focused on online social networks. In terms of study types, editorials, study protocols, conference proceedings, comments, reviews, qualitative studies, grey literature, case studies, and intervention studies were excluded. An overview of the studies that appeared to meet the inclusion criteria but were ultimately excluded and the reasons for this can be found in the Appendix, Table A2-2.

2.2.1 Search strategy

The systematic database search was performed from date of data base inception up to 11 July 2023. The keywords used for the search strategy included related terms for: "depression" AND "social networks" AND "older adults" (see pre-registered review-protocol). These were informed by related systematic reviews about the three main terms (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini, Koyanagi, Tyrovoloas, et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018). The following seven databases were searched using the same keywords and search designs: APA PsycINFO, ProQuest, PSYINDEX, PubMed, Scopus, SocINDEX, and Web of Science. We also conducted manual searches for potentially eligible studies from reference lists of related systematic reviews (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini, Koyanagi, Tyrovoloas, et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018).

2.2.2 Study selection

References from the seven databases were imported into Rayyan (Ouzzani et al., 2016). After deduplication, two researchers (AR, PS) independently screened titles and abstracts, forwarding potentially eligible papers for full text review. Two researchers (AR, PS) independently assessed the full text of potentially eligible citations against the eligibility criteria. Disagreements and discrepancies were resolved by consensus between the researchers. The study selection process was piloted twice with a random sample of a hundred studies of the overall sample per pilot. Piloting the study selection process improves the reliability and validity of the review by ensuring all reviewers have a clear and consistent understanding of the selection process (Lefebvre et al., 2019).

2.2.3 Data extraction

Using a standardized data collection form informed by related reviews (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini, Koyanagi, Tyrovoloas, et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018), two reviewers (AR, AL) independently extracted data on the study population including their sample size, average age and age range, gender ratio, and country. Further, we extracted information on the measurement of depression, the social network assessment, type of social ties, potential exclusion of population groups, data source, the statistical methods, and the results. The outcomes of interest were structural aspects of social networks and/or depression scores among community-dwelling older adults. Any disagreements were resolved by discussion. If this failed, a third reviewer (PS) was consulted. The data extraction process was piloted once with a random sample of twenty studies to ensure the completeness of all relevant information in the data collection form (T. Li et al., 2019).

2.2.4 Quality appraisal

Quality was assessed using the Newcastle Ottawa Scale (NOS; Wells et al., 2014) for cross-sectional and longitudinal studies by one reviewer (AR) and double-checked by another reviewer (PS). The NOS has been used in systematic reviews before (Hakeem et al., 2019; Mohd et al., 2019; Shamsrizi et al., 2020; Vivekanantham et al., 2019). The NOS awards each article an amount of stars within three domains, with a greater number of stars indicate a higher-quality study (Wells et al., 2014). The study quality is evaluated in terms of design, participant selection, comparability and assessment of exposure and outcome. Following the approach of several reviews (Mohd et al., 2019; Shamsrizi et al., 2020; Vivekanantham et al., 2019), we adopted a rigorous methodology to assess the quality of studies, adhering to predetermined thresholds for converting the NOS to Agency for Health Research and Quality (AHRQ) standards. For a cross-sectional study to be considered of good quality, it needed to attain between 3 and 5 stars in the selection domain, alongside 1 or 2 stars in the comparability domain, and finally, 2 or 3 stars in the outcome domain. Those studies that achieved 2 stars in the selection domain, coupled with 1 or 2 stars in comparability, and 2 or 3 stars in outcome were classified as fair quality. However, studies falling short of these criteria were deemed poor quality; they either obtained 0 or 1 star in the selection domain, 0 stars in comparability, or 0 or 1 stars in outcome. In contrast, a longitudinal study was considered of good quality if it garnered between 3 and 4 stars in the selection domain, along with 1 or 2 stars in the comparability domain, and finally, 2 or 3 stars in the outcome domain. Those longitudinal studies achieving 2 stars in the selection domain, paired with 1 or 2 stars in comparability, and 2 or 3 stars in outcome were categorized as fair quality. Conversely, studies failing to meet these benchmarks were classified as poor quality; they either received 0 or 1 star in the selection domain, 0 stars in comparability, or 0 or 1 stars in outcome. For the analyses, we included all studies irrespective of the quality assessment results. However, when excluding studies which were considered as poor quality in a sensitivity analysis, the results were found to remain largely stable.

2.2.5 Synthesis method

Citations were firstly sub-grouped by direction of the relationship, then by structural aspect of social networks, and afterwards by the cross-sectional or longitudinal study design. In a further step, we count the significant associations against the insignificant associations. We compare the significant results across study design to identify differences between cross-sectional and longitudinal relationships. Further, we compare the effects of interest across structural aspects of social networks in the discussion. Tables are used to display the sub-grouped evidence. Further comparisons were carried out by geographical location, gender, family versus friends' social ties and functional versus structural social network aspects. Findings are reported narratively.

2.3 Results

2.3.1 Sample description

Starting from an initial result of 47,702 entries, 26,915 unique citations were identified. The two authors (AR, PS) independently screened the titles and abstracts, resulting in 320 potentially eligible articles. Any disagreement over the eligibility of individual studies was resolved through discussion. After adhering to strict inclusion and exclusion criteria, 127 unique publications were identified. Figure 2-1 visualizes a PRISMA flowchart of the selection process.

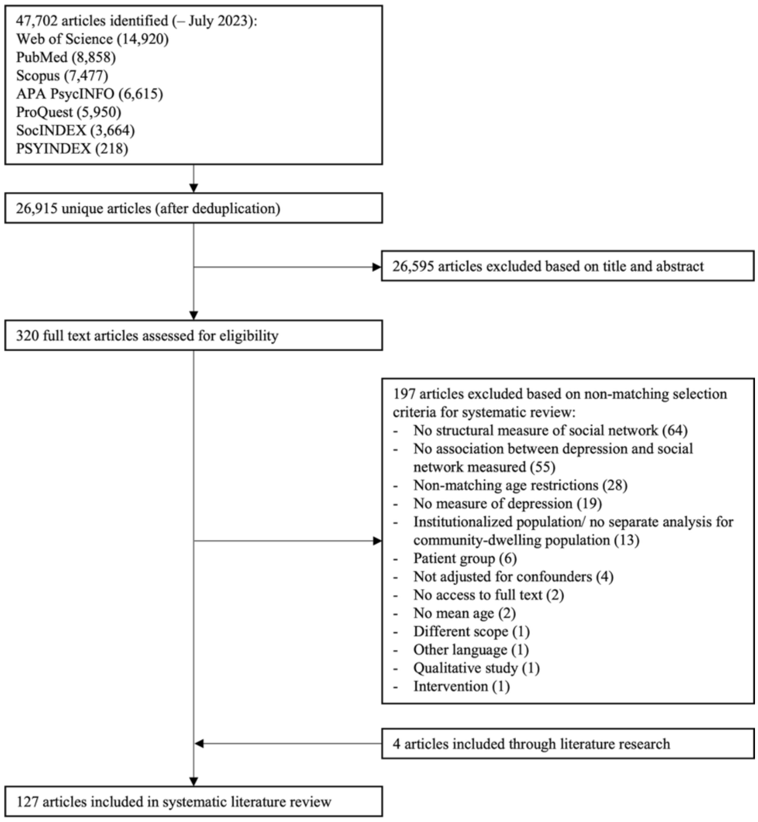


Figure 2-1 Selection flowchart for papers included in the systematic review

The quality appraisal for each NOS-domain and overall evaluation can be found in in the Appendix, Table A2-3 for cross-sectional studies and Table A2-4 for longitudinal studies. Two thirds of the studies (n = 86) were classified as good-quality studies, 27 articles with fair quality and 15 articles with poor quality.

The included articles were published between 1985 and 2023, with half published later than 2016. This highlights the vast body of research that has been conducted on this association, particularly in the last decade. The range of sample sizes was 53 to 60918, with a median sample size of 1349 respondents. The geographic location of most of the studies was North America (n = 46), followed by Asian countries (n = 42). Thirty-four studies were conducted in European countries (and Israel), and only three were conducted in South American countries. One study has a mixed geographical location by comparing older adults in North America to those in Asia (Liu et al., 2016). One study did not specify its geographic location (Miller & Lago, 1990).

The majority of studies made use of validated instruments to assess particularly depression. They either used various forms of the Center for Epidemiologic Studies Depression Scale (CES-D, n = 58) or the Geriatric Depression Scale (GDS, n = 42) to assess depression. Other studies used the EURO-D scale (n = 12), the Composite International Diagnostic Interview (CIDI, n = 3), the nine-item Patient Health Questionnaire (PHQ-9, n = 3) or other validated instruments (n = 9).

Most studies focused on the cross-sectional relationship between the social networks of older adults and depression (n = 96), while 30 articles examined the relationship longitudinally. Only one article had both a cross-sectional and longitudinal focus (Blumstein et al., 2004). In most aspects of social networks, there were no apparent differences between the cross-sectional and longitudinal investigations. Additionally, 90% (n = 114) of the studies exclusively used depression as an outcome variable, while 6% (n = 8) exclusively used social network variables as outcome variables. Only five studies focused on the existence of a bi-directional relationship (Bui, 2020; Domènech-Abella et al., 2019; Reynolds et al., 2020; Sugie et al., 2022; Zhang et al., 2023).

All risk factors for depression related to social networks used within the studies were categorized. Seven structural aspects of social networks were identified: network composition, contact frequency, network density, homo-/heterogeneity, network size, geographic proximity, and network scales. Table 2-1 provides an overview of the social network aspect descriptions. Notably, ties to friends and family were the covered most frequently in social network measures. The results were largely stable across geographic areas.

Table 2-1 Description of the structural aspects of social networks

Structural aspect of social networks	Description
Composition	Measures that describe how a network is composed, either through proportions of family/friends or building a network typology
Contact frequency	Frequency of various forms of contact with different social ties
Density	Indices indicating the extent to which a network is loosely connected (Keim-Klärner et al., 2023)
Geographic proximity	Travel distance to social ties in km or time
Homogeneity	Indices for the similarity of one's social ties to one's own personality (Keim-Klärner et al., 2023)
Scales	Scales mainly capture an individual's marital status, number and frequency of contacts with children, close relatives, close friends, church group membership, and membership in other community organizations (Berkman & Syme, 1979)
Size	Number of social relations in the individual's personal network

2.3.2 Depression as outcome variable

In total, 119 articles examined structural network aspects' effects on depression. Ninety articles did so cross-sectionally, and 28 articles did so longitudinally. One article focused on the relationship both cross-sectionally and longitudinally (Blumstein et al., 2004).

Most publications focused on network scales (n = 44), network size (n = 44), network composition (n = 30), and contact frequency (n = 28) as structural network factors determining depression outcomes in older adults. Significantly fewer articles used density (n = 4), geographic proximity (n = 3), and homogeneity (n = 2). The results are presented below according to their frequency.

Network scales

Some articles used standardized network scales to examine various aspects of social networks' effects on depression among older adults. Most articles used (modifications or translations of) the Lubben Social Network Scale (LSNS) or the Social Network Index (SNI), with higher scores indicating greater social engagement.

Most associations (40 out of 60 = 67%) between network scales and depression among older adults were reported to be significant (Table 2-2). No meaningful difference was identified between cross-sectional and longitudinal studies concerning effect significance or direction. Consistently, scholars found higher scores on social network scales to buffer depression outcomes among older adults. However, different subscales were used to assess family and friends variables. While some studies suggested that family networks were more predictive of depression outcomes in older adults (Fernández & Rosell, 2022; Gao et al., 2022; D. Tang et al., 2023), Singh et al. (2016) indicated the opposite, suggesting that the friend network scale was significantly associated with depression. They found no significant associations in the children, relatives, and confidant network scales.

The results appear to be largely stable across gender. Most of the studies considering gender differences did not find the association of network scales and depression to differ in women and men (Chan et al., 2011; Klug et al., 2014; Park et al., 2013; D. Tang et al., 2023). The evidence of studies finding gender differences is inconclusive. While two studies found network scales to be only significant associated with depression in men but not women (Roh et al., 2015; Santini et al., 2016), another study found a significant association for the friends' subscale in women but not men (Boey & Chiu, 2005). Conversely, no gender differences were found regarding the family subscale (Boey & Chiu, 2005).

Table 2-2 Overview of results: network scales and depression

Author	**Depression measure**	**Social network measure**	**N** [a]	**Results** [b]	**Quality**
Cross-sectional studies					
Aung et al., 2016	GDS-30	SNI	435	+	Good
Bae et al., 2020	GDS-15	NCGG Social Network Scale	2,445	+	Good
Boey & Chiu, 2005	GDS-15	LSNS Family network Friend network	1,034	 + 0/+ (significant in older women, but not men)	Good
Chan & Zeng, 2009	GDS-15	Social Network Scale (SNS) (family network; networks of friends; helping others; confidence in relationships and living arrangements)	1,042	+	Good
Chan & Zeng, 2011	GDS-15	LSNS	839	+	Good
Chan et al., 2011	CES-D (11)	LSNS (friends and relatives)	4,489	+	Good
Chou & Chi, 2001	CES-D (20)	LSNS	411	+	Good
Fernández & Rosell, 2022	PHQ-9	LSNS Family Network (subscale) Friend Network (subscale)	2,132	 + +	Good
Gao et al., 2022	CES-D (10)	LSNS Family Network (subscale) Friend Network (subscale) Total	5,934	 + + 0	Good
Gu et al., 2023	GDS-15	LSNS Family Network (subscale) Friend Network (subscale)	824	 0/+ (sig. only among rural older adults, but not urban) 0/+ (sig. only among urban older	Good

Author	**Depres-sion measure**	**Social network measure**	**N [a]**	**Results [b]**	**Quality**
				adults, but not rural)	
Hamid et al., 2019	GDS-15	LSNS	594	+	Good
Jang et al., 2002	GDS-15	LSNS	406	+	Good
Jang et al., 2011	CES-D (10)	LSNS	230	0	Fair
Jiang et al., 2022	GDS-15	LSNS	3,769	+	Good
Kim & Lee, 2015	SGDS-K	LSNS Family Network (subscale) Friend Network (subscale)	949	 + +	Good
Kim et al., 2012	GDS-15	LSNS	210	+	Good
Kim et al., 2015	GDS-15	LSNS	147	0	Fair
Klug et al., 2014	GDS-15	SNI (dichotomous measure: 1-2 = low social network; 3-4 = high social network)	969	0	Good
Lee et al., 2017	GDS-30	LSNS	200	+	Good
Mehrabi & Béland, 2021	GDS-15	Social contact score: Number of ties, Number of ties seen least once a month, number of ties being close with, number of ties having called at least once a month Friends Children Grandchildren Siblings	1,643	 0 0 0 0	Fair
Okwumabua et al., 1997	CES-D (20)	LSNS	110	+	Poor
Palinkas et al., 1990	BDI (18)	SNI	1,615	+	Poor
Park & Roh, 2013	GDS-30	LSNS	200	+	Good
Park et al., 2013	GDS-15 (Korean translation)	SNI	674	+	Good
Park et al., 2019	CES-D (10)	LSNS Family Network (subscale) Friend Network (subscale)	353	 0 0	Good
Roh et al., 2015	GDS-30 Korean Version	LSNS	200	+	Good
Santini, Koyanagi, Tyrovolas, et al., 2015	CES-D (20)	SNI	4,988	+	Good
Singh et al., 2016	CIDI	Social network scale (Summary scores: number of ties, visual contact, non-visual contact) Children Network Relatives Network Friends Network Confidant Network	630	 0 0 + 0	Fair
Sugie et al., 2022	GDS-15	LSNS (dichotomous, scores <12 limited network)	268	+	Good
Tang & Xie, 2021	CES-D	LSNS Family Network (subscale) Friend Network (subscale)	2,484	 + +	Good
Tang et al., 2020	CES-D (9)	LSNS Family Network (subscale) Friend Network (subscale)	7,662	 + +	Good

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
D. Tang et al., 2023	CES-D	LSNS Family Network (subscale) Friend Network (subscale)	7,601	 + +	Good
Tanikaga et al., 2023	GDS-15	LSNS	74	+	Good
Taylor, 2021	CES-D (7)	SNI	2,323	0	Good
Tsai et al., 2005	GDS-15	Social support network: number of relatives or friends who would likely contact the elder and by the quantity of contacts (either by phone or in person) during previous week	1,200	+	Good
Wee et al., 2014	GDS-15	LSNS	559	+	Fair
Longitudinal studies					
Byers et al., 2012	GDS-15	LSNS (dichotomized: below the median averaged LSNS = small social network)	7,240	+	Good
Domènech-Abella et al., 2019	CIDI-SF	SNI	5,066	+	Good
Förster et al., 2021	GDS-15	LSNS-6	679	0	Good
Kuchibhatla et al., 2012	CES-D (20)	social interaction scale (summary measure of contact frequency with friends and relatives, and membership in social organizations)	3,973	0	Good
Ruan et al., 2022	CES-D (9)	LSNS	4,466	+	Good
Santini et al., 2016	CES-D (20)	SNI	6,105	+	Good
Santini et al., 2017	CES-D (20)	SNI	6,098	+	Good
Zhang et al., 2023	DASS-21 (depression subscale)	LSNS	634	0	Good

[a] *n: Sample size, baseline sample was used in longitudinal studies*
[b] *Results: 0 indicates no sig. relationship ($p \geq 0.05$), + indicates sig. relationship ($p < 0.05$)*

Depression measures: *BDI – Beck Depression Inventory; CES-D – Centre of Epidemiologic Studies Depression Scale; CIDI-SF – Composite International Diagnostic Interview (Short Form); DASS-21 – Depression Anxiety Stress Scale; EURO-D – EURO geriatric depression scale; GDS – Geriatric Depression Scale; SGDS-K – Geriatric Depression Scale Short Form Korean Version; PHQ-9 – Patient Health Questionnaire*

Social network measures: *LSNS – Lubben Social Network Scale; NCGG Social Network Scale – National Center for Geriatrics and Gerontology Social Network Scale; SNI – Social Network Index*

Network size

Network size was the most frequently studied variable besides network scales. In total, 66 measured associations were found in 44 articles (see Table 2-3). No meaningful difference was identified between cross-sectional and longitudinal studies concerning effect significance or direction. The results were inconclusive: Half of the studies found no significant association, while the other half provided significant evidence for an effect of social network size on depression in older adults. Of the effects significantly associated with depression, 32 of 33 were negative.

This suggests that more extensive social networks are associated with lower levels of depression in older adults.

There seems to be no consensus regarding the association of the size of different social spheres and depression outcomes among older adults. While Palinkas et al. (1990) and Harada et al. (2023) found friend network size to be more important than relative network size, Lee & Chou (2019) found these variables to be equally important. Furthermore, Minicuci et al. (2002) and Oxman et al. (1992) found them equally unimportant for depression outcomes.

There also seems to be no consensus regarding gender differences in the association of network size and depression. While two scholars found a significant association of network size and depression only in women but not men (Becker et al., 2019; Hajek & König, 2016), three scholars found no evidence for gender differences (Ermer & Proulx, 2022; Pavlidis et al., 2023; Sonnenberg et al., 2013). Minicuci et al. (2002) found the numbers of relatives with close contacts to only be significantly associated with depression in women but not men, while the number of close contacts was significantly associated with depression in men and women.

Table 2-3 Overview of results: network size and depression

Author	**Depression measure**	**Social network measure**	**N [a]**	**Results [b]**	**Quality**
Cross-sectional studies					
Antonucci et al., 1997	CES-D	Total Network Size (people who are important to them; network size: 0-3, 4-7, 8 or more people)	3,777	+	Good
Becker et al., 2019	Euro-D	Total Network Size (up to 7 persons)	52,513	+	Poor
Bisconti & Bergeman, 1999	CES-D (20)	Network size Family (number of family members who are met or talked to on the phone in a typical week) Friends (number of family members who are met or talked to on the phone in a typical week)	232	 0 0	Poor
Braam et al., 1997	CES-D (20)	Total Network Size (Number of people named in the seven categories: persons living in the same household, children and children-in-law, other relatives, neighbors, people with whom one is working or studying, contacts in organizations and other contacts)	2,817	+	Good
Cheng et al., 2014	GDS-4	Total Network Size (Social convoy questionnaire, network members that are important)	273	+	Poor
Chi & Chou, 2001	CES-D (20)	Relatives/Kin size Number of relatives seen once a month Number of relatives felt close to Number of friends seen once a month Number of friends felt close to	1,106	0 0 + 0 +	Good
Cho et al., 2019	CES-D (10)	Total Network Size (number of close friends and close relatives: 0, 1–2, 3–5, 6–9, 10+)	2,541	0	Good

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
Domènech-Abella et al., 2017	CIDI 3.0	Total Network Size (Berkman-Syme Social Network Index)	3,535	+	Good
Dorrance Hall et al., 2019	CES-D (9)	Total Network Size (persons with whom they talk about important matters and regularly interact)	2,249	+	Good
Ermer & Proulx, 2022	CES-D (11)	Total Network Size (Social network roster)	865	0	Fair
Fredriksen-Goldsen et al., 2013	CES-D (10)	Total Network Size (Interaction with friends, family members, colleagues, and neighbors in a typical month; calculated and summarized by quartiles)	2,439	+	Good
Fuller-Iglesias et al., 2008	CES-D (20)	Total Network Size (Hierarchical mapping technique)	99	+	Poor
Goldberg et al., 1985	CES-D (20)	Total Network Size (household members, friends, family members outside of the household in touch during six months before; household members and up to 10 friends and 10 family members) Number of confidants	1,104	0 +	Good
Han et al., 2007	KDSKA	Family size/network (number of living parents, spouse, children, grandchildren, and other relatives)	205	0	Fair
Harada et al., 2023	GDS-15	Kin network (number of siblings, cousins, grandchildren or other relatives with whom respondent or respondent's spouse interacts on a regular basis (except household members) Friends network (number of friends with whom respondent interacts on a regular basis)	739	+ +	Good
Jeon & Lubben, 2016	CES-D (20)	Relatives/Kin size Non-kin network size (Total number of relatives/non-relatives participants talked to at least once a month)	424	0 0	Fair
Lee & Chou, 2019	GDS-15	Friendship size Number of children Relatives/Kin size (Number of children, family members, and friends they felt close to)	850	+ 0 +	Good
Lee et al., 1996	CES-D (20)	Total Network Size (numbers of living parents, children, and friends)	162	+	Poor
M. Li et al., 2019	PHQ-9	Total Network Size (up to 5 people with whom they discuss important things)	3,157	+	Fair
Litwin & Levinsky, 2023	Euro-D	Total Network Size (up to 6 persons with whom they discuss personal matters; one additional person who was important for any reason)	35,145	+	Good
Litwin et al., 2015	Euro-D	Total Network Size (up to 6 persons with whom they discuss personal matters; one additional person who was important for any reason)	25,245	+	Good
Liu et al., 2016	CES-D (9)	Friendship size/network (friends in local community: none or few, some or quite a few, a lot)	529	+	Poor
Miller & Lago, 1990	GDS-15	Total Network Size (hierarchical mapping technique)	53	0	Poor

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
Minicuci et al., 2002	CES-D (20)	Number of relatives with close contact Number of close friends	2,398	0 0	Good
Palinkas et al., 1990	BDI (18)	Friendship network size Relatives/Kin size	1,615	+ 0	Poor
Pavlidis et al., 2023	Euro-D	Small network (1-2 members) vs. large network (3+ members) (up to 6 persons with whom they discuss personal matters; one additional person who was important for any reason)	60,918	0	Fair
Pilehvari et al., 2023	CES-D (20)	Number of people in social network	1,170	0	Good
Sonnenberg et al., 2013	CES-D (20)	Total Network Size (people in important and regular contact)	2,823	+	Good
Vicente & Guadalupe, 2022	GDS-15	Total Network Size	612	0	Poor
Longitudinal studies					
Bisschop et al., 2004	CES-D (20)	Total Network Size (people in important and frequent contact, except partner)	2,278	0	Good
Bui, 2020	CES-D (11)	Total Network Size Confidant size/network	2,200	0 0	Good
Chao, 2011	CES-D (10)	Number of children/Children network Relatives/Kin size Friendship Size (Contacted at least once a week)	4,049	+ + +	Good
Coleman et al., 2022	GDS-5	Overall network size (number of people in network) Effective size (number of non-overlapping groups with which a person interacts)	113	0 0	Good
Hajek & König, 2016	CES-D (15)	Number of important people regular in contact	2,201	0	Good
Harlow et al., 1991	CES-D (20)	Total Network Size Family Size Friendship size/network Confident Size (Number of friends and family members outside of the household with whom the respondent had been in touch during the 6 months before interview and total size of the network which additionally included family and friends who lived with the respondent)	545	+ 0 + +	Fair
Holwerda et al., 2023	CES-D (10)	Number of network members (≥ 18 years) with whom respondent had important/frequent contact	899	0	Good
Kuchibhatla et al., 2012	CES-D (20)	Total Network Size (summarizing seven variables on number of relatives and close friends)	3,973	+	Good
Oxman et al., 1992	CES-D (20)	Number of close relatives phoning/writing yearly Number of close friends phoning/writing yearly Relatives/Kin size Number of children/Children seen weekly	1,962	0 0 0 +	Poor

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
Reynolds et al., 2020	CES-D	Number of important people regular in contact	3,005	0	Good
Santini et al., 2021	Euro-D	Total Network Size (number of close relations in the social network; up to 7 persons)	38,300	+	Fair
Schwartz & Litwin, 2017	Euro-D	Total Network Size (up to 7 persons with whom they discuss important matters)	14,101	0	Good
Stringa et al., 2020	CES-D	Total Network Size (people in important and regular contact)	2,279	+	Fair
F. Tang et al., 2023	PHQ-9	Total number of network members with whom respondent could discuss important things	1,970	0	Good
Werneck et al., 2023	Euro-D	Network size (number of people in network)	10,569	+	Good

[a] n: Sample size, baseline sample was used in longitudinal studies
[b] Results: 0 indicates no sig. relationship ($p \geq 0.05$), + indicates sig. relationship ($p < 0.05$)

Depression measures: *BDI – Beck Depression Inventory; CES-D – Centre of Epidemiologic Studies Depression Scale; CIDI – Composite International Diagnostic Interview; EURO-D – EURO geriatric depression scale; GDS – Geriatric Depression Scale; KDSKA – Kim Depression Scale for Korean Americans; MADRS – Montgomery–Åsberg Depression Rating Scale; PHQ-9 – Patient Health Questionnaire*

Network composition

Network composition was primarily measured by forming network typologies through clustering (see Table 2-4). This method makes it particularly challenging to compare results; however, studies consistently showed that diverse social networks protect against depression compared to more restricted networks (Choi & Jeon, 2021; Fiori et al., 2006; Harasemiw et al., 2019; Kim & Lee, 2019; Litwin, 2011, 2012; Park et al., 2014, 2018; Sohn et al., 2017; Ye & Zhang, 2019). Concerning network transitions, individuals remaining in and changing to restricted networks showed significantly higher levels of depression than those remaining in non-restricted networks (Förster et al., 2018; Kim et al., 2016). Consistently, Sicotte et al. (2008) found that an increasing diversity of links (measured by diversity of relationship ties) was associated with lower odds of depressive symptoms. Other studies found no significant association (Coleman et al., 2022; Pilehvari et al., 2023). When prestige occupation scores were used as a diversity measure, higher diversity was associated with lower levels of depression compared to less diverse networks (Cao et al., 2015). Conversely, Becker et al. (2019) found diverse networks to be less associated with a lack of depressive symptoms compared to those relying solely on their partner as their social network.

Some studies included the share of particular social aspects, such as gender, family, or friends. Consistently, the proportions of females or kin were not identified as significant predictors of depression (Bui, 2020; M. Li et al., 2019; Vicente & Guadalupe, 2022; Webster et al., 2015). Furthermore, there was no consensus about the composition of family and friends. Social networks primarily consisting of family were found to buffer depression more than networks primarily consisting of friends (Antonucci et al., 1997; Chi & Chou, 2001). This was also the case for network transitions (Litwin et al., 2020). Conversely, Fiori et al. (2006) found that the absence of family within a friend context was less detrimental than the absence of friends within a family context. Also, Chao (2011) identified that a network proportion of 25–50% family and 50–75% friends was the most advantageous for preventing depression.

While two scholars found no evidence for gender differences in the association of network composition and depression in older adults (Mechakra-Tahiri et al., 2010; Sicotte et al., 2008), Choi & Jeon (2021) identified gender-specific network types and their association with depression to differ by gender. They found that restricted social network types were associated with increased depressive symptoms in both men and women, whereas a family-centered network was associated with more depressive symptoms only in women.

Table 2-4 Overview of results: network composition and depression

Author	**Depression measure**	**Social network measure**	**N [a]**	**Results [b]**	**Quality**
Cross-sectional studies					
Antonucci et al., 1997	CES-D	Network composition (all family, mostly family, equal members of family and friends, mostly friends, all friends)	3,777	+	Good
Becker et al., 2019	Euro-D	Network types (partner, children, other relatives, family, friends, diverse)	52,513	+	Poor
Cao et al., 2015	GDS-30	Network types (prestige occupation scores: low, middle and high network)	928	+	Good
Chi & Chou, 2001	CES-D (20)	Network composition Of relatives and friends felt close to Of relatives and friends seen once a month (all family, mostly family, equal members of family and friends, mostly friends, all friends)	1,106	 0 +	Good
Choi & Jeon, 2021	GDS-15	Network types (men: diverse, restricted couple-focused, restricted-unmarried, social-activity-focused, family focused; women: diverse-married, family-focused, restricted-couple-focused, restricted-unmarried, diverse-unmarried)	4,608	+	Good
Fiori et al., 2006	CES-D (11)	Network types (nonfamily restricted, nonfriends, family, diverse, friends)	1,669	+	Good
Golden et al., 2009	GMS	Network types (locally integrated social network vs. any other sort of network)	1,299	+	Good
Gumà & Fernández-Carro, 2021	Euro-D	Network types (partner and others, only relatives, only friends, mixed composition)	6,820	0	Good
Harasemiw et al., 2019	CES-D (10)	Network types (diverse, family-focused, few children, few friends, restricted)	8,782	+	Good
Kim & Lee, 2019	GDS-15	Network types based on LSNS (Friend, Family, Restricted, Diverse)	1,000	+	Fair
M. Li et al., 2019	PHQ-9	Proportion kin	3,157	0	Fair

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
		Proportion female Proportion coresident		0 +	
Litwin, 2011	CES-D (8)	Network types (Diverse, friend, congregant, family, restricted)	1,350	+	Fair
Litwin, 2012	CES-D (8)	Network types (only focusing on family and restricted) Family network Restricted network	1,275	 0 +	Fair
Mechakra-Tahiri et al., 2010	ESA-Q	Role diversity: number of different types of relationships that participants had, including those with a partner, adult children, siblings, friends, and members of a community group (low, medium, high)	2,670	0	Good
Park et al., 2014	CES-D (10)	Network types (restricted, couple-focused, friend, diverse)	4,251	+	Fair
Park et al., 2018	GDS-15	Network types (diverse/family, diverse/friend, friend-focused, distant, restricted)	6,900	+	Good
Pilehvari et al., 2023	CES-D (20)	Diversity: Index of Qualitative Variation based on various relationship ties	1,170	0	Good
Sicotte et al., 2008	GDS-15	Diversity: number of different types of relationships each participant had: spouse, children, siblings, relatives/friends (range: 0-4)	1,714	+	Good
Sohn et al., 2017	CES-D (20)	Network types (restricted, diverse, congregant-restricted, congregant, family)	795	+	Good
Stoeckel & Litwin, 2016	Euro-D	Network types (distal children, proximal family, spouse, other family, friend, other, no network)	26,401	+	Fair
Vicente & Guadalupe, 2022	GDS-15	Proportion of each of the following relational categories: Family Friends Neighbors Workplace Institutional relations	612	 0 0 0 0 +	Poor
Webster et al., 2015	CES-D (11)	Type proportions (geographically distant male youth, geographically close/emotionally distant family, close family)	195	0	Fair
Ye & Zhang, 2019	GDS-15	Network types (diverse, restricted, family-restricted, family, friends)	405	+	Fair
Longitudinal studies					
Bui, 2020	CES-D (11)	Proportion female	2,200	0	Good
Chao, 2011	CES-D (10)	Proportion of close family members (spouses, children, and grandchildren) in the network	4,049	+	Good
Coleman et al., 2022	GDS-15	Proportion of alters in the network with whom ego has a very close relationship Proportion of alters in the network with whom ego is in frequent contact Proportion of alters in the network who are related to ego Diversity: number of unique relationship types in a person's network divided by network size	113	0 0 0 0	Good

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
Förster et al., 2018	CES-D (20)	Changes in network types (family dependent, local self-contained, private restricted, restricted mixed)	783	+	Good
Kim et al., 2016	CES-D (10)	Changes in network types (restricted, modern-family, friend, diverse)	3,501	+	Good
Litwin & Levinsky, 2021	Euro-D	Changes in network types (remains without network, transitions to close-family networks, transition to other networks, transitions from close-family networks, transitions from other networks)	834	+	Fair
Litwin et al., 2020	Euro-D	Changes in network types (remains in close-family type, remaining in other network types, transition to other network types, transitions to close-family network types)	13,767	+	Fair

[a] *n: Sample size, baseline sample was used in longitudinal studies*
[b] *Results: 0 indicates no sig. relationship ($p \geq 0.05$), + indicates sig. relationship ($p < 0.05$)*

Depression measures: *CES-D – Centre of Epidemiologic Studies Depression Scale; EURO-D – EURO geriatric depression scale; ESA-Q – Enquête sur la Santé des Aînés Questionnaire; GDS – Geriatric Depression Scale; GMS – Geriatric Mental State; PHQ-9 – Patient Health Questionnaire*

Contact frequency

Less consistency was found in social interaction frequency's influence on depression in older adults (see Table 2-5). The cross-sectional studies found 14 significant and 15 insignificant associations. In contrast, among the longitudinal studies, only one significant piece of evidence was found (Chao, 2011), while six effects were identified as insignificant. Three effects were found to be significant only in certain population groups (Gan & Best, 2021; Husaini, 1997). Furthermore, Blumstein et al. (2004) found a significant negative association between weekly contact with friends and children and depression cross-sectionally; this became insignificant when examined longitudinally. Although cross-sectional results are inconclusive, this could indicate that the frequency of contact has the potential to buffer depression at the time of the event but is not necessarily a sustainable buffer for depression.

There was no consensus among studies about the association of depression with contact frequencies in particular social spheres, such as friends, children, and non-kin (Blumstein et al., 2004; Castro-Costa et al., 2008; Chao, 2011; Chi & Chou, 2001; Forsman et al., 2012; Gan & Best, 2021; Husaini, 1997; Jeon & Lubben, 2016; La Gory & Fitzpatrick, 1992; Lee et al., 1996; Palinkas et al., 1990; Taylor et al., 2018). Chi & Chou (2001) found contact frequency with relatives to be more advantageous in buffering depression than the frequency of contact with friends. In contrast, Jeon & Lubben (2016) found contact frequency with non-kin to be negatively associated with depressive symptoms in older Korean immigrants, while contact frequency with kin was not significantly associated.

Only two scholars accounted for gender differences in the association of contact frequency and depression among older adults. Ermer & Proulx (2022) found no significant association of contact frequency and depression in women or men. In their cross-sectional analysis, Blumstein et al. (2004) also found no gender differences in the association between weekly contact with children and depression, but identified weekly contact with friends to only be significantly associated with depression in women but not men. However, these gender differences did not hold longitudinally.

Table 2-5 Overview of results: contact frequency and depression

Author	**Depression measure**	**Social network measure**	**N [a]**	**Results [b]**	**Quality**
Cross-sectional studies					
Becker et al., 2019	Euro-D	Contact index: contact with each person in network over the last 12 months (daily, several times a week, about once a week, about every two weeks, about once a month, less than once a month, never)	52,513	+	Poor
Blumstein et al., 2004	CES-D (20)	Weekly contact with friends Weekly contact with children	1,290	+ +	Poor
Castro-Costa et al., 2008	GHQ-12	Weekly frequency of visits from offspring, relatives and friends	1,510	0	Poor
Chi & Chou, 2001	CES-D (20)	Contact frequency with relatives Contact frequency with friends (Less than once a month, once a month, two to three times a month, once a week, two to six times a week, everyday)	1,106	+ 0	Good
Domènech-Abella et al., 2017	CIDI 3.0	Contact with network members at least once per month in the previous 12 months	3,535	0	Good
Ermer & Proulx, 2022	CES-D (11)	Contact with network member (every day, several times a week, once a week, once every two weeks, once a month, a couple times a year, once a year, and less than once a year)	865	0	Fair
Forsman et al., 2012	GDS-4	Contact frequency with friends Contact frequency with neighbors (Frequent contact: several times a week, several times a month; infrequent contact: few times a year, never, does not exist)	6,838	+ +	Good
Jeon & Lubben, 2016	CES-D (20)	Contact frequency with non-kin Contact frequency with kin (Less than once a month, monthly, 2-3 times a month, weekly, 2-3 times a week, daily)	424	0 +	Fair
La Gory & Fitzpatrick, 1992	CES-D (20)	Contact scale: visiting friends and relatives, being visited by them, phoning or writing them and meeting them in a social setting	725	+	Poor
Lee et al., 1996	CES-D (20)	Contact frequency with children Contact frequency with friends (Monthly or less, almost weekly, almost daily)	162	+ +	Poor
M. Li et al., 2019	PHQ-9	Average contact frequencies that a participant talked to network members in the past one year (less than once a year to every day)	3,157	0	Fair
Litwin & Levinsky, 2022	Euro-D	In-person contact Electronic contact	33,403	+ 0	Good

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
		(daily, several times a week, about once a week, less often, never)			
Litwin & Levinsky, 2023	Euro-D	Contact to confidants (7-point scale: 1 = never; 7 = daily)	35,145	+	Good
Litwin et al., 2015	Euro-D	Contact frequency (never to daily) to network persons	25,245	0	Good
Marshall & Rue, 2012	CES-D (20)	Index of contact frequency to family members/ friends/ church members (never to nearly every day)	1,108	+	Good
Marshall-Fabien & Miller, 2016	CES-D (12)	Index of contact frequency to family members/ friends/ church members (never to nearly every day)	1,108	0	Good
Minicuci et al., 2002	CES-D (20)	Personal contact with family members Telephone contact with family members (never, every 6 months, every 2-3 months, every month, more often)	2,398	0 0	Good
Palinkas et al., 1990	BDI (18)	Frequency of face-to-face contact with close family and friends (at least once a week vs. less than once a week)	1,615	0	Poor
Pilehvari et al., 2023	CES-D (20)	Contact to people that immediately surround them (0 = have never spoken to each other to 8 = every day)	1,170	0	Good
Taylor et al., 2018	CES-D (12)	Contact frequency with family members and friends (no isolation: nearly every day, at least once a week, a few times a month; isolation: at least once a month, a few times a year, hardly ever or never) to combination variable (objectively isolated from both family members and friends, objectively isolated from family only, objectively isolated from friends only, not objectively isolated from family and friends)	1,439	0	Good
Vicente & Guadalupe, 2022	GDS-15	Contact frequency (1 = a few times per year to 5 = daily)	612	0	Poor
Wu et al., 2017	CES-D (20)	Interpersonal contacts over the past year (dichotomized: poor social support was defined as ≤1 episode of contact with neighbors, relatives, or friends per month)	5,635	+	Good
Longitudinal studies					
Blumstein et al., 2004	CES-D (20)	Weekly contact with friends Weekly contact with children	746	0 0	Good
Bui, 2020	CES-D (11)	Contact frequency with named alters (less than once a year to every day)	2,200	0	Good
Chao, 2011	CES-D (10)	Contact frequency (mean frequency of meeting with children who were not living with respondent; never or not available to everyday)	4,049	+	Good
Gan & Best, 2021	CES-D (8)	In-person contact with friends Tele-conversation with friends Contact with neighbors (Less than once a month to three or more times a week)	3,105	0 0 0/+ (+ only in average outcome profile)	Fair
Husaini, 1997	CES-D (20)	Contact frequency with friends Contact frequency with relatives	1,200	0/+ 0/+	Poor

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
		(Daily to once a year)			
Schwartz & Litwin, 2017	Euro-D	Contact frequency to alters (daily to never)	14,101	0	Good

[a] n: Sample size, baseline sample was used in longitudinal studies
[b] Results: 0 indicates no sig. relationship ($p \geq 0.05$), + indicates sig. relationship ($p < 0.05$)

Depression measures: *BDI – Beck Depression Inventory; CES-D – Centre of Epidemiologic Studies Depression Scale; CIDI – Composite International Diagnostic Interview; EURO-D – EURO geriatric depression scale; GDS – Geriatric Depression Scale; GHQ – General Health Questionnaire; MADRS – Montgomery–Åsberg Depression Rating Scale; PHQ-9 – Patient Health Questionnaire*

Density

Four articles examined how social network density was associated with depression in older adults (see Table 2-6). The results were inconclusive, cross-sectionally as well as longitudinally. Coleman et al. (2022) and Vicente & Guadalupe (2022) found no significant associations. Furthermore, the significant associations found were contradictory even though the same data and measurements were used. Dorrance Hall et al. (2019) found that confidant network density was negatively associated with levels of depression cross-sectionally. In contrast, Bui (2020) conducted a longitudinal study and found that a higher network density was significantly associated with increased depressive symptoms.

Table 2-6 Overview of results: network density and depression

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
Cross-sectional studies					
Dorrance Hall et al., 2019	CES-D (9)	Number of observed links divided by perceived potential links among network members (indicated by respondent; links is being defined as speaking on a monthly basis)	2,249	+	Good
Vicente & Guadalupe, 2022	GDS-15	Proportion of network members that knows one another; calculated by dividing the number of actual connections between network members by the number of potential connections	612	0	Poor
Longitudinal studies					
Bui, 2020	CES-D (11)	Ratio of actual ties to perceived possible ties (indicated by respondent; ties is being defined as having any contact)	2,200	+	Good
Coleman et al., 2022	GDS-5	Mean of closeness of the tie between alters	113	0	Good

[a] n: Sample size, baseline sample was used in longitudinal studies
[b] Results: 0 indicates no sig. relationship ($p \geq 0.05$), + indicates sig. relationship ($p < 0.05$)

Depression measures: *CES-D – Centre of Epidemiologic Studies Depression Scale; GDS – Geriatric Depression Scale*

Geographic proximity

Three cross-sectional articles considered geographical proximity as a social network determinant for depression among older adults (see Table 2-7). No study focused on the respective relationship longitudinally. All the articles found significant but inconclusive results. While Litwin et al. (2015) and Vicente & Guadalupe (2022) found that geographically closer social networks buffer depression, Becker et al. (2019) identified that geographically closer social networks increased depression. This may be attributable to the measurement used to assess geographic proximity: Litwin et al. (2015) included individuals living within the respondent's household, while Becker et al. (2019) did not. This strongly suggests that the direction of effects is dependent on operationalization.

Table 2-7 Overview of results: geographic proximity and depression

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
Cross-sectional studies					
Becker et al., 2019	Euro-D	Proximity index (Average geographical proximities to network members: more than 500 km, 100 km to 500 km, 25 km to 100 km, 5 km to 25 km, 1 km to 5 km, and less than 1 km)	52,513	+	Poor
Litwin et al., 2015	Euro-D	Proximity (Scores ranged from "more than 500 km away" (1) to "in the same household" (8))	25,245	+	Good
Vicente & Guadalupe, 2022	GDS-15	Proximity index (Average of geographical proximities to network members; more than 50 km, less than 50 km, in the same city/village, in the same street/neighborhood, in the same household)	612	+	Poor

[a] *n: Sample size, baseline sample was used in longitudinal studies*
[b] *Results: 0 indicates no sig. relationship ($p \geq 0.05$), + indicates sig. relationship ($p < 0.05$)*

Depression measures: *EURO-D – EURO geriatric depression scale; GDS – Geriatric Depression Scale*

Homogeneity

Furthermore, two cross-sectional studies examined homo-/heterogeneity (see Table 2-8). Their evidence suggested no significant relationship between network homo-/ heterogeneity and depression among older adults. Goldberg et al. (1985) determined network homogeneity through questions about the sex, age, and religion of all network members. They found no significant association with depression. Murayama et al. (2015) measured homo-/heterogeneity through respondents' perceptions of the (dis)similarity of characteristics. They found a significant negative association with depression. This was only found for individuals with a strongly homogenous network and not for those with a weakly homogenous network. No significant relationship was found between network heterogeneity and depression outcomes.

Table 2-8 Overview of results: network homogeneity and depression

Author	Depression measure	Social network measure	N [a]	Results [b]	Quality
Cross-sectional studies					
Goldberg et al., 1985	CES-D (20)	Homogeneity determined by questions about sex, age, and religion of all network members	1,104	0	Good
Murayama et al., 2015	GDS-15	Homogeneity Heterogeneity (Perceived (dis)similarity to network members regarding social characteristics age, gender, and SES)	6,416	+ 0	Fair

[a] n: Sample size, baseline sample was used in longitudinal studies
[b] Results: 0 indicates no sig. relationship ($p \geq 0.05$), + indicates sig. relationship ($p < 0.05$)

Depression measures: *CES-D – Centre of Epidemiologic Studies Depression Scale; GDS – Geriatric Depression Scale*

2.3.3 Structural social network variables as outcome variable

Thirteen studies focused on social networks as outcome variables of depression (see Table 2-9). Seven articles examined this association cross-sectionally, while six articles did so longitudinally.

The articles examining the relationship between depression and social networks specifically focused on social network scale outcomes, network size, network composition, density, and contact frequency.

Network scales

Evidence about the relationship between depression and network scales was mixed. While Merchant et al. (2020) found no evidence cross-sectionally, other scholars found significant evidence that depression was associated with lower scores on network scales (Bincy et al., 2022; Li et al., 2022; Sugie et al., 2022) and subscales (Wendel et al., 2022). However, the longitudinal evidence found was contradictory (Domènech-Abella et al., 2019; Zhang et al., 2023).

Network size

Depression was primarily identified as a significant predictor for network size. This was found cross-sectionally (Shouse et al., 2013) and longitudinally (Bui, 2020; Houtjes et al., 2014; Voils et al., 2007). Shouse et al. (2013) found depression to be a predictor for a smaller inner circle network size. Furthermore, Bui (2020) found that depressive symptoms significantly affected an individual's number of close ties but not total social network size. In contrast, Houtjes et al. (2014) examined differences in network size depending on depression course types. They found decreasing network sizes for all depression course types in older adults.

Network composition

Cross-sectionally, Ali et al. (2022) found that individuals with more depressive symptoms had smaller and more strained networks. Bui (2020) did not identify depressive symptoms as a significant predictor of the proportion of females in an individual's network.

Contact frequency

No significant evidence suggested that depression affects contact frequency (Bui, 2020; Voils et al., 2007).

Network density

Bui (2020) did not find depressive symptoms to significantly predict network density.

Table 2-9 Overview of articles focusing on structural network aspects as outcome variable

Author	**Depression measure**	**Social network measure**	**N** [a]	**Results** [b]	**Quality**
Cross-sectional studies					
Ali et al., 2022	NDSM	Composition (large with strain; large without strain; small, diverse, low contact; small, restricted, high contact; medium size and support)	5,192	+	Good
Bincy et al., 2022	GDS-15	Scale (LSNS)	1,000	+	Good
M. Li et al., 2019	GDS-15	Scale (LSNS)	2,267	+	Good
Merchant et al., 2020	GDS	Scale (LSNS)	202	0	Fair
Shouse et al., 2013	GDS-15	Network size (Hierarchical mapping technique) Total Inner circle Middle circle Outer circle	79	 + + + 0	Fair
Sugie et al., 2022	GDS-15	LSNS (dichotomous, scores <12 limited network)	268	+	Good
Wendel et al., 2022	GDS	Scale (LSNS) Total Family subscale Friends subscale	1,030	 + + +	Good
Longitudinal studies					
Bui, 2020	CES-D (11)	Network size: Total network size, Number of close ties Composition: Proportion female Density: ratio of actual ties to theoretically possible ties Contact frequency (less than once a year to every day)	2,200	 0 + 0 0 0	Good
Domènech-Abella et al., 2019	CIDI-SF	Scale (SNI)	5,066	0	Good
Houtjes et al., 2014	CES-D (20)	Network size (Socially active relationships of the respondent)	277	+	Good
Reynolds et al., 2020	CES-D	Network size	3,005	0	Good

Author	Depres-sion meas-ure	Social network measure	N [a]	Results [b]	Quality
		(Number of important people regular in contact)			
Voils et al., 2007	MADRS	Network size (assessed by 4 items, no further specification) Contact frequency (Weekly contact assessed by four items; not at all, once, twice, three times, four times, five times, six times, seven times or more)	339	+ 0	Fair
Zhang et al., 2023	DASS-21 (depression subscale)	Scale (LSNS)	634	+	Good

[a] n: Sample size, baseline sample was used in longitudinal studies
[b] Results: 0 indicates no sig. relationship ($p \geq 0.05$), + indicates sig. relationship ($p < 0.05$)

Depression measures: *CES-D – Centre of Epidemiologic Studies Depression Scale; CIDI-SF – Composite International Diagnostic Interview (Short Form); DASS-21 – Depression Anxiety Stress Scale; GDS – Geriatric Depression Scale; NDSM – NSHAP Depressive Symptoms Measure*

Social network measures: *LSNS – Lubben Social Network Scale; SNI – Social Network Index*

2.3.4 Reciprocal relationship of structural network aspects and depression

Only five articles examined the relationship between structural network aspects and depression reciprocally (Bui, 2020; Domènech-Abella et al., 2019; Reynolds et al., 2020; Sugie et al., 2022; Zhang et al., 2023). However, no reciprocal relationship was found between depression and network size (Bui, 2020; Reynolds et al., 2020), composition (Bui, 2020), contact frequency (Bui, 2020), and network scales (Domènech-Abella et al., 2019; Sugie et al., 2022; Zhang et al., 2023). Bui (2020) only identified greater network density to significantly reduce depressive symptoms five years later, but not the other way around. Network size, number of close ties, contact frequency, or network composition did not significantly affect depressive symptoms five years later. Furthermore, Domènech-Abella et al. (2019) found that the social network index significantly affects depression longitudinally; however, this relationship was not reciprocal. In contrast, Zhang et al. (2023) found that higher depression scores at baseline predicted lower social network scores at a 6-month follow-up. However, social network scores did not predict depression at a 6-month follow-up. Bui (2020) found more depressive symptoms to be associated with fewer close ties five years later. However, all other structural network measures (network size, composition, and contact frequency) were insignificant; therefore, the author concluded that there was no clear reciprocal relationship between structural network measures and depression (Bui, 2020).

2.3.5 Importance of functional network aspects

Thirty articles included social support in their analysis and examined whether social networks' structural or functional aspects were more important in predicting depression outcomes in older adults. Singh et al.'s (2016) article was excluded because social support measures' effect sizes and significance were not presented.

However, no consensus can be reached. Seven studies identified structural aspects as more critical in predicting depression in terms of significant effects (Blumstein et al., 2004; Hamid et al., 2019; Jang et al., 2002; Lee & Chou, 2019; Sonnenberg et al., 2013; Stringa et al., 2020; Tsai et al., 2005), while nine scholars found social support to be more relevant (Antonucci et al., 1997; Bisschop et al., 2004; Coleman et al., 2022; Han et al., 2007; Mehrabi & Béland, 2021; Miller & Lago, 1990; Oxman et al., 1992; Vicente & Guadalupe, 2022; Ye & Zhang, 2019). Sixteen studies found that social support and social network aspects were equally (not) predictive of depressive symptoms (Braam et al., 1997; Bui, 2020; Cao et al., 2015; Chao, 2011; Cheng et al., 2014; Chi & Chou, 2001; Dorrance Hall et al., 2019; Fredriksen-Goldsen et al., 2013; Harasemiw et al., 2019; Husaini, 1997; Mechakra-Tahiri et al., 2010; Minicuci et al., 2002; Santini et al., 2016; Sicotte et al., 2008; F. Tang et al., 2023; Webster et al., 2015).

2.4 Discussion

2.4.1 Social network characteristics and depression among older adults

This study aimed to systematize the evidence about the relationship between social networks and depression in older adults. It focused on the structural aspects of social networks because these are particularly suited for understanding their association with critical health outcomes (Holt-Lunstad et al., 2010; Kuiper et al., 2015, 2016). It differentiated between the causality of relationships and structural and functional social network characteristics' impact on depression.

Most articles followed the main-effect model (Kawachi & Berkman, 2001) and considered depression as an outcome variable of social network characteristics in examining the relationship between structural social network aspects and depression among older adults. Only eight articles exclusively accounted for the reversed logic of causality: social network characteristics as an outcome of depression (Ali et al., 2022; Bincy et al., 2022; Houtjes et al., 2014; Li et al., 2022; Merchant et al., 2020; Shouse et al., 2013; Voils et al., 2007; Wendel et al., 2022). Five out of 127 articles examined the reciprocal relationship between structural social network characteristics and depression (Bui, 2020; Domènech-Abella et al., 2019; Reynolds et al., 2020; Sugie et al., 2022; Zhang et al., 2023). However, these articles found no clear reciprocal relationship. Therefore, no theoretical conclusions can be drawn based on these findings.

The majority of articles focused on depression as an outcome of older adults' social network characteristics. They primarily used cross-sectional evidence. Structural network characteristics were predominantly operationalized through network scales, size, composition, and contact frequency. Conversely, they generally neglected network density, homogeneity, and geographical proximity. Evidence about whether and how the latter three social network aspects affect depression outcomes in older adults was inconsistent (Becker et al., 2019; Bui, 2020; Coleman et al., 2022; Dorrance Hall et al., 2019; Goldberg et al., 1985; Litwin et al., 2015; Murayama et al., 2015; Vicente & Guadalupe, 2022). Most evidence supported the assumption that higher scores on social network scales buffer depression (Aung et al., 2016; Bae et al., 2020; Boey & Chiu, 2005; Byers et al., 2012; Chan et al., 2011; Chan & Zeng, 2009, 2011; Chou & Chi, 2001; Domènech-Abella et al., 2019; Fernández & Rosell, 2022; Gao et al., 2022; Gu et al., 2023; Hamid et al., 2019; Jang et al., 2002; Jiang et al., 2022; Kim et al., 2012; Kim & Lee, 2015; Lee et al., 2017; Okwumabua et al., 1997; Palinkas et al., 1990; Park & Roh, 2013; Park et al., 2013; Roh et al., 2015; Ruan et al., 2022; Santini et al., 2016, 2017; Santini, Koyanagi, Tyrovolas, et al., 2015; Sugie et al., 2022; D. Tang et al., 2020, 2023; Tang & Xie, 2021; Tanikaga et al., 2023; Tsai et al., 2005; Wee et al., 2014). Corroborating previous literature reviews (Mohd et al., 2019; Santini, Koyanagi, Tyrovoloas, et al., 2015), some evidence suggested that a more extensive network size buffers depression outcomes in older adults compared to a smaller network size (Antonucci et al., 1997; Becker et al., 2019; Braam et al., 1997; Chao, 2011; Cheng et al., 2014; Chi & Chou, 2001; Dorrance Hall et al., 2019; Fredriksen-Goldsen et al., 2013; Fuller-Iglesias et al., 2008; Goldberg et al., 1985; Harada et al., 2023; Harlow et al., 1991; Kuchibhatla et al., 2012; Lee et al., 1996; Lee & Chou, 2019; M. Li et al., 2019; Litwin et al., 2015; Litwin & Levinsky, 2023; Liu et al., 2016; Oxman et al., 1992; Palinkas et al., 1990; Santini et al., 2021; Sonnenberg et al., 2013; Stringa et al., 2020; Werneck et al., 2023). Three-quarters of the studies also identified that network composition was significantly associated with depression outcomes in older adults; diverse social networks were found to be more beneficial than restricted networks (Choi & Jeon, 2021; Fiori et al., 2006; Förster et al., 2018; Harasemiw et al., 2019; Kim et al., 2016; Kim & Lee, 2019; Litwin, 2011, 2012; Park et al., 2014, 2018; Sohn et al., 2017; Ye & Zhang, 2019). This aligns with Santini et al.'s (2015) findings, who consistently identified diverse types of social networks as associated with favorable depression outcomes. Results on the effect of contact frequency on depression were less consistent: no clear evidence was found cross-sectionally, and no substantial effects of contact frequency were found in longitudinal studies. This confirms Schwarzbach et al.'s (2014) findings, which reported inconsistent results cross-sectionally and longitudinally.

Furthermore, the effects of social network aspects on depression seem to be largely stable for women and men (Becker et al., 2019; Blumstein et al., 2004; Boey & Chiu, 2005; Chan et al., 2011; Choi & Jeon, 2021; Ermer & Proulx, 2022; Hajek & König, 2016; Klug et al., 2014; Mechakra-Tahiri et al., 2010; Minicuci et al., 2002; Murayama et al., 2015; Park et al., 2013; Pavlidis et al., 2023; Roh et al., 2015; Santini et al., 2016; Sicotte et al., 2008; Sonnenberg et al., 2013; D. Tang et al., 2023). Notably, no consensus can be reached about whether family or friends are more critical for favorable depression outcomes in older adults (Antonucci et al., 1997; Chao, 2011; Chi & Chou, 2001; Fernández & Rosell, 2022; Fiori et al., 2006; Gao et al., 2022; Litwin et al., 2020; Singh et al., 2016; D. Tang et al., 2023). This challenges the previous assumption that family is the most crucial source of good health (Antonucci et al., 2011).

A minority of articles found social network characteristics to be outcomes of depression. While depression did not influence density (Bui, 2020) and contact frequency (Bui, 2020; Voils et al., 2007), an unclear effect was found for network scales (Bincy et al., 2022; Domènech-Abella et al., 2019; Li et al., 2022; Merchant et al., 2020; Sugie et al., 2022; Wendel et al., 2022; Zhang et al., 2023) and network composition (Ali et al., 2022; Bui, 2020). However, depression significantly reduced the size of an individual's social network and their number of close relationships (Bui, 2020; Houtjes et al., 2014; Shouse et al., 2013; Voils et al., 2007).

This review does not confirm the previous systematic reviews' findings (Santini, Koyanagi, Tyrovoloas, et al., 2015; Schwarzbach et al., 2014) that social networks' functional aspects are more important than their structural aspects in predicting depression. The articles that considered functional network characteristics showed no consensus about whether structural or functional network aspects were more important in buffering depression outcomes in older adults (Antonucci et al., 1997; Bisschop et al., 2004; Blumstein et al., 2004; Braam et al., 1997; Bui, 2020; Cao et al., 2015; Chao, 2011; Cheng et al., 2014; Chi & Chou, 2001; Coleman et al., 2022; Dorrance Hall et al., 2019; Fredriksen-Goldsen et al., 2013; Hamid et al., 2019; Han et al., 2007; Harasemiw et al., 2019; Husaini, 1997; Jang et al., 2002; Lee & Chou, 2019; Mechakra-Tahiri et al., 2010; Mehrabi & Béland, 2021; Miller & Lago, 1990; Minicuci et al., 2002; Oxman et al., 1992; Santini et al., 2016; Sicotte et al., 2008; Sonnenberg et al., 2013; Stringa et al., 2020; F. Tang et al., 2023; Tsai et al., 2005; Vicente & Guadalupe, 2022; Webster et al., 2015; Ye & Zhang, 2019).

Furthermore, very few studies reported effect sizes. However, the studies that reported standardized coefficients almost exclusively identified small effect sizes across all structural social network aspects (Bincy et al., 2022; Boey & Chiu, 2005; Braam et al., 1997; Cao et al., 2015; Cheng et al., 2014; Chi & Chou, 2001; Choi & Jeon, 2021; Chou & Chi, 2001; Fernández

& Rosell, 2022; Fiori et al., 2006; Fuller-Iglesias et al., 2008; Gu et al., 2023; Hamid et al., 2019; Harada et al., 2023; Harlow et al., 1991; Jang et al., 2002, 2011; Jiang et al., 2022; Kim et al., 2012; Kim et al., 2015; Kim & Lee, 2019; Lee et al., 1996; Lee et al., 2017; Li et al., 2022; Litwin, 2012; Litwin et al., 2015, 2020; Litwin & Levinsky, 2021, 2023; Marshall & Rue, 2012; Okwumabua et al., 1997; Palinkas et al., 1990; Park & Roh, 2013; Park et al., 2013, 2014; Pavlidis et al., 2023; Sohn et al., 2017; Stoeckel & Litwin, 2016; D. Tang et al., 2023; Ye & Zhang, 2019). Although the studies covered a wide sample size range, there were no differences in the results. This suggests that structural network aspects have a rather small but stable influence on depression. However, future studies should report effect sizes (e.g., by standardized coefficients) to ensure the comparability of studies and individual effects.

2.4.2 Limitations and future implications

This systematic review is the first to specifically focus on the relationship between structural social network aspects and depression outcomes among older adults. While previous systematic reviews have been helpful, they have loosely applied the constructs of social networks and limited their focus to particular geographic areas. Additionally, the vast body of evidence that has emerged during the last decade highlights the importance of this updated systematic review. However, our review has some limitations. Like other reviews, the articles included in this review may be prone to publication bias. In addition, we did not use controlled vocabulary terms such as MeSH and Psychological Index Terms in our search strategy. As our search strategy and keywords were informed by other reviews (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini, Koyanagi, Tyrovoloas, et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018), we used a diverse range of keywords relevant to the field. Our comprehensive search strategy is reflected in the high number of initial articles found. Consequently, we anticipate having identified all relevant articles. Furthermore, we only included articles published in English, neglecting the findings reported in different languages. However, we did this to counteract possible regional bias induced by language knowledge of the authors. Additionally, the exclusion of non-English articles was found to have minimal impact on the results and overall conclusions of a review (Hartling et al., 2017; Nussbaumer-Streit et al., 2020). However, future research could employ machine translation to counteract selection bias induced by language restrictions. This should be particularly beneficial in contexts in which limited evidence exists.

Further, it must be emphasized that we focused on community-dwelling older adults, excluding institutionalized individuals from analysis. It should be acknowledged that regional bias may arise, given the different proportions of older adults living in institutions across countries.

However, we decided to do this as institutionalized individuals are likely to have predetermined social networks which may affect depression outcomes differently.

Additionally, the use of the term "social network" may exclude studies focusing solely on family networks, which are highly relevant for the mental health of older adults. However, as the individual network should not be limited to family networks alone, we have deliberately opted for the holistic term here, to capture the social network in its entirety. This approach is supported by the ambiguous results on the importance of family and friendship relationships for depression among older adults (see analysis above).

Furthermore, this systematic review included studies from peer-reviewed journals, excluding gray literature. This may limit our findings. However, it ensures that the included articles are high quality. Furthermore, systematic reviews do not allow qualitative studies to be included. While qualitative studies are limited in their potential to establish causal relationships between variables, they provide valuable insights into the understanding and interpretation of psychosocial phenomena that quantitative research often cannot access.

This systematic review aimed to understand the potential of structural social network characteristics holistically by reviewing them all and not limiting the focus on only a few. That is why we did not conduct a meta-analysis. Firstly, evidence is too small to be statistically analyzed, such as in the social network domains network density, homogeneity, and geographical proximity. Secondly, particularly in the social network domain composition, results are not necessarily comparable since cluster analysis results in different numbers of clusters which are consequently characterized differently. However, future research should conduct a meta-analysis with the more comparable domains network scale, size, and contact frequency.

Despite this review's limitations, its strength lies in its systematic search; multiple keywords and broad terminologies were used to capture as many articles as possible. This is reflected in the significant number of publications included in this review.

Much of the evidence reported here came from cross-sectional studies. Additionally, only eight of the 127 articles exclusively considered social networks as dependent variables, and only four studies examined the reciprocal relationship. This makes it particularly difficult to draw causal conclusions about the relationship between social networks and depression among older adults. Further research is needed to disentangle the reciprocal relationship using longitudinal data. Furthermore, limited literature focused on the relationship between depression and network density, homogeneity, and geographical proximity. Additionally, these results were inconclusive. Therefore, these relationships should be closely examined in future research.

2.5 Conclusion

This review gathered evidence and confirmed that having larger and more diverse social networks and closer ties buffers depression among older adults. Evidence about the relationship between contact frequency and depression was inconclusive. Literature on the relationships between depression and network density, homogeneity, and geographical proximity is scarce and inconclusive; therefore, further research is needed. Although this review examined a vast body of research about the relationship between social network aspects and depression among older adults, no conclusions about causality could be drawn. Contrary to other reviews, the evidence suggests that functional and structural networks are equally important in determining depression outcomes in older adults.

This review highlights that quantifying older adults' social relations is crucial to understanding depression outcomes in older adults. As the population ages and multimorbidity and social isolation increase, appropriate social gerontological interventions are needed. Based on this review, interventions could potentially promote the integration of older adults into larger and more diverse social settings. Following the recommendations of a systematic review about the effectiveness of interventions targeting social isolation in older adults (Dickens et al., 2011), group interventions like social activities are the most effective in broadening older adults' social networks and increasing their contacts. These interventions can help to counteract depression in older adults.

2.6 References

Ali, T., Elliott, M. R., Antonucci, T. C., Needham, B. L., Zelner, J., & Mendes de Leon, C. F. (2022). Multidimensional social network types and their correlates in older Americans. *Innovation in Aging, 6*(1), 1–16. https://doi.org/10.1093/geroni/igab053

Antonucci, T. C., Birditt, K. S., Sherman, C. W., & Trinh, S. (2011). Stability and change in the intergenerational family: A convoy approach. *Ageing and Society, 31*(7), 1084–1106. https://doi.org/10.1017/S0144686X1000098X

Antonucci, T. C., Fuhrer, R., & Dartigues, J.-F. (1997). Social relations and depressive symptomatology in a sample of community-dwelling French older adults. *Psychology and Aging*, *12*(1), 189–195. https://doi.org/10.1037/0882-7974.12.1.189

Aung, M. N., Moolphate, S., Aung, T. N. N., Kantonyoo, C., Khamchai, S., & Wannakrairot, P. (2016). The social network index and its relation to later-life depression among the elderly aged >= 80 years in Northern Thailand. *Clinical Interventions in Aging*, *11*, 1067–1074. https://doi.org/10.2147/CIA.S108974

Ayalon, L., & Levkovich, I. (2019). A systematic review of research on social networks of older adults. *The Gerontologist*, *59*(3), e164–e176. https://doi.org/10.1093/geront/gnx218

Bae, S., Harada, K., Chiba, I., Makino, K., Katayama, O., Lee, S., Shinkai, Y., & Shimada, H. (2020). A new social network scale for detecting depressive symptoms in older Japanese adults. *International Journal of Environmental Research and Public Health*, *17*(23), 8874. https://doi.org/10.3390/ijerph17238874

Becker, C., Kirchmaier, I., & Trautmann, S. (2019). Marriage, parenthood and social network: Subjective well-being and mental health in old age. *PLOS ONE*, *14*(7), e0218704. https://doi.org/10.1371/journal.pone.0218704

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social Science & Medicine*, *51*(6), 843–857. https://doi.org/10.1016/S0277-9536(00)00065-4

Berkman, L. F., & Syme, S. L. (1979). Social networks, host resistance, and mortality: A nine-year follow-up study of alameda county residents. *American Journal of Epidemiology*, *109*(2), 186–203. https://doi.org/10.1093/oxfordjournals.aje.a112674

Bincy, K., Logaraj, M., & Anantharaman, V. V. (2022). Social network and its effect on selected dimension of health and quality of life among community dwelling urban and rural geriatric population in India. *Clinical Epidemiology and Global Health*, *16*, 101083. https://doi.org/10.1016/j.cegh.2022.101083

Bisconti, T. L., & Bergeman, C. S. (1999). Perceived Social Control as a Mediator of the Relationships Among Social Support, Psychological Weil-Being, and Perceived Health. *The Gerontologist*, *39*(1), 94–104. https://doi.org/10.1093/geront/39.1.94

Bisschop, M. I., Kriegsman, D. M. W., Beekman, A. T. F., & Deeg, D. J. H. (2004). Chronic diseases and depression: The modifying role of psychosocial resources. *Social Science & Medicine*, *59*(4), 721–733. https://doi.org/10.1016/j.socscimed.2003.11.038

Blazer, D. G. (2003). Depression in late life: Review and commentary. *The Journals of Gerontology: Series A*, *58*(3), 249–265. https://doi.org/10.1093/gerona/58.3.M249

Blumstein, T., Benyamini, Y., Fuchs, Z., Shapira, Z., Novikov, I., Walter-Ginzburg, A., & Modan, B. (2004). The effect of a communal lifestyle on depressive symptoms in late life. *Journal of Aging and Health*, *16*(2), 151–174. https://doi.org/10.1177/0898264303262650

Boey, K. W., & Chiu, H. F. K. (2005). Life strain and psychological distress of older women and older men in Hong Kong. *Aging & Mental Health*, *9*(6), 555–562. https://doi.org/10.1080/13607860500193351

Braam, A. W., Beekman, A. T. F., van Tilburg, T. G., Deeg, D. J. H., & van Tilburg, W. (1997). Religious involvement and depression in older Dutch citizens. *Social Psychiatry and Psychiatric Epidemiology: The International Journal for Research in Social and Genetic Epidemiology and Mental Health Services*, *32*(5), 284–291. https://doi.org/10.1007/BF00789041

Bui, B. K. H. (2020). The relationship between social network characteristics and depressive symptoms among older adults in the United States: Differentiating between network structure and network function. *Psychogeriatrics*, *20*(4), 458–468. https://doi.org/10.1111/psyg.12530

Byers, A. L., Vittinghoff, E., Lui, L.-Y., Hoang, T., Blazer, D. G., Covinsky, K. E., Ensrud, K. E., Cauley, J. A., Hillier, T. A., Fredman, L., & Yaffe, K. (2012). Twenty-year depressive trajectories among older women. *JAMA Psychiatry*, *69*(10), 1073–1079. https://doi.org/10.1001/archgenpsychiatry.2012.43

Cao, W., Li, L., Zhou, X., & Zhou, C. (2015). Social capital and depression: Evidence from urban elderly in China. *Aging & Mental Health*, *19*(5), 418–429. https://doi.org/10.1080/13607863.2014.948805

Castro-Costa, É., Lima-Costa, M. F., Carvalhais, S., Firmo, J. O. A., & Uchoa, E. (2008). Factors associated with depressive symptoms measured by the 12-item General Health Questionnaire in community-dwelling older adults (The Bambuí Health Aging Study). *Revista Brasileira de Psiquiatria*, *30*(2), 104–109. https://doi.org/10.1590/S1516-44462008005000007

Chan, A., Malhotra, C., Malhotra, R., & Østbye, T. (2011). Living arrangements, social networks and depressive symptoms among older men and women in Singapore. *International Journal of Geriatric Psychiatry*, *26*(6), 630–639. https://doi.org/10.1002/gps.2574

Chan, M. F., & Zeng, W. (2009). Investigating factors associated with depression of older women in Macau. *Journal of Clinical Nursing*, *18*(21), 2969–2977. https://doi.org/10.1111/j.1365-2702.2009.02867.x

Chan, M. F., & Zeng, W. (2011). Exploring risk factors for depression among older men residing in Macau. *Journal of Clinical Nursing*, *20*(17–18), 2645–2654. https://doi.org/10.1111/j.1365-2702.2010.03689.x

Chao, S. F. (2011). Assessing social support and depressive symptoms in older Chinese adults: A longitudinal perspective. *Aging & Mental Health*, *15*(6), 765–774. https://doi.org/10.1080/13607863.2011.562182

Cheng, S.-T., Leung, E. M. F., & Chan, T. W. S. (2014). Physical and social activities mediate the associations between social network types and ventilatory function in Chinese older adults. *Health Psychology*, *33*(6), 524–534. https://doi.org/10.1037/hea0000026

Chi, I., & Chou, K.-L. (2001). Social support and depression among elderly Chinese people in Hong Kong. *The International Journal of Aging & Human Development*, *52*(3), 231–252. https://doi.org/10.2190/V5K8-CNMG-G2UP-37QV

Cho, J. H.-J., Olmstead, R., Choi, H., Carrillo, C., Seeman, T. E., & Irwin, M. R. (2019). Associations of objective versus subjective social isolation with sleep disturbance, depression, and fatigue in community-dwelling older adults. *Aging & Mental Health*, *23*(9), 1130–1138. https://doi.org/10.1080/13607863.2018.1481928

Choi, K.-W., & Jeon, G.-S. (2021). Social network types and depressive symptoms among older Korean men and women. *International Journal of Environmental Research and Public Health*, *18*(21), 11175. https://doi.org/10.3390/ijerph182111175

Chou, K.-L., & Chi, I. (2001). Stressful life events and depressive symptoms: Social support and sense of control as mediators or moderators? *The International Journal of Aging & Human Development*, *52*(2), 155–171. https://doi.org/10.2190/9C97-LCA5-EWB7-XK2W

Cohen, S. (2004). Social relationships and health. *American Psychologist*, *59*(8), 676–684. https://doi.org/10.1037/0003-066X.59.8.676

Cohen, S., Underwood, L. G., & Gottlieb, B. H. (Eds.). (2000). *Social support measurement and intervention: A guide for health and social scientists*. Oxford University Press.

Coleman, M. E., Manchella, M. K., Roth, A. R., Peng, S., & Perry, B. L. (2022). What kinds of social networks protect older adults' health during a pandemic? The tradeoff between preventing infection and promoting mental health. *Social Networks*, *70*, 393–402. https://doi.org/10.1016/j.socnet.2022.05.004

Dickens, A. P., Richards, S. H., Greaves, C. J., & Campbell, J. L. (2011). Interventions targeting social isolation in older people: A systematic review. *BMC Public Health*, *11*(1), 647. https://doi.org/10.1186/1471-2458-11-647

Domènech-Abella, J., Lara, E., Rubio-Valera, M., Olaya, B., Moneta, M. V., Rico-Uribe, L. A., Ayuso-Mateos, J. L., Mundó, J., & Haro, J. M. (2017). Loneliness and depression in the elderly: The role of social network. *Social Psychiatry and Psychiatric Epidemiology*, *52*(4), 381–390. https://doi.org/10.1007/s00127-017-1339-3

Domènech-Abella, J., Mundó, J., Haro, J. M., & Rubio-Valera, M. (2019). Anxiety, depression, loneliness and social network in the elderly: Longitudinal associations from The Irish Longitudinal Study on Ageing (TILDA). *Journal of Affective Disorders*, *246*, 82–88. https://doi.org/10.1016/j.jad.2018.12.043

Dorrance Hall, E., Meng, J., & Reynolds, R. M. (2019). Confidant network and interpersonal communication associations with depression in older adulthood. *Health Communication*, *35*(7), 872–881. https://doi.org/10.1080/10410236.2019.1598616

Ermer, A. E., & Proulx, C. M. (2022). The association between relationship strain and emotional well-being among older adult couples: The moderating role of social connectedness. *Aging & Mental Health*, *26*(6), 1198–1206. https://doi.org/10.1080/13607863.2021.1910786

Fernández, M. B., & Rosell, J. (2022). An analysis of the relationship between religiosity and psychological well-being in Chilean older people using structural equation modeling. *Journal of Religion and Health*, *61*(2), 1585–1604. https://doi.org/10.1007/s10943-021-01442-z

Fiori, K. L., Antonucci, T. C., & Cortina, K. S. (2006). Social network typologies and mental health among older adults. *The Journals of Gerontology: Series B*, *61*(1), P25–P32. https://doi.org/10.1093/geronb/61.1.P25

Forsman, A. K., Nyqvist, F., Schierenbeck, I., Gustafson, Y., & Wahlbeck, K. (2012). Structural and cognitive social capital and depression among older adults in two Nordic regions. *Aging & Mental Health*, *16*(6), 771–779. https://doi.org/10.1080/13607863.2012.667784

Förster, F., Luppa, M., Pabst, A., Heser, K., Kleineidam, L., Fuchs, A., Pentzek, M., Kaduszkiewicz, H., van der Leeden, C., Hajek, A., König, H.-H., Oey, A., Wiese, B., Mösch, E., Weeg, D., Weyerer, S., Werle, J., Maier, W., Scherer, M., … Riedel-Heller, S. G. (2021). The role of social isolation and the development of depression. A comparison of the widowed and married oldest old in Germany. *International Journal of Environmental Research and Public Health*, *18*(13), 6986. https://doi.org/10.3390/ijerph18136986

Förster, F., Stein, J., Löbner, M., Pabst, A., Angermeyer, M. C., König, H.-H., & Riedel-Heller, S. G. (2018). Loss experiences in old age and their impact on the social network and depression– Results of the Leipzig Longitudinal Study of the Aged (LEILA 75+). *Journal of Affective Disorders*, *241*, 94–102. https://doi.org/10.1016/j.jad.2018.07.070

Fredriksen-Goldsen, K. I., Emlet, C. A., Kim, H.-J., Muraco, A., Erosheva, E. A., Goldsen, J., & Hoy-Ellis, C. P. (2013). The physical and mental health of lesbian, gay male, and bisexual (LGB) older adults: The role of key health indicators and risk and protective factors. *The Gerontologist*, *53*(4), 664–675. https://doi.org/10.1093/geront/gns123

Fuller-Iglesias, H., Sellars, B., & Antonucci, T. C. (2008). Resilience in old age: Social relations as a protective factor. *Research in Human Development*, *5*(3), 181–193. https://doi.org/10.1080/15427600802274043

Gan, D. R. Y., & Best, J. R. (2021). Prior social contact and mental health trajectories during Covid-19: neighborhood friendship protects vulnerable older adults. *International Journal of Environmental Research and Public Health*, *18*(19), 9999. https://doi.org/10.3390/ijerph18199999

Gao, J., Hu, H., & He, H. (2022). Household indebtedness and depressive symptoms among older adults in China: The moderating role of social network and anticipated support. *Journal of Affective Disorders*, *298*, 173–181. https://doi.org/10.1016/j.jad.2021.10.133

Gariépy, G., Honkaniemi, H., & Quesnel-Vallée, A. (2016). Social support and protection from depression: Systematic review of current findings in Western countries. *British Journal of Psychiatry*, *209*(4), 284–293. https://doi.org/10.1192/bjp.bp.115.169094

Goldberg, E. L., Natta, P. V., & Comstock, G. W. (1985). Depressive symptoms social networks and social support of elderly women. *American Journal of Epidemiology*, *121*(3), 448–456. https://doi.org/10.1093/oxfordjournals.aje.a114017

Golden, J., Conroy, R. M., Bruce, I., Denihan, A., Greene, E., Kirby, M., & Lawlor, B. A. (2009). Loneliness, social support networks, mood and wellbeing in community-dwelling elderly. *International Journal of Geriatric Psychiatry*, *24*(7), 694–700. https://doi.org/10.1002/gps.2181

Gu, Y., Ali, S. H., & Guo, A. (2023). Comparing the role of social connectivity with friends and family in depression among older adults in China: Evaluating the moderating effect of urban–rural status. *Frontiers in Psychiatry*, *14*, 1162982. https://doi.org/10.3389/fpsyt.2023.1162982

Gumà, J., & Fernández-Carro, C. (2021). Life goes on: The influence of the perceived quality of social relations on older women's mental health after the loss of a partner in Europe. *Aging & Mental Health*, *25*(1), 53–60. https://doi.org/10.1080/13607863.2019.1675141

Hajek, A., & König, H.-H. (2016). Effect of health comparisons on functional health and depressive symptoms—Results of a population-based longitudinal study of older adults in Germany. *PLOS ONE*, *11*(5), e0156235. https://doi.org/10.1371/journal.pone.0156235

Hakeem, F. F., Bernabé, E., & Sabbah, W. (2019). Association between oral health and frailty: A systematic review of longitudinal studies. *Gerodontology*, *36*(3), 205–215. https://doi.org/10.1111/ger.12406

Hamid, T. A., Dzaher, A., & Ching, S. M. (2019). The role of social network, social support, religiosity and depression among elderly Malaysians who had experienced major life events. *The Medical Journal of Malaysia*, *74*(3), 198–204.

Han, H.-R., Kim, M., Lee, H. B., Pistulka, G., & Kim, K. B. (2007). Correlates of depression in the Korean American elderly: Focusing on personal resources of social support. *Journal of Cross-Cultural Gerontology*, *22*(1), 115–127. https://doi.org/10.1007/s10823-006-9022-2

Harada, K., Sugisawa, H., Sugihara, Y., Yanagisawa, S., & Shimmei, M. (2023). Big five personality traits, social networks, and depression among older adults in Japan: A multiple mediation analysis. *The International Journal of Aging and Human Development*, *97*(1), 111–128. https://doi.org/10.1177/00914150221109893

Harandi, T. F., Mohammad Taghinasab, M., & Dehghan Nayeri, T. (2017). The correlation of social support with mental health: A meta-analysis. *Electronic Physician*, *9*(9), 5212–5222. https://doi.org/10.19082/5212

Harasemiw, O., Newall, N., Mackenzie, C. S., Shooshtari, S., & Menec, V. (2019). Is the association between social network types, depressive symptoms and life satisfaction mediated by the perceived availability of social support? A cross-sectional analysis using the Canadian Longitudinal Study on Aging. *Aging & Mental Health*, *23*(10), 1413–1422. https://doi.org/10.1080/13607863.2018.1495176

Harlow, S. D., Goldberg, E. L., & Comstock, G. W. (1991). A longitudinal study of risk factors for depressive symptomatology in elderly widowed and married women. *American Journal of Epidemiology*, *134*(5), 526–538. https://doi.org/10.1093/oxfordjournals.aje.a116125

Hartling, L., Featherstone, R., Nuspl, M., Shave, K., Dryden, D. M., & Vandermeer, B. (2017). Grey literature in systematic reviews: A cross-sectional study of the contribution of non-English reports, unpublished studies and dissertations to the results of meta-analyses in child-relevant reviews. *BMC Medical Research Methodology*, *17*(1), 64. https://doi.org/10.1186/s12874-017-0347-z

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *PLoS Medicine*, *7*(7), e1000316. https://doi.org/10.1371/journal.pmed.1000316

Holwerda, T. J., Jaarsma, E., Van Zutphen, E. M., Beekman, A. T. F., Pan, K.-Y., Van Vliet, M., Stringa, N., Van Den Besselaar, J. H., MacNeil-Vroomen, J. L., Hoogendijk, E. O., & Kok, A. A. L. (2023). The impact of COVID-19 related adversity on the course of mental health during the pandemic and the role of protective factors: A longitudinal study among older adults in The Netherlands. *Social Psychiatry and Psychiatric Epidemiology*, *58*(7), 1109–1120. https://doi.org/10.1007/s00127-023-02457-5

Houtjes, W., van Meijel, B., van de Ven, P. M., Deeg, D., van Tilburg, T., & Beekman, A. (2014). The impact of an unfavorable depression course on network size and loneliness in older people: A longitudinal study in the community. *International Journal of Geriatric Psychiatry*, *29*(10), 1010–1017. https://doi.org/10.1002/gps.4091

Husaini, B. A. (1997). Predictors of depression among the elderly: Racial differences over time. *American Journal of Orthopsychiatry*, *67*(1), 48–58. https://doi.org/10.1037/h0080210

Jang, Y., Haley, W. E., Small, B. J., & Mortimer, J. A. (2002). The role of mastery and social resources in the associations between disability and depression in later life. *The Gerontologist*, *42*(6), 807–813. https://doi.org/10.1093/geront/42.6.807

Jang, Y., Kim, G., & Chiriboga, D. A. (2011). Gender differences in depressive symptoms among older Korean American immigrants. *Social Work in Public Health*, *26*(1), 96–109. https://doi.org/10.1080/10911350902987003

Jeon, H., MGS, MSW, PhD, & Lubben, J., DSW, MPH. (2016). The influence of social networks and supports on depression symptoms: differential pathways for older Korean immigrants and non-Hispanic white Americans. *Care Management Journals*, *17*(1), 13–23. https://doi.org/10.1891/1521-0987.17.1.13

Jiang, F., Kuper, H., Zhou, C., Qin, W., & Xu, L. (2022). Relationship between hearing loss and depression symptoms among older adults in China: The mediating role of social isolation and loneliness. *International Journal of Geriatric Psychiatry*, *37*(6), 1–8. https://doi.org/10.1002/gps.5729

Kawachi, I., & Berkman, L. F. (2001). Social ties and mental health. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, *78*(3), 458–467. https://doi.org/10.1093/jurban/78.3.458

Keim-Klärner, S., Adebahr, P., Brandt, S., Gamper, M., Klärner, A., Knabe, A., Kupfer, A., Müller, B., Reis, O., Vonneilich, N., Ganser, M. A., De Bruyn, C., & Von Der Lippe, H. (2023). Social inequality, social networks, and health: A scoping review of research on health inequalities from a social network perspective. *International Journal for Equity in Health*, *22*(1), 74. https://doi.org/10.1186/s12939-023-01876-9

Kelly, M. E., Duff, H., Kelly, S., McHugh Power, J. E., Brennan, S., Lawlor, B. A., & Loughrey, D. G. (2017). The impact of social activities, social networks, social support and social relationships on the cognitive functioning of healthy older adults: A systematic review. *Systematic Reviews*, *6*(1), 259. https://doi.org/10.1186/s13643-017-0632-2

Kim, B. J., Sangalang, C. C., & Kihl, T. (2012). Effects of acculturation and social network support on depression among elderly Korean immigrants. *Aging & Mental Health*, *16*(6), 787–794. https://doi.org/10.1080/13607863.2012.660622

Kim, B., Park, S., & Antonucci, T. C. (2016). Longitudinal changes in social networks, health and wellbeing among older Koreans. *Ageing and Society*, *36*(9), 1915–1936. https://doi.org/10.1017/S0144686X15000811

Kim, K., & Lee, M. (2015). Depressive symptoms of older adults living alone: The role of community characteristics. *The International Journal of Aging & Human Development*, *80*(3), 248–263. https://doi.org/10.1177/0091415015590315

Kim, T., Nguyen, E. T., Yuen, E. J., Nguyen, T., Sorn, R., & Nguyen, G. T. (2015). Differential role of social connectedness in geriatric depression among southeast Asian ethnic groups. *Progress in Community Health Partnerships: Research, Education, and Action*, *9*(4), 483–493. https://doi.org/10.1353/cpr.2015.0075

Kim, Y. B., & Lee, S. H. (2019). Social support network types and depressive symptoms among community-dwelling older adults in South Korea. *Asia-Pacific Journal of Public Health*, *31*(4), 367–375. https://doi.org/10.1177/1010539519841287

Klug, G., Lacruz, M. E., Emeny, R. T., Häfner, S., Ladwig, K.-H., & Huber, D. (2014). Aging without depression: A cross-sectional study. *Psychodynamic Psychiatry*, *42*(1), 5–22. https://doi.org/10.1521/pdps.2014.42.1.5

Kuchibhatla, M. N., Fillenbaum, G. G., Hybels, C. F., & Blazer, D. G. (2012). Trajectory classes of depressive symptoms in a community sample of older adults: Trajectory classes of depressive symptoms. *Acta Psychiatrica Scandinavica*, *125*(6), 492–501. https://doi.org/10.1111/j.1600-0447.2011.01801.x

Kuiper, J. S., Zuidersma, M., Oude Voshaar, R. C., Zuidema, S. U., van den Heuvel, E. R., Stolk, R. P., & Smidt, N. (2015). Social relationships and risk of dementia: A systematic review and meta-analysis of longitudinal cohort studies. *Ageing Research Reviews*, *22*, 39–57. https://doi.org/10.1016/j.arr.2015.04.006

Kuiper, J. S., Zuidersma, M., Zuidema, S. U., Burgerhof, J. G. M., Stolk, R. P., Oude Voshaar, R. C., & Smidt, N. (2016). Social relationships and cognitive decline: A systematic review and meta-analysis of longitudinal cohort studies. *International Journal of Epidemiology, 45*(4), 1169–1206. https://doi.org/10.1093/ije/dyw089

La Gory, M., & Fitzpatrick, K. (1992). The Effects of Environmental Context on Elderly Depression. *Journal of Aging and Health*, *4*(4), 459–479. https://doi.org/10.1177/089826439200400401

Lee, M. S., Crittenden, K. S., & Yu, E. (1996). Social support and depression among elderly Korean immigrants in the United States. *The International Journal of Aging & Human Development*, *42*(4), 313–327. https://doi.org/10.2190/2VHH-JLXY-EBVG-Y8JB

Lee, S., & Chou, K. (2019). Assessing the relative contribution of social exclusion, income-poverty, and financial strain on depressive symptoms among older people in Hong Kong. *Aging & Mental Health*, *23*(11), 1487–1495. https://doi.org/10.1080/13607863.2018.1506740

Lee, Y.-S., Park, S.-Y., Roh, S., Koenig, H. G., & Yoo, G. J. (2017). The role of religiousness/spirituality and social networks in predicting depressive symptoms among older Korean Americans. *Journal of Cross-Cultural Gerontology*, *32*(2), 239–254. https://doi.org/10.1007/s10823-017-9317-5

Lefebvre, C., Glanville, J., Briscoe, S., Littlewood, A., Marshall, C., Metzendorf, M., Noel-Storr, A., Rader, T., Shokraneh, F., Thomas, J., Wieland, L. S., & on behalf of the Cochrane Information Retrieval Methods Group. (2019). Searching for and selecting studies. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), *Cochrane Handbook for Systematic Reviews of Interventions* (1st ed., pp. 67–107). Wiley. https://doi.org/10.1002/9781119536604.ch4

Li, M., Dong, X., & Kong, D. (2019). Social networks and depressive symptoms among Chinese older immigrants: Does quantity, quality, and composition of social networks matter? *Clinical Gerontologist,* *44*(2), 181–191. https://doi.org/10.1080/07317115.2019.1642973

Li, T., Higgins, J. P., & Deeks, J. J. (2019). Collecting data. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), *Cochrane Handbook for Systematic Reviews of Interventions* (1st ed., pp. 109–141). Wiley. https://doi.org/10.1002/9781119536604.ch5

Li, W., Wang, Q., Yin, H., Song, Y., Tu, W., Wang, L., Liang, Y., Bai, Y., & Xu, G. (2022). Construction of path analysis model on related factors of social isolation in older people. *Psychogeriatrics*, *22*(5), 743–756. https://doi.org/10.1111/psyg.12879

Litwin, H. (2011). The association between social network relationships and depressive symptoms among older Americans: What matters most? *International Psychogeriatrics*, *23*(6), 930–940. https://doi.org/10.1017/S1041610211000251

Litwin, H. (2012). Physical activity, social network type, and depressive symptoms in late life: An analysis of data from the National Social Life, Health and Aging Project. *Aging & Mental Health*, *16*(5), 608–616. https://doi.org/10.1080/13607863.2011.644264

Litwin, H., & Levinsky, M. (2021). Always alone? Network transitions among detached older Europeans and their effects. *Ageing and Society*, *41*(10), 2299–2313. https://doi.org/10.1017/S0144686X20000240

Litwin, H., & Levinsky, M. (2022). Social networks and mental health change in older adults after the Covid-19 outbreak. *Aging & Mental Health*, *26*(5), 925–931. https://doi.org/10.1080/13607863.2021.1902468

Litwin, H., & Levinsky, M. (2023). The interplay of personality traits and social network characteristics in the subjective well-being of older adults. *Research on Aging*, *45*(7–8), 538–549. https://doi.org/10.1177/01640275221113048

Litwin, H., Levinsky, M., & Schwartz, E. (2020). Network type, transition patterns and well-being among older Europeans. *European Journal of Ageing*, *17*(2), 241–250. https://doi.org/10.1007/s10433-019-00545-7

Litwin, H., Stoeckel, K. J., & Schwartz, E. (2015). Social networks and mental health among older Europeans: Are there age effects? *European Journal of Ageing*, *12*(4), 299–309. https://doi.org/10.1007/s10433-015-0347-y

Liu, J., Guo, M., Xu, L., Mao, W., & Chi, I. (2016). Family relationships, social connections, and depressive symptoms among Chinese older adults in international migrant families. *Journal of Ethnic & Cultural Diversity in Social Work*, *26*(3), 167–184. https://doi.org/10.1080/15313204.2016.1206496

Marshall, G. L., & Rue, T. C. (2012). Perceived discrimination and social networks among older African Americans and Caribbean Blacks. *Family & Community Health*, *35*(4), 300–311. https://doi.org/10.1097/FCH.0b013e318266660f

Marshall-Fabien, G. L., & Miller, D. B. (2016). Exploring ethnic variation in the relationship between stress, social networks, and depressive symptoms among older black Americans. *Journal of Black Psychology*, *42*(1), 54–72. https://doi.org/10.1177/0095798414562067

Mechakra-Tahiri, S.-D., Zunzunegui, M. V., Preville, M., & Dube, M. (2010). Gender, social relationships and depressive disorders in adults aged 65 and over in Quebec. *Chronic Diseases in Canada*, *30*(2), Article 2. https://www.proquest.com/docview/1113346452/abstract/F5D01F9A26FA40ADPQ/1

Mehrabi, F., & Béland, F. (2021). Frailty as a moderator of the relationship between social isolation and health outcomes in community-dwelling older adults. *International Journal of Environmental Research and Public Health*, *18*(4), 1675. https://doi.org/10.3390/ijerph18041675

Merchant, R. A., Liu, S. G., Lim, J. Y., Fu, X., & Chan, Y. H. (2020). Factors associated with social isolation in community-dwelling older adults: A cross-sectional study. *Quality of Life Research*, *29*(9), 2375–2381. https://doi.org/10.1007/s11136-020-02493-7

Miller, M., & Lago, D. (1990). The well-being of older women: the importance of pet and human relations. *Anthrozoös*, *3*(4), 245–252. https://doi.org/10.2752/089279390787057504

Minicuci, N., Maggi, S., Pavan, M., Enzi, G., & Crepaldi, G. (2002). Prevalence rate and correlates of depressive symptoms in older individuals: The Veneto Study. *The Journals of Gerontology: Series A*, *57*(3), Article 3. https://doi.org/10.1093/gerona/57.3.M155

Mohd, T., Yunus, R., Hairi, F., Hairi, N., & Choo, W. (2019). Social support and depression among community dwelling older adults in Asia: A systematic review. *BMJ OPEN*, *9*(7), e026667. https://doi.org/10.1136/bmjopen-2018-026667

Murayama, H., Nofuji, Y., Matsuo, E., Nishi, M., Taniguchi, Y., Fujiwara, Y., & Shinkai, S. (2015). Are neighborhood bonding and bridging social capital protective against depressive mood in old age? A multilevel analysis in Japan. *Social Science & Medicine*, *124*, 171–179. https://doi.org/10.1016/j.socscimed.2014.11.042

Nussbaumer-Streit, B., Klerings, I., Dobrescu, A. I., Persad, E., Stevens, A., Garritty, C., Kamel, C., Affengruber, L., King, V. J., & Gartlehner, G. (2020). Excluding non-English publications from evidence-syntheses did not change conclusions: A meta-epidemiological study. *Journal of Clinical Epidemiology*, *118*, 42–54. https://doi.org/10.1016/j.jclinepi.2019.10.011

Okwumabua, J. O., Baker, F. M., Wong, S. P., & Pilgram, B. O. (1997). Characteristics of depressive symptoms in elderly urban and rural African Americans. *The Journals of Gerontology: Series A*, *52*(4), M241–M246. https://doi.org/10.1093/gerona/52A.4.M241

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan—A web and mobile app for systematic reviews. *Systematic Reviews*, *5*(1), 210. https://doi.org/10.1186/s13643-016-0384-4

Oxman, T. E., Berkman, L. F., Kasl, S., Freeman, D. H., & Barrett, J. (1992). Social support and depressive symptoms in the elderly. *American Journal of Epidemiology*, *135*(4), 356–368. https://doi.org/10.1093/oxfordjournals.aje.a116297

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, n71. https://doi.org/10.1136/bmj.n71

Palinkas, L. A., Wingard, D. L., & Barrett-Connor, E. (1990). The biocultural context of social networks and depression among the elderly. *Social Science & Medicine*, *30*(4), 441–447. https://doi.org/10.1016/0277-9536(90)90346-T

Park, J., & Roh, S. (2013). Daily spiritual experiences, social support, and depression among elderly Korean immigrants. *Aging & Mental Health*, *17*(1), 102–108. https://doi.org/10.1080/13607863.2012.715138

Park, N. S., Jang, Y., Lee, B. S., Chiriboga, D. A., Chang, S., & Kim, S. Y. (2018). Associations of a social network typology with physical and mental health risks among older adults in South Korea. *Aging & Mental Health*, *22*(5), 631–638. https://doi.org/10.1080/13607863.2017.1286456

Park, N. S., Jang, Y., Lee, B. S., Haley, W. E., & Chiriboga, D. A. (2013). The mediating role of loneliness in the relation between social engagement and depressive symptoms among older Korean Americans: Do men and women differ? *The Journals of Gerontology: Series B*, *68*(2), 193–201. https://doi.org/10.1093/geronb/gbs062

Park, N. S., Jang, Y., Lee, B. S., Ko, J. E., & Chiriboga, D. A. (2014). The impact of social resources on depressive symptoms in racially and ethnically diverse older adults: Variations by groups with differing health risks. *Research on Aging*, *36*(3), 322–342. https://doi.org/10.1177/0164027513486991

Park, N. S., Lee, B. S., Chiriboga, D. A., & Chung, S. (2019). Loneliness as a mediator in the relationship between social engagement and depressive symptoms: Age differences among community-dwelling Korean adults. *Health & Social Care in the Community*, *27*(3), 706–716. https://doi.org/10.1111/hsc.12687

Pavlidis, G., Motel-Klingebiel, A., & Aartsen, M. (2023). Exclusion from social relations in later life: On the gendered associations of social networks with mental wellbeing. *Aging & Mental Health*, *27*(7), 1313–1321. https://doi.org/10.1080/13607863.2022.2116397

Pilehvari, A., You, W., & Lin, X. (2023). Retirement's impact on health: What role does social network play? *European Journal of Ageing*, *20*(1). https://doi.org/10.1007/s10433-023-00759-w

Piolatto, M., Bianchi, F., Rota, M., Marengoni, A., Akbaritabar, A., & Squazzoni, F. (2022). The effect of social relationships on cognitive decline in older adults: An updated systematic review and meta-analysis of longitudinal cohort studies. *BMC Public Health*, *22*(1), 278. https://doi.org/10.1186/s12889-022-12567-5

Reynolds, R. M., Meng, J., & Dorrance Hall, E. (2020). Multilayered social dynamics and depression among older adults: A 10-year cross-lagged analysis. *Psychology and Aging*, *35*(7), 948–962. https://doi.org/10.1037/pag0000569

Roh, S., Lee, Y.-S., Kim, Y., Park, S.-Y., & Chaudhuri, A. (2015). Gender differences in the roles of religious support and social network support in reducing depressive symptoms among older Korean Americans. *Journal of Social Service Research*, *41*(4), 484–497. https://doi.org/10.1080/01488376.2015.1037041

Ruan, H., Shen, K., & Chen, F. (2022). Negative life events, social ties, and depressive symptoms for older adults in China. *Frontiers in Public Health*, *9*, 774434. https://doi.org/10.3389/fpubh.2021.774434

Santini, Z. I., Fiori, K. L., Feeney, J., Tyrovolas, S., Haro, J. M., & Koyanagi, A. (2016). Social relationships, loneliness, and mental health among older men and women in Ireland: A prospective community-based study. *Journal of Affective Disorders*, *204*, 59–69. https://doi.org/10.1016/j.jad.2016.06.032

Santini, Z. I., Jose, P. E., Koyanagi, A., Meilstrup, C., Nielsen, L., Madsen, K. R., Hinrichsen, C., Dunbar, R. I. M., & Koushede, V. (2021). The moderating role of social network size in the temporal association between formal social participation and mental health: A longitudinal analysis using two consecutive waves of the Survey of Health, Ageing and Retirement in Europe (SHARE). *Social Psychiatry and Psychiatric Epidemiology*, *56*(3), 417–428. https://doi.org/10.1007/s00127-020-01961-2

Santini, Z. I., Koyanagi, A., Tyrovolas, S., & Haro, J. M. (2015). The association of relationship quality and social networks with depression, anxiety, and suicidal ideation among older married adults: Findings from a cross-sectional analysis of the Irish Longitudinal Study on Ageing (TILDA). *Journal of Affective Disorders*, *179*, 134–141. https://doi.org/10.1016/j.jad.2015.03.015

Santini, Z. I., Koyanagi, A., Tyrovolas, S., Haro, J. M., Donovan, R. J., Nielsen, L., & Koushede, V. (2017). The protective properties of Act-Belong-Commit indicators against incident depression, anxiety, and cognitive impairment among older Irish adults: Findings from a prospective community-based study. *Experimental Gerontology*, *91*, 79–87. https://doi.org/10.1016/j.exger.2017.02.074

Santini, Z. I., Koyanagi, A., Tyrovoloas, S., Mason, C., & Haro, J. M. (2015). The association between social relationships and depression: A systematic review. *Journal of Affective Disorders*, *175*, 53–65. http://dx.doi.org/10.1016/j.jad.2014.12.049

Schwartz, E., & Litwin, H. (2017). Are newly added and lost confidants in later life related to subsequent mental health? *International Psychogeriatrics*, *29*(12), 2047–2057. https://doi.org/10.1017/S1041610217001338

Schwarzbach, M., Luppa, M., Forstmeier, S., König, H., & Riedel-Heller, S. G. (2014). Social relations and depression in late life—A systematic review. *International Journal of Geriatric Psychiatry*, *29*(1), 1–21. https://doi.org/10.1002/gps.3971

Shamsrizi, P., Gladstone, B. P., Carrara, E., Luise, D., Cona, A., Bovo, C., & Tacconelli, E. (2020). Variation of effect estimates in the analysis of mortality and length of hospital stay in patients with infections caused by bacteria-producing extended-spectrum beta-lactamases: A systematic review and meta-analysis. *BMJ Open*, *10*(1), e030266. https://doi.org/10.1136/bmjopen-2019-030266

Shouse, J. N., Rowe, S. V., & Mast, B. T. (2013). Depression and cognitive functioning as predictors of social network size. *Clinical Gerontologist: The Journal of Aging and Mental Health*, *36*(2), 147–161. https://doi.org/10.1080/07317115.2012.749320

Sicotte, M., Alvarado, B. E., León, E.-M., & Zunzunegui, M.-V. (2008). Social networks and depressive symptoms among elderly women and men in Havana, Cuba. *Aging & Mental Health*, *12*(2), 193–201. https://doi.org/10.1080/13607860701616358

Siette, J., Gulea, C., & Priebe, S. (2015). Assessing social networks in patients with psychotic disorders: A systematic review of instruments. *PLOS ONE*, *10*(12), e0145250. https://doi.org/10.1371/journal.pone.0145250

Singh, L., Singh, P. K., & Arokiasamy, P. (2016). Social network and mental health among older adults in rural Uttar Pradesh, India: A cross-sectional study. *Journal of Cross-Cultural Gerontology*, *31*(2), 173–192. https://doi.org/10.1007/s10823-016-9286-0

Sohn, S. Y., Joo, W., Kim, W. J., Kim, S. J., Youm, Y., Kim, H. C., Park, Y.-R., & Lee, E. (2017). Social network types among older Korean adults: Associations with subjective health. *Social Science & Medicine*, *173*, 88–95. https://doi.org/10.1016/j.socscimed.2016.11.042

Sonnenberg, C. M., Deeg, D. J. H., van Tilburg, T. G., Vink, D., Stek, M. L., & Beekman, A. T. F. (2013). Gender differences in the relation between depression and social support in later life. *International Psychogeriatrics*, *25*(1), 61–70. https://doi.org/10.1017/S1041610212001202

Stoeckel, K. J., & Litwin, H. (2016). The impact of social networks on the relationship between functional impairment and depressive symptoms in older adults. *International Psychogeriatrics*, *28*(1), 39–47. https://doi.org/10.1017/S1041610215000538

Stringa, N., Milaneschi, Y., van Schoor, N. M., Suanet, B., van der Lee, S., Holstege, H., Reinders, M. J. T., Beekman, A. T. F., & Huisman, M. (2020). Genetic liability for depression, social factors and their interaction effect in depressive symptoms and depression over time in older adults. *The American Journal of Geriatric Psychiatry*, *28*(8), 844–855. https://doi.org/10.1016/j.jagp.2020.02.011

Sugie, M., Harada, K., Nara, M., Kugimiya, Y., Takahashi, T., Kitagou, M., Kim, H., Kyo, S., & Ito, H. (2022). Prevalence, overlap, and interrelationships of physical, cognitive, psychological, and social frailty among community-dwelling older people in Japan. *Archives of Gerontology and Geriatrics*, *100*, 104659. https://doi.org/10.1016/j.archger.2022.104659

Tajvar, M., Fletcher, A., Grundy, E., & Arab, M. (2013). Social support and health of older people in Middle Eastern countries: A systematic review. *Australasian Journal on Ageing*, *32*(2), 71–78. https://doi.org/10.1111/j.1741-6612.2012.00639.x

Tang, D., Lin, Z., & Chen, F. (2020). Moving beyond living arrangements: The role of family and friendship ties in promoting mental health for urban and rural older adults in China. *Aging & Mental Health*, *24*(9), 1523–1532. https://doi.org/10.1080/13607863.2019.1602589

Tang, D., Mair, C. A., & Hu, Q. (2023). Widowhood, social networks, and mental health among Chinese older adults: The moderating effects of gender. *Frontiers in Psychology*, *14*, 1142036. https://doi.org/10.3389/fpsyg.2023.1142036

Tang, D., & Xie, L. (2021). Whose migration matters? The role of migration in social networks and mental health among rural older adults in China. *Ageing and Society*, *43*(6), 1389–1408. https://doi.org/10.1017/S0144686X21001197

Tang, F., Jiang, Y., Li, K., & Rosso, A. L. (2023). Residential segregation and depressive symptoms in older Chinese immigrants: the mediating role of social processes. *The Gerontologist*, *63*(8), 1376–1384. https://doi.org/10.1093/geront/gnad027

Tanikaga, M., Uemura, J., Hori, F., Hamada, T., & Tanaka, M. (2023). Changes in community-dwelling elderly's activity and participation affecting depression during Covid-19 pandemic: A cross-sectional study. *International Journal of Environmental Research and Public Health*, *20*(5), 4228. https://doi.org/10.3390/ijerph20054228

Taylor, H. (2021). Social isolation, loneliness, and physical and mental health among black older adults. *Annual Review of Gerontology and Geriatrics*, *41*(1), 123–144. https://doi.org/10.1891/0198-8794.41.123

Taylor, H. O., Taylor, R. J., Nguyen, A. W., & Chatters, L. (2018). Social isolation, depression, and psychological distress among older adults. *Journal of Aging and Health*, *30*(2), 229–246. https://doi.org/10.1177/0898264316673511

Tsai, Y.-F., Yeh, S.-H., & Tsai, H.-H. (2005). Prevalence and risk factors for depressive symptoms among community-dwelling elders in Taiwan. *International Journal of Geriatric Psychiatry*, *20*(11), 1097–1102. https://doi.org/10.1002/gps.1413

Vicente, H. T., & Guadalupe, S. (2022). Childlessness, personal social networks and wellbeing at advanced ages: A cross-sectional study in a Southern European familistic welfare state. *Ageing and Society*, *44*(3), 597–621. https://doi.org/10.1017/S0144686X22000320

Visentini, C., Cassidy, M., Bird, V. J., & Priebe, S. (2018). Social networks of patients with chronic depression: A systematic review. *Journal of Affective Disorders*, *241*, 571–578. https://doi.org/10.1016/j.jad.2018.08.022

Vivekanantham, A., Edwin, C., Pincus, T., Matharu, M., Parsons, H., & Underwood, M. (2019). The association between headache and low back pain: A systematic review. *The Journal of Headache and Pain*, *20*(1), 82. https://doi.org/10.1186/s10194-019-1031-y

Voils, C. I., Allaire, J. C., Olsen, M. K., Steffens, D. C., Hoyle, R. H., & Bosworth, H. B. (2007). Five-year trajectories of social networks and social support in older adults with major depression. *International Psychogeriatrics*, *19*(6), 1110–1124. https://doi.org/10.1017/S1041610207005303

Webster, N. J., Antonucci, T. C., Ajrouch, K. J., & Abdulrahim, S. (2015). Social networks and health among older adults in Lebanon: The mediating role of support and trust. *The Journals of Gerontology: Series B*, *70*(1), 155–166. https://doi.org/10.1093/geronb/gbu149

Wee, L. E., Yong, Y. Z., Chng, M. W. X., Chew, S. H., Cheng, L., Chua, Q. H. A., Yek, J. J. L., Lau, L. J. F., Anand, P., Hoe, J. T. M., Shen, H. M., & Koh, G. C.-H. (2014). Individual and area-level socioeconomic status and their association with depression amongst community-dwelling elderly in Singapore. *Aging & Mental Health*, *18*(5), 628–641. https://doi.org/10.1080/13607863.2013.866632

Wells, G. A., Shea, B., O'Connell, D., Peterson, J., Welch, V., Losos, M., & Tugwell, P. (2014). *The Newcastle-Ottawa Scale (NOS) for assessing the quality of nonrandomised studies in meta-analyses*. https://www.ohri.ca/programs/clinical_epidemiology/oxford.asp

Wendel, F., Bauer, A., Blotenberg, I., Brettschneider, C., Buchholz, M., Czock, D., Döhring, J., Escales, C., Frese, T., Hoffmann, W., Kaduszkiewicz, H., König, H.-H., Löbner, M., Luppa, M., Schwenker, R., Thyrian, J. R., Weißenborn, M., Wiese, B., Zöllinger, I., … Gensichen, J. (2022). Social network and participation in elderly primary care patients in Germany and associations with depressive symptoms—A cross-sectional analysis from the AgeWell.de Study. *Journal of Clinical Medicine*, *11*(19), 5940. https://doi.org/10.3390/jcm11195940

Werneck, A. O., Cunha, P. M., & Silva, D. R. (2023). The mediation role of social network size and perception in the association between physical activity and depressive symptoms: A prospective analysis from the SHARE study. *Aging & Mental Health, 27*(9), 1738–1743. https://doi.org/10.1080/13607863.2023.2177831

World Health Organization. (2021). *Depression*. https://www.who.int/news-room/fact-sheets/detail/depression

World Health Organization. (n.d.). *Ageing*. https://www.who.int/health-topics/ageing#tab=tab_1

Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: A meta-analysis. *Psychological Bulletin*, *139*(1), 53–80. https://doi.org/10.1037/a0028601

Wu, C.-S., Yu, S.-H., Lee, C.-Y., Tseng, H.-Y., Chiu, Y.-F., & Hsiung, C. A. (2017). Prevalence of and risk factors for minor and major depression among community-dwelling older adults in Taiwan. *International Psychogeriatrics*, *29*(7), 1113–1121. https://doi.org/10.1017/S1041610217000199

Ye, L., & Zhang, X. (2019). Social network types and health among older adults in rural China: the mediating role of social support. *International Journal of Environmental Research and Public Health*, *16*(3), 410. https://doi.org/10.3390/ijerph16030410

Zhang, Y., Kuang, J., Xin, Z., Fang, J., Song, R., Yang, Y., Song, P., Wang, Y., & Wang, J. (2023). Loneliness, social isolation, depression and anxiety among the elderly in Shanghai: Findings from a longitudinal study. *Archives of Gerontology and Geriatrics*, *110*, 104980. https://doi.org/10.1016/j.archger.2023.104980

During the preparation of this work the author(s) used Cambridge Proofreading and DeepL in order to refine the manuscript's language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

2.7 Appendix

Table A2-1 PRISMA Checklist

Topic	No.	Item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist	Abstract
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Introduction
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Introduction
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	2.1 Eligibility criteria
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	2.2 Search strategy
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	2.2 Search strategy; Review-protocol online: https://doi.org/10.17605/OSF.IO/6QDPK
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	2.3 Study selection
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	2.4 Data extraction
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	2.4 Data extraction
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	2.4 Data extraction
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	2.5 Quality appraisal
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	n.a.
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item 5)).	2.6 Synthesis method

Topic	No.	Item	Location where item is reported
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	n.a.
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	2.6 Synthesis method
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	n.a.
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	n.a.
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	n.a.
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	n.a.
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	n.a.
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Figure 2-1
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Appendix, Table A2-2
Study characteristics	17	Cite each included study and present its characteristics.	Table 2-2 – Table 2-9
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	n.a.
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Table 2-2 – Table 2-9
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	3 Results
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	3 Results
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	3 Results
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	n.a.
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	n.a.
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	n.a.
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	4.1 Social network characteristics and depression among older adults
	23b	Discuss any limitations of the evidence included in the review.	4.1 Social network characteristics and depression among older adults
	23c	Discuss any limitations of the review processes used.	4.2 Limitations and future implications

Topic	No.	Item	Location where item is reported
	23d	Discuss implications of the results for practice, policy, and future research.	4.2 Limitations and future implications, 5 Conclusion
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	2 Methods
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	2 Methods
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	n.a.
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Funding
Competing interests	26	Declare any competing interests of review authors.	Competing interests
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	up on request

Table A2-2 Excluded studies and exclusion reason

Author(s)	Title	Exclusion reason
Adams et al., 2004	Loneliness and Depression in Independent Living Retirement Communities: Risk and Resilience Factors	Institutionalized population/ no separate analysis for community-dwelling population
Adams et al., 2023	The Risk for Loneliness and Major Depression among Solo Agers	No structural measure of social network
Allen et al., 2022	Longitudinal Cohort Study of Depression and Anxiety Among Older Informal Caregivers Following the Initial COVID-19 Pandemic Response in Aotearoa New Zealand	No structural measure of social network
Ang, 2022	Changing Relationships Between Social Contact, Social Support, and Depressive Symptoms During the COVID-19 Pandemic	No structural measure of social network
Baek et al., 2021	Gender differences in the longitudinal association between husbands' and wives' depressive symptoms among Korean older adults: the moderating effects of the spousal relationship	No structural measure of social network
Baiyewu et al., 2015	Depression in elderly people living in rural Nigeria and its association with perceived health poverty and social network	No structural measure of social network
Baker et al., 1996	Screening African-American elderly for the presence of depressive symptoms: A preliminary investigation	Not adjusted for confounders
Barnes et al., 2022	Cumulative effect of loneliness and social isolation on health outcomes among older adults	No association between depression and social network measured
Bartucz et al., 2022	The Protective Effect of Culture on Depression During Covid-19 Pandemic: A Romanian National Study	No structural measure of social network
Bassett & Moore, 2013	Social capital and depressive symptoms: The association of psychosocial and network dimensions of social capital with depressive symptoms in Montreal Canada	Non-matching age restrictions
Beekman et al., 2002	The impact of depression on the well-being disability and use of services in older adults: A longitudinal perspective	No association between depression and social network measured
Bélanger et al., 2016	Sources of social support associated with health and quality of life: a cross-sectional study among Canadian and Latin American older adults	No structural measure of social network
Bianchi et al., 2023	Structure of personal networks and cognitive abilities: A study on a sample of Italian older adults	No association between depression and social network measured
Biegel et al., 1991	Social support networks of White and Black elderly people at risk for institutionalization	No association between depression and social network measured
Bijnsdorp et al., 2018	Het combineren van meerdere rollen onder ouderen: vermindert of verbetert dit het welbevinden?	Other language
Bizzozero-Peroni et al., 2022	Proinflammatory dietary pattern and depression risk in older adults: Prospective analyses from the Seniors-ENRICA studies	No structural measure of social network
Blazer, 1983	Impact of late-life depression on the social network	No structural measure of social network
Boey, 1999	Cross-validation of a short form of the CES-D in Chinese elderly	Institutionalized population/ no separate analysis for community-dwelling population
Bowling & Farquhar, 1991	Associations with social networks, social support, health status and psychiatric morbidity in three samples of elderly people	No measure of depression
Burger et al., 2020	Bereavement or breakup: Differences in networks of depression	No association between depression and social network measured

Author(s)	Title	Exclusion reason
Buys et al., 2008	Prevalence and predictors of depressive symptoms among rural older Australians and Americans	No association between depression and social network measured
Canbal et al., 2012	Effects of depression and life factors on social network score in elderly people in Cankaya Ankara	Patient group
Cao et al., 2023	The impact of hearing loss on cognitive impairment: The mediating role of depressive symptoms and the moderating role of social relationships	No association between depression and social network measured
Cappeliez et al., 2007	Recovery from depression in older depressed patients in primary care: Relation with depression severity and social support	Intervention
Castell-Alcalá et al., 2022	Evolution of physical function, cognition, depressive mood, and quality of life during the Covid-19 pandemic in prefrail elderly people: A longitudinal cohort study (Covid-Mefap)	Patient group
Cené et al., 2022	Social Isolation and Incident Heart Failure Hospitalization in Older Women: Women's Health Initiative Study Findings	No association between depression and social network measured
Chang, 2019	Cross-cultural comparative study of psychological distress between older Korean immigrants in the United States and older Koreans in South Korea	No measure of depression
Chen et al., 2016	Neighborhood support network perceived proximity to community facilities and depressive symptoms among low socioeconomic status Chinese elders	No structural measure of social network
Chen et al., 2019	The influence of social support on loneliness and depression among older elderly people in China: Coping styles as mediators	No structural measure of social network
Chen et al., 2022	Depression and PTSD in the aftermath of strict COVID-19 lockdowns: a cross-sectional and longitudinal network analysis	Non-matching age restrictions
Chen et al., 2023	Later-life depressive symptoms during the Covid-19 pandemic: Investigations of individual, cumulative, and synergistic effects of social isolation	No structural measure of social network
Child & Lawton, 2020	Personal networks and associations with psychological distress among young and older adults	No measure of depression
Choi & Lee, 2022	Factors Affecting Depression in Middle-Aged and Elderly Men Living Alone: A Cross-Sectional Path Analysis Model	No structural measure of social network
Copeland et al., 1999	Community-based case-control study of depression in older people. Cases and sub-cases from the MRC-ALPHA Study	Patient group
Cornwell & Waite, 2009	Social Disconnectedness Perceived Isolation and Health among Older Adults	No structural measure of social network
Cui et al., 2022	The Role of Perceived and Objective Social Connectedness on Risk for Suicidal Thoughts and Behavior in Late-Life and Their Moderating Effect on Cognitive Deficits	No association between depression and social network measured
Curran et al., 2019	Symptom profiles of late-life anxiety and depression: The influence of migration religion and loneliness	No association between depression and social network measured
de Feijter et al., 2022	The network of psychosocial health in middle-aged and older adults during the first covid-19 lockdown	No structural measure of social network
De Main et al., 2023	Longitudinal associations between mental health and social environment in older adults: a multilevel growth modeling	Non-matching age restrictions
Dean et al., 1990	Effects of social support from various sources on depression in elderly persons	No structural measure of social network
Djundeva et al., 2019	Is Living Alone "Aging Alone"? Solitary Living Network Types and Well-Being	No mean age

Author(s)	Title	Exclusion reason
Dobrota et al., 2022	The association of hearing problems with social network strength and depressive symptoms: the cardiovascular health study	No association between depression and social network measured
Domenech-Abella et al., 2021	Social network size loneliness physical functioning and depressive symptoms among older adults: Examining reciprocal associations in four waves of the Longitudinal Aging Study Amsterdam (LASA)	Not adjusted for confounders
Dos Santos et al., 2023	Positive attributes in elderly people with different degrees of depression: a study based on network analysis	No structural measure of social network
Doubova et al., 2010	Social network types and functional dependency in older adults in Mexico	No association between depression and social network measured
DuPertuis et al., 2001	Does the source of support matter for different health outcomes? Findings from the Normative Aging Study	No structural measure of social network
Eymundsdottir et al., 2022	Social network and the risk for developing mild cognitive impairment and dementia among older adults	No association between depression and social network measured
Fernandez et al., 1998	Moderating the effects of stress on depressive symptoms	No structural measure of social network
Field et al., 2002	Social networks and health of older people living in sheltered housing	Institutionalized population/ no separate analysis for community-dwelling population
Finch & Zautra, 1992	Testing latent longitudinal models of social ties and depression among the elderly: A comparison of distribution-free and maximum likelihood estimates with nonnormal data	No structural measure of social network
Fiordelli et al., 2020	Differentiating objective and subjective dimensions of social isolation and apprasing their relations with physical and mental health in italian older adults	Institutionalized population/ no separate analysis for community-dwelling population
Forsell & Winblad, 1999	Incidence of major depression in a very elderly population	Patient group
Freyne et al., 2005	A longitudinal study of depression in old age I: outcome and relationship to social networks	Patient group
Fuhrer et al., 1999	Psychological disorder and mortality in French older adults: Do social relations modify the association?	No association between depression and social network measured
Fuller-Iglesias et al., 2015	The Complex Nature of Family Support Across the Life Span: Implications for Psychological Well-Being	No structural measure of social network
Fuller-Iglesias, 2015	Social ties and psychological well-being in late life: the mediating role of relationship satisfaction	Institutionalized population/ no separate analysis for community-dwelling population
Golden et al., 2009	Social support network structure in older people: underlying dimensions and association with psychological and physical health	No association between depression and social network measured
Gureje et al., 2008	Determinants of quality of life of elderly Nigerians: results from the Ibadan study of ageing	No association between depression and social network measured
Gureje et al., 2011	Incidence and risk factors for late-life depression in the Ibadan Study of Ageing	Institutionalized population/ no separate analysis for community-dwelling population
Győri, 2023	The impact of social-relationship patterns on worsening mental health among the elderly during the COVID-19 pandemic: Evidence from Hungary	No measure of depression
Hajek & König, 2021	Determinants of psychosocial factors among the oldest old¬†-¬†Evidence from the representative "Survey on quality of¬†life and subjective well-being of the very old in North¬†Rhine-Westphalia (NRW80+)"	Institutionalized population/ no separate analysis for community-dwelling population
Hamid et al., 2021	Do Living Arrangements and Social Network Influence the Mental Health Status of Older Adults in Malaysia?	No association between depression and social network measured

Author(s)	Title	Exclusion reason
Harrison et al., 2010	Alone? Perceived social support and chronic interpersonal difficulties in suicidal elders	No structural measure of social network
Hed et al., 2020	Gender differences in resources related to depressive symptoms during the early years of retirement: A Swedish population-based study	No structural measure of social network
Henderson et al., 1986	The elderly who live alone: Their mental health and social relationships	No structural measure of social network
Herbolsheimer et al., 2018	Why Is Social Isolation Among Older Adults Associated with Depressive Symptoms? The Mediating Role of Out-of-Home Physical Activity	No structural measure of social network
Hill et al., 2023	Mental health impact of the COVID-19 pandemic in U.S. military veterans: a population-based, prospective cohort study	Non-matching age restrictions
Hopper et al., 2023	Contributors to mental health resilience in middle-aged and older adults: an analysis of the Canadian Longitudinal Study on Aging	No measure of depression
Houtjes et al., 2017	Is the naturalistic course of depression in older people related to received support over time? Results from a longitudinal population-based study	No structural measure of social network
Huang et al., 2022	Hearing loss and depressive symptoms in older Chinese: whether social isolation plays a role	No association between depression and social network measured
Husaini et al., 1990	Social support and depression among the Black and White elderly	No structural measure of social network
Jang et al., 2010	Correlates of Depressive Symptoms Among Hispanic Older Adults Living in Public Housing	Institutionalized population/ no separate analysis for community-dwelling population
Jang et al., 2016	Emotional Confidants in Ethnic Communities: Social Network Analysis of Korean American Older Adults	No association between depression and social network measured
Jang et al., 2021	Health risks posed by social and linguistic isolation in older Korean Americans	No measure of depression
Jayakody et al., 2022	Is There an Association Between Untreated Hearing Loss and Psychosocial Outcomes?	No association between depression and social network measured
Jeon et al., 2016	The Influence of Social Networks and Social Support on Health Among Older Koreans at High Risk of Depression	No association between depression and social network measured
Kabo et al., 2019	A Social Relations and Networks Perspective of Depressive Symptoms in Older African Americans Relative to Two Other Ethno-racial Groups	Non-matching age restrictions
Katsumata et al., 2005	Gender differences in the contributions of risk factors to depressive symptoms among the elderly persons dwelling in a community Japan	No association between depression and social network measured
Ke et al., 2019	Social capital and the health of left-behind older adults in rural China: a cross-sectional study	No measure of depression
Killian & Turner, 2014	Latent Class Typologies for Emotional Support Among Midlife and Aging Americans: Evidence from the National Health and Human Nutrition Examination Survey	No structural measure of social network
Kim & Jung, 2022	Relational burden depression and loneliness among american older adults: An inquiry into the ‚Äòdark side of social capital‚Äô	No structural measure of social network
Kim et al., 2019	Social Network Position Moderates the Relationship between Late-life Depressive Symptoms and Memory Differently in Men and Women	No association between depression and social network measured
Kotozaki et al., 2021	Association between the social isolation and depressive symptoms after the great East Japan earthquake: findings from the baseline survey of the TMM CommCohort study	No association between depression and social network measured

Author(s)	Title	Exclusion reason
Krause & Liang, 1993	Stress social support and psychological distress among the Chinese elderly	No structural measure of social network
Krause, 1991	Stress and isolation from close ties in later life	No structural measure of social network
Kuittinen et al., 2014	Depressive Symptoms and Their Psychosocial Correlates Among Older Somali Refugees and Native Finns	No association between depression and social network measured
Lahdenperä et al., 2022	Psychological Distress During the Retirement Transition and the Role of Psychosocial Working Conditions and Social Living Environment	No measure of depression
Lamar et al., 2022	Social Engagement and All-Cause Mortality: A Focus on Participants of the Minority Aging Research Study	No association between depression and social network measured
Lau et al., 2019	Social support network typologies and their association with dementia and depression among older adults in Singapore: a cross-sectional analysis	No measure of depression
Lebowitz et al., 2018	Correlating Post-disaster Support Network Density with Reciprocal Support Relation Satisfaction: An Elderly Cohort Within One Year of the 2011 Japan Disasters	No structural measure of social network
Lebowitz et al., 2019	Post-flood social support networks and morbidity in Joso City Japan	No structural measure of social network
Lee & Holm, 2011	Family Relationships and Depression among Elderly Korean Immigrants	No structural measure of social network
Lee & Min, 2023	Racial Differences in C-Reactive Protein, Depression Symptoms, and Social Relationships in Older Adults: A Moderated Network Analysis	No structural measure of social network
Lee et al., 2020	Gender differences in social network of cognitive function among community-dwelling older adults	No association between depression and social network measured
Lee et al., 2022	Association of social network properties with resilience and depression among community-based Korean population	Non-matching age restrictions
Lee et al., 2023	Social integration and risk of mortality among African-Americans: the Jackson heart study	Non-matching age restrictions
Lee, 2021	Different Discussion Partners and Their Effect on Depression among Older Adults	Non-matching age restrictions
Lei et al., 2016	Social networks and health-related quality of life among Chinese old adults in urban areas: results from 4th National Household Health Survey	No measure of depression
Levula et al., 2018	The Association Between Social Network Factors with Depression and Anxiety at Different Life Stages	No structural measure of social network
Li et al., 2013	Social Support Resources and Post-Acute Recovery for Older Adults with Major Depression	Patient group
Lim et al., 2023	Friendship in Later Life: A Pathway Between Volunteering Hours and Depressive Symptoms	No association between depression and social network measured
Litwin, 2010	Social networks and well-being: a comparison of older people in Mediterranean and non-Mediterranean countries	No structural measure of social network
Liu et al., 2022	Role of Multifaceted Social Relationships on the Association of Loneliness with Depression Symptoms: A Moderated Mediation Analysis	No measure of depression
Lohmann et al., 2023	Social Mediators of the Association Between Depression and Falls Among Older Adults	No association between depression and social network measured
Loibl et al., 2022	Worry about debt is related to social loneliness in older adults in the Netherlands	No association between depression and social network measured

Author(s)	Title	Exclusion reason
Löwenstein & Frank, 2023	Social Support Networks of Individuals with Depressive Disorders: A Cross-sectional Survey in Former Psychiatric Inpatients in Germany	Non-matching age restrictions
Luo & Li, 2023	Trajectories of social isolation and depressive symptoms in mid- and later life: a parallel process latent growth curve analysis	No structural measure of social network
Luppa et al., 2012	Natural course of depressive symptoms in late life. An 8-year population-based prospective study	Institutionalized population/ no separate analysis for community-dwelling population
Luppa et al., 2012	Prevalence and risk factors of depressive symptoms in latest life - Results of the Leipzig Longitudinal Study of the Aged (LEILA 75+)	Institutionalized population/ no separate analysis for community-dwelling population
Ma et al., 2022	Association between frailty and cognitive function in older Chinese people: A moderated mediation of social relationships and depressive symptoms	No association between depression and social network measured
Maity & Mukhopadhyay, 2015	Social Support Social Network and Mental Health of Elderly: Rural-urban Differentials	No measure of depression
Mann & Walker, 2022	The role of equanimity in mediating the relationship between psychological distress and social isolation during COVID-19	Non-matching age restrictions
Mao & Chen, 2021	Neighborhood-Based Social Capital and Depressive Symptoms among Adults: Evidence from Guangzhou China	Non-matching age restrictions
Masini & Barrett, 2008	Social Support as a Predictor of Psychological and Physical Well-Being and Lifestyle in Lesbian Gay and Bisexual Adults Aged 50 and Over	Non-matching age restrictions
Maulik et al., 2010	The effect of social networks and social support on common mental disorders following specific life events	No association between depression and social network measured
McHugh & Lawlor, 2012	Social support differentially moderates the impact of neuroticism and extraversion on mental wellbeing among community-dwelling older adults	No association between depression and social network measured
Mechakra-Tahiri et al., 2009	Social relationships and depression among people 65 years and over living in rural and urban areas of Quebec	No structural measure of social network
Meyer et al., 2022	Neighborhood Characteristics and Caregiver Depressive Symptoms in the National Study of Caregiving	Non-matching age restrictions
Miller et al., 2006	Feeling Blue? The Importance of a Confidant for the Well-Being of Older Rural Married Australian and American Men	No measure of depression
Milton et a., 2023	Family of origin, not chosen family, predicts psychological health in a LGBTQ+ sample	Non-matching age restrictions
Monserud & Wong, 2015	Depressive Symptoms Among Older Mexicans: The Role of Widowhood Gender and Social Integration	No structural measure of social network
Morita et al., 2022	Depressive symptoms homophily among community-dwelling older adults in japan: A social networks analysis	No structural measure of social network
Myagmarjav et al., 2019	Comparison of the 18-item and 6-item Lubben Social Network Scales with community-dwelling older adults in Mongolia	No association between depression and social network measured
Na & Streim, 2017	Psychosocial Well-Being Associated With Activity of Daily Living Stages Among Community-Dwelling Older Adults	No association between depression and social network measured
Nadimpalli et al., 2015	The Association Between Discrimination and Depressive Symptoms Among Older African Americans: The Role of Psychological and Social Factors	No association between depression and social network measured
Narendran et al., 2023	Loneliness, social support networks, mood, and well-being among the community-dwelling elderly, Mysore	No structural measure of social network
Nyqvist et al., 2006	Social Capital and Health in the Oldest Old: The Umea 85+ Study	No structural measure of social network

Author(s)	Title	Exclusion reason
Osborn et al., 2003	Factors associated with depression in a representative sample of 14 217 people aged 75 and over in the United Kingdom: results from the MRC trial of assessment and management of older people in the community	No structural measure of social network
Pan & Liu, 2021	Difference of depression between widowed and non-widowed older people in China: A network analysis approach	No structural measure of social network
Panes et al., 2023	Predictors of loneliness onset and maintenance in European older adults during the COVID-19 pandemic	No association between depression and social network measured
Park et al., 2015	An empirical typology of social networks and its association with physical and mental health: a study with older Korean immigrants	No association between depression and social network measured
Park et al., 2020	A Typology of Social Networks and Its Relationship to Psychological Well-Being in Korean Adults	Non-matching age restrictions
Pengpid & Peltzer, 2023	Prevalence and correlates of major depressive disorder among a national sample of middle-aged and older adults in India	No structural measure of social network
Phongtankuel, 2023	The relationship of caregiver self-efficacy to caregiver outcomes: a correlation and mediation analysis	Non-matching age restrictions
Ramos-Vera et al., 2023	Psychological impact of COVID-19: A cross-lagged network analysis from the English Longitudinal Study of Aging COVID-19 database	Different scope
Rico-Uribe et al., 2016	Loneliness Social Networks and Health: A Cross-Sectional Study in Three Countries	Non-matching age restrictions
Roberts et al., 1994	Physical, Psychological, and Social Resources As Moderators of the Relationship of Stress to Mental Health of the Very Old	No measure of depression
Robinson & Austin, 1998	Wife caregivers' and supportive others' perceptions of the caregivers' health and social support	No structural measure of social network
Roh et al., 2015	Friends Depressive Symptoms and Life Satisfaction Among Older Korean Americans	Not adjusted for confounders
Rudert & Janke, 2023	Call me maybe: Risk factors of impaired social contact during the COVID-19 pandemic and associations with well-being	Non-matching age restrictions
Ryu et al., 2022	Impact of COVID-19 on the social relationships and mental health of older adults living alone: A two-year prospective cohort study	No association between depression and social network measured
Sahoo et al., 2022	Depression and quality of life among elderly: Comparative cross-sectional study between elderly in community and old age homes in Eastern India	Institutionalized population/ no separate analysis for community-dwelling population
Sakurai et al., 2019	Poor Social Network Not Living Alone Is Associated With Incidence of Adverse Health Outcomes in Older Adults	No association between depression and social network measured
Sakurai et al., 2021	Association of Eating Alone With Depression Among Older Adults Living Alone: Role of Poor Social Networks	No association between depression and social network measured
Salazar et al., 2022	Risk factors for depression in older adults in Bogotá, Colombia.	No structural measure of social network
Santini et al., 2020	Social disconnectedness perceived isolation and symptoms of depression and anxiety among older Americans (NSHAP): a longitudinal mediation analysis	No measure of depression
Sasiwongsaroj et al., 2015	Buddhist social networks and health in old age: A study in central Thailand	No structural measure of social network
Savela et al., 2022	Addressing the Experiences of Family Caregivers of Older Adults During the COVID-19 Pandemic in Finland	No structural measure of social network
Schaefer et al., 1981	The health-related functions of social support	Non-matching age restrictions

Author(s)	Title	Exclusion reason
Schnittger et al., 2012	Psychological distress as a key component of psychosocial functioning in community-dwelling older people	No association between depression and social network measured
Schutter et al., 2020	'Big Five' personality characteristics are associated with loneliness but not with social network size in older adults irrespective of depression	No association between depression and social network measured
Schwartz & Litwin, 2019	The Reciprocal Relationship Between Social Connectedness and Mental Health Among Older European Adults: A SHARE-Based Analysis	No association between depression and social network measured
Schwartz et al., 2019	Contact frequency and cognitive health among older adults in Israel	No structural measure of social network
Segrin, 2003	Age Moderates the Relationship between Social Support and Psychosocial Problems	Non-matching age restrictions
Shahaj et al., 2023	Psychological Distress Among Older Adults During the First Wave of SARS-CoV-2 Pandemic: Survey of Health, Ageing, and Retirement in Europe	No measure of depression
Sharma et al., 2023	Does emotion regulation network mediate the effect of social network on psychological distress among older adults?	No measure of depression
Shou et al., 2018	Quality of life and its contributing factors in an elderly community-dwelling population in Shanghai China	No association between depression and social network measured
Shrum et al., 2021	The Burden of Elders Anxiety Depression and Personal Networks in Two African Slums	Non-matching age restrictions
Simning et al., 2012	Mental healthcare need and service utilization in older adults living in public housing	No measure of depression
Steffens et al., 2005	Biological and social predictors of long-term geriatric depression outcome	No association between depression and social network measured
Stewart et al., 2022	Functional and structural social support in DSM-5 mood and anxiety disorders: A population-based study	Non-matching age restrictions
Stokes et al., 2018	Influence of the Social Network on Married and Unmarried Older Adults' Mental Health	No association between depression and social network measured
Sugisawa & Sugihara, 2020	Mediators and Moderators of the Influences of Living Alone on Psychological Distress Among Japanese Older Adults	No measure of depression
Sugisawa et al., 2022	Mediators of Life-Course and Late-Life Financial Strain on Late-Life Health in Japan: Based on a Cross-Sectional Survey	No structural measure of social network
Sunderland et al., 2014	Comparing profiles of mental disorder across birth cohorts: Results from the 2007 Australian National Survey of Mental Health and Wellbeing	No structural measure of social network
Tang et al., 2023	Residential Segregation and Depressive Symptoms in Older Chinese Immigrants: The Mediating Role of Social Processes	No access to full text (first author has been contacted)
Thiyagarajan et al., 2014	Social support network typologies and health outcomes of older people in low and middle income countries--a 10/66 Dementia Research Group population-based study	Institutionalized population/ no separate analysis for community-dwelling population
Thomas, 2016	The Impact of Relationship-Specific Support and Strain on Depressive Symptoms Across the Life Course	No structural measure of social network
Tiedt, 2010	The gender gap in depressive symptoms among Japanese elders: evaluating social support and health as mediating factors	No structural measure of social network
Tinghog et al., 2010	The Association of Immigrant- and Non-Immigrant-Specific Factors With Mental Ill Health Among Immigrants in Sweden	Non-matching age restrictions
Triolo et al., 2020	Social engagement in late life may attenuate the burden of depressive symptoms due to financial strain in childhood	No association between depression and social network measured

Author(s)	Title	Exclusion reason
Triolo et al., 2022	Pre-pandemic Physical Function and Social Network in Relation to COVID-19-Associated Depressive Burden in Older Adults in Sweden	No structural measure of social network
Tucker et al., 2022	Marital Transitions, Change in Depressive Symptomology, and Quality of Social Relationships in Midlife and Older U.S. Adults: An Analysis of the Health and Retirement Study	No structural measure of social network
van Beljouw et al., 2014	"Being all alone makes me sad": loneliness in older adults with depressive symptoms	No association between depression and social network measured
van den Brink et al., 2018	Prognostic significance of social network social support and loneliness for course of major depressive disorder in adulthood and old age	Non-matching age restrictions
Vancampfort et al., 2020	Sedentary behavior and depression among community-dwelling adults aged >= 50 years: Results from the Irish longitudinal study on Ageing	No association between depression and social network measured
Villamil et al., 2006	Low Prevalence of Depression and Anxiety Is Linked to Statutory Retirement Ages Rather than Personal Work Exit: A National Survey	No structural measure of social network
Wahlin et al., 2015	Prevalence of depressive symptoms and suicidal thoughts among elderly persons in rural Bangladesh	No structural measure of social network
Wallsten et al., 1999	Disability and depressive symptoms in the elderly: The effects of instrumental support and its subjective appraisal	No structural measure of social network
Wang et al., 2023	Economic development, weak ties, and depression: Evidence from China	Non-matching age restrictions
Watanabe et al., 2004	Social support and depressive symptoms among displaced older adults following the 1999 Taiwan earthquake	No structural measure of social network
Weitzer et al., 2022	Dispositional optimism and depression risk in older women in the Nurses' Health Study: a prospective cohort study	No association between depression and social network measured
Werner-Seidler et al., 2017	The relationship between social support networks and depression in the 2007 National Survey of Mental Health and Well-being	No mean age
Wilby, 2011	Depression and social networks in community dwelling elders: a descriptive study	No association between depression and social network measured
Williams et al., 1995	Identifying depressive symptoms among elderly Medicare HMO enrollees	No access to full text (first author has been contacted)
Wojszel & Politynska, 2021	The structure and functional correlates of social support networks of people in advanced old age living in chosen urban and rural areas in Poland: a cross-sectional study	Not adjusted for confounders
Won et al., 2021	The mediating effect of life satisfaction and the moderated mediating effect of social support on the relationship between depression and suicidal behavior among older adults	No structural measure of social network
Woo et al., 1994	The prevalence of depressive symptoms and predisposing factors in an elderly Chinese population	Institutionalized population/ no separate analysis for community-dwelling population
Wu et al., 2018	Network-based and cohesion-based social capital and variations in depressive symptoms among Taiwanese adults	Non-matching age restrictions
Xiong et al., 2023	The Relationship between Physical Activity and Mental Depression in Older Adults during the Prevention and Control of COVID-19: A Mixed Model with Mediating and Moderating Effects	No association between depression and social network measured
Yao et al., 2008	Relationships between personal depression and social network factors and sleep quality in community-dwelling older adults	No association between depression and social network measured

Author(s)	**Title**	**Exclusion reason**
Yu & Mahendran, 2021	COVID-19 lockdown has altered the dynamics between affective symptoms and social isolation among older adults: results from a longitudinal network analysis	No structural measure of social network
Yu et al., 2023	Social network and mental health of chinese immigrants in affordable senior housing during the covid-19 pandemic: A mixed-methods study	Qualitative
Zeng et al., 2013	Family and social aspects associated with depression among older persons in a Chinese context	No association between depression and social network measured
Zhang & Chen, 2022	Association between workplace and mental health and its mechanisms during COVID-19 pandemic: A cross-sectional, population-based, multi-country study	Non-matching age restrictions
Zhou et al., 2022	Association between social capital and depression among older adults of different genders: Evidence from Hangzhou, China	No structural measure of social network
Zwar et al., 2023	Mental health, social integration and support of informal caregivers during the second wave of the COVID-19 pandemic: A population-based representative study from Germany	Non-matching age restrictions

Table A2-3 Quality appraisal: Newcastle-Ottawa-Scale (NOS) for cross-sectional studies

Author(s), Year	Selection	Comparability	Outcome	Evaluation
Ali et al., 2022	3	2	2	*Good*
Antonucci et al., 1997	4	2	2	*Good*
Aung et al., 2016	3	2	2	*Good*
Bae et al., 2020	3	2	2	*Good*
Becker et al., 2019	2	2	1	*Poor*
Bincy et al., 2022	4	2	2	*Good*
Bisconti & Bergeman, 1999	1	1	1	*Poor*
Blumstein et al., 2004	3	2	1	*Poor*
Boey & Chiu, 2005	4	2	2	*Good*
Braam et al., 1997	4	2	2	*Good*
Cao et al., 2015	3	2	2	*Good*
Castro-Costa et al., 2008	0	1	2	*Poor*
Chan & Zeng, 2009	5	2	2	*Good*
Chan & Zeng, 2011	4	2	2	*Good*
Chan et al., 2011	4	2	2	*Good*
Cheng et al., 2014	3	2	1	*Poor*
Chi & Chou, 2001	3	2	2	*Good*
Cho et al., 2018	4	2	2	*Good*
Choi & Jeon, 2021	3	2	2	*Good*
Chou & Chi, 2001	4	2	2	*Good*
Domènech-Abella et al., 2017	3	2	2	*Good*
Dorrance Hall et al., 2019	3	2	2	*Good*
Ermer & Proulx, 2022	2	2	2	*Fair*
Fernández & Rosell, 2022	4	2	2	*Good*
Fiori et al., 2006	3	2	2	*Good*
Forsman et al., 2012	4	2	2	*Good*
Frediksen-Goldsen et al., 2013	3	2	2	*Good*
Fuller-Iglesias et al., 2008	4	2	1	*Poor*
Gao et al., 2022	4	2	2	*Good*
Goldberg et al., 1985	3	1	2	*Good*
Golden et al., 2009	4	2	2	*Good*
Gu et al., 2023	3	2	2	*Good*
Gumà & Fernández-Carro, 2021	3	2	2	*Good*
Hamid et al., 2019	3	1	2	*Good*
Han et al., 2007	2	2	2	*Fair*
Harada et al., 2023	3	2	2	*Good*
Harasemiw et al., 2019	3	2	2	*Good*
Jang et al., 2002	4	2	2	*Good*
Jang et al., 2011	2	2	2	*Fair*
Jeon & Lubben, 2016	2	1	2	*Fair*
Jiang et al., 2022	3	2	2	*Good*
Kim & Lee, 2015	4	2	2	*Good*
Kim & Lee, 2019	2	2	2	*Fair*
Kim et al., 2012	3	2	2	*Good*
Kim et al., 2015	2	2	2	*Fair*

Author(s), Year	Selection	Comparability	Outcome	Evaluation
Klug et al., 2014	5	2	2	*Good*
La Gory & Fitpatrick, 1992	2	2	1	*Poor*
Lee & Chou, 2019	3	2	2	*Good*
Lee et al., 1996	2	1	1	*Poor*
Lee et al., 2017	3	2	2	*Good*
M. Li et al., 2019	2	2	2	*Fair*
Li et al., 2022	4	2	2	*Good*
Litwin & Levinsky, 2022	3	2	2	*Good*
Litwin & Levinsky, 2023	3	2	2	*Good*
Litwin et al., 2015	4	2	2	*Good*
Litwin, 2011	2	2	2	*Fair*
Litwin, 2012	2	2	2	*Fair*
Liu et al., 2016	1	2	2	*Poor*
Marshall & Rue, 2012	3	2	2	*Good*
Marshall-Fabien & Miller, 2016	3	2	2	*Good*
Mechakra-Tahiri et al., 2010	4	2	2	*Good*
Merchant et al., 2020	2	1	2	*Fair*
Merhabi & Béland, 2021	2	2	2	*Fair*
Miller & Lago, 1990	3	1	1	*Poor*
Minicuci et al., 2002	3	2	2	*Good*
Murayama et al., 2014	2	2	2	*Fair*
Okwumabua et al., 1997	3	2	1	*Poor*
Palinkas et al., 1990	1	2	2	*Poor*
Park & Roh, 2013	3	2	2	*Good*
Park et al., 2013	3	2	2	*Good*
Park et al., 2014	2	2	2	*Fair*
Park et al., 2018	3	2	2	*Good*
Park et al., 2019	3	2	2	*Good*
Pavlidis et al., 2023	2	2	2	*Fair*
Pilehvari et al., 2023	3	2	2	*Good*
Roh et al., 2015	3	2	2	*Good*
Santini, Koyanagi, Tyrovoloas, et al., 2015	4	2	2	*Good*
Shouse et al., 2013	2	1	2	*Fair*
Sicotte et al., 2008	3	2	2	*Good*
Singh et al., 2016	2	2	2	*Fair*
Sohn et al., 2017	3	2	2	*Good*
Sonnenberg et al., 2013	4	2	2	*Good*
Stoeckel & Litwin, 2016	2	2	2	*Fair*
Sugie et al., 2022	3	2	2	*Good*
Tang & Xie, 2021	4	2	2	*Good*
Tang et al., 2020	5	2	2	*Good*
D. Tang et al., 2023	4	2	2	*Good*
Tanikaga et al., 2023	3	2	2	*Good*
Taylor et al., 2018	3	2	2	*Good*
Taylor, 2021	3	2	2	*Good*
Tsai et al., 2005	3	1	2	*Good*

Author(s), Year	Selection	Comparability	Outcome	Evaluation
Vicente & Guadalupe, 2022	1	2	2	*Poor*
Webster et al., 2015	2	2	2	*Fair*
Wee et al., 2014	2	2	2	*Fair*
Wendel et al., 2022	3	2	2	*Good*
Wu et al., 2017	3	2	2	*Good*
Ye & Zhang, 2019	2	2	2	*Fair*

Threshold for converting the NOS for cross-sectional studies: good quality (3 to 5 stars in selection domain AND 1 or 2 stars in comparability domain AND 2 or 3 stars in outcome domain), fair quality (2 stars in selection domain AND 1 or 2 stars in comparability domain AND 2 or 3 stars in outcome domain), poor quality (0 or 1 star in selection domain OR 0 stars in comparability domain OR 0 or 1 stars in outcome domain)

Table A2-4 Quality appraisal: Newcastle-Ottawa-Scale (NOS) for longitudinal studies

Author(s), Year	Selection	Comparability	Outcome	Evaluation
Bisschop et al., 2004	3	2	3	*Good*
Blumstein et al., 2004	3	2	2	*Good*
Bui, 2020	4	2	2	*Good*
Byers et al., 2012	4	1	2	*Good*
Chao, 2011	3	2	3	*Good*
Coleman et al., 2022	3	2	2	*Good*
Domènech-Abella et al., 2019	4	2	3	*Good*
Förster et al., 2018	3	2	2	*Good*
Förster et al., 2021	4	2	2	*Good*
Gan & Best, 2021	2	2	2	*Fair*
Hajek & König, 2016	3	2	2	*Good*
Harlow et al., 1991	2	1	3	*Fair*
Holwerda et al., 2023	3	2	2	*Good*
Houtjes et al., 2014	3	2	3	*Good*
Husaini, 1997	2	0	1	*Poor*
Kim et al., 2016	3	2	2	*Good*
Kuchibhatla et al., 2012	3	2	3	*Good*
Litwin & Levinsky, 2021	2	2	2	*Fair*
Litwin et al., 2020	2	2	2	*Fair*
Oxman et al., 1992	2	0	3	*Poor*
Reynolds et al., 2020	3	2	3	*Good*
Ruan et al., 2022	4	2	3	*Good*
Santini et al., 2016	4	2	2	*Good*
Santini et al., 2017	3	2	2	*Good*
Santini et al., 2021	2	1	2	*Fair*
Schwartz & Litwin, 2017	3	2	3	*Good*
Stringa et al., 2020	2	1	2	*Fair*
F. Tang et al., 2023	3	2	2	*Good*
Voils et al., 2007	2	1	3	*Fair*
Werneck et al., 2023	4	2	2	*Good*
Zhang et al., 2023	4	2	3	*Good*

Threshold for converting the NOS for longitudinal studies: good quality (3 to 4 stars in selection domain AND 1 or 2 stars in comparability domain AND 2 or 3 stars in outcome domain), fair quality (2 stars in selection domain AND 1 or 2 stars in comparability domain AND 2 or 3 stars in outcome domain), poor quality (0 or 1 star in selection domain OR 0 stars in comparability domain OR 0 or 1 stars in outcome domain)

CHAPTER 3. SOCIAL NETWORKS AND THEIR ASSOCIATION WITH DEPRESSION IN COMMUNITY-DWELLING OLDER ADULTS: A META-ANALYSIS

Amelie Reiner, Elena De Gioannis & Paula Steinhoff

Abstract

Depression is a common mental health condition among older adults, while social networks offer protection. This meta-analysis quantifies the relationship between the structural aspects of social networks and depression in this population. Seven electronic databases were searched from inception until July 2023. Eligible studies focused on community-dwelling older adults (mean age ≥60), defined depression, referenced social networks in the abstract, and were published in English. Random-effects meta-analyses combined standardized beta coefficients for continuous depression outcomes and log odds for binary outcomes. Study quality, heterogeneity and potential publication bias were evaluated. Sixty-two studies met the inclusion criteria. Larger network size, frequent contact, and higher network scale scores were linked to lower depression levels, though effect sizes were modest. Network scales, incorporating structural and functional aspects, showed the strongest association with reduced depression, though this finding was rather suggestive. The distinction between family and friend networks was less significant, with combined measures and family ties showing stronger associations. Gender did not significantly influence the association, and continuous depression measures provided more nuanced insights than binary ones. Social networks offer modest protection against depression in older adults. Future research should standardize depression measures, further investigate gender and network differences, and explore long-term effects.

Keywords: social network, mental health, depression, older adults, meta-analysis

3.1 Background and objective

Depression is a prevalent mental health condition among older adults, significantly affecting their quality of life and well-being. It is closely linked to cardiovascular diseases, cancer, diabetes, and respiratory illnesses (World Health Organization, 2023). Research consistently shows that older adults who are more socially integrated experience lower levels of depression than those with fewer social connections (Mohd et al., 2019; Schwarzbach et al., 2014). However, as individuals age, their social networks often shrink due to life changes such as retirement, bereavement, and declining health, diminishing the number and quality of their relationships (Wrzus et al., 2013). This reduction increases the risk of depression in older adults, highlighting the need to understand how various aspects of social networks influence depression outcomes.

With the anticipated rise in depression prevalence as the population ages, it is crucial to identify which aspects of social networks are most effective in mitigating depressive symptoms. This understanding is essential for developing targeted social gerontological interventions that enhance older adults' mental health by fostering supportive social environments.

The definition and measurement of social networks differ widely across studies, often leading to inconsistencies in the literature (Ayalon & Levkovich, 2019; Siette et al., 2021). Broadly, social networks refer to the web of connections linking individuals, families, or communities (Berkman et al., 2000; Cohen et al., 2000). Researchers typically categorize social network characteristics into two broad dimensions: functional and structural aspects (Cohen, 2004; Santini et al., 2015). Functional aspects pertain to the perceived quality and role of relationships, encompassing social support, relationship satisfaction, and experiences of loneliness or isolation (Kuiper et al., 2016). In contrast, structural aspects focus on measurable features such as network size, composition, and interaction frequency. Growing evidence suggests that structural aspects—being objective and quantifiable—may serve as key predictors of critical health outcomes, including cognitive decline (Kuiper et al., 2016), dementia (Kuiper et al., 2015), and mortality (Holt-Lunstad et al., 2010).

Social networks and depression have a complex, reciprocal relationship. According to the main effect model (Kawachi & Berkman, 2001), social networks contribute positively to mental well-being by promoting a sense of belonging, social reinforcement, and support for health-related behaviors. Conversely, depression can negatively impact social networks by leading to social withdrawal and reduced engagement with others (Blazer, 2003). While much of the research has focused on how social networks influence depression, there has been limited attention to how depression, in turn, affects social networks (Reiner & Steinhoff, 2024).

Traditionally, family has been seen as the primary source of support, particularly important for health outcomes in older adults (Antonucci et al., 2011). However, research indicates that diverse networks–including family and friends–are more beneficial for reducing depression than restricted networks (Litwin, 2011, 2012; for a review, see Reiner & Steinhoff, 2024). Further examination of effect size differences is needed to determine the relative importance of family and friends in depression outcomes.

Additionally, gender differences in the association between social networks and depression have been explored due to the gendered nature of social roles and support. While the relationships between social network aspects and depression are largely similar for women and men (Reiner & Steinhoff, 2024), a more nuanced understanding is needed. Gender differences could have important implications for targeted interventions to reduce depression in older adults. Therefore, estimating gender differences through meta-analysis could provide deeper insights into these associations.

While previous systematic reviews have offered valuable insights into the relationship between social networks and mental health, they often have limitations, such as focusing on specific geographic areas or relying on outdated data. Additionally, previous studies and literature reviews have used the concept of social networks inconsistently, often conflating it with social isolation or social support, despite focusing specifically on social networks (Ayalon & Levkovich, 2019; Siette et al., 2021). Reiner & Steinhoff (2024) addressed these gaps by conducting a comprehensive review of 127 articles examining the relationship between various structural aspects of social networks and depression in community-dwelling older adults. Their findings indicated that larger, more diverse networks and closer social ties were generally associated with lower levels of depression. However, while systematic reviews summarize and synthesize existing literature, they remain largely descriptive.

In contrast, this meta-analysis builds upon this systematic review by statistically integrating findings across studies, providing a clearer estimate of the relationship between structural aspects of social networks and depression. While the review synthesized existing literature, it remained descriptive, leaving uncertainty about the magnitude and consistency of associations across different studies. By pooling data, this meta-analysis offers a more precise quantification of these relationships and helps reconcile inconsistencies in previous findings. Additionally, it allows for a systematic examination of variations across study populations, geographical contexts, and methodological approaches, addressing gaps in the existing review. Moreover, statistical techniques enable an assessment of potential publication bias, further strengthening the reliability of the conclusions (Deeks et al., 2019).

Despite Reiner & Steinhoff's (2024) holistic understanding of structural social network characteristics, further investigation is needed to clarify how these networks influence depression in older adults. In particular, it is essential to determine whether family or friends play a more significant role in mitigating depression and how these effects may differ by gender.

This meta-analysis aims to systematically assess and quantify the strength of the association between structural aspects of social networks and depression outcomes in older adults. Given the limited statistical evidence on how depression affects social networks, the relationship is not yet considered bidirectional, and we focus solely on how social networks influence depression. Building on Reiner & Steinhoff's (2024) systematic review, this study employs a meta-analytic approach to provide a more precise estimate of these associations. Specifically, this meta-analysis addresses the following research questions: [RQ1] What is the overall magnitude of the association between structural network aspects–namely, network size, network scales, and contact frequency–and depression in older adults? [RQ2] How does the effect of these structural network aspects on depression differ by gender? [RQ3] Which type of social network–mixed, family, or friends–has the strongest influence on depression outcomes in older adults?

By addressing these questions, this meta-analysis aims to enhance our understanding of social networks' role in older adults' mental health. The findings will inform the development of targeted interventions that consider this population's specific needs and vulnerabilities.

3.2 Methods

This meta-analysis builds on the pre-registered systematic review conducted by Reiner & Steinhoff (2024). The review protocol is available at https://doi.org/10.17605/OSF.IO/6QDPK. We adapted the selection process from the systematic review for this meta-analysis. Additionally, the reporting of this meta-analysis follows the Journal Article Reporting Standards guidelines (Appelbaum et al., 2018), particularly suited for psychological research.

3.2.1 Eligibility criteria

We included peer-reviewed studies examining the relationship between structural social network characteristics and depression among community-dwelling older adults, defined by the World Health Organization (WHO, 2020) as individuals aged 60 years and older. To minimize regional selection bias, we restricted our search to studies published in English. There were no restrictions based on publication year or geographic location.

The inclusion and exclusion criteria were informed by prior systematic reviews (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018). Studies were included if they focused on community-dwelling adults aged 40 and older, with a mean age of at least 60. The minimum age of 40 allowed the inclusion of relevant studies (e.g. the German DEAS), while the mean age requirement ensured a focus on older adults.

The exposure or outcome of interest had to be explicitly mentioned as social networks in the study abstracts. Depression was defined based on diagnostic criteria or a cutoff on a depression rating scale. The association between social networks and depression had to be reported through multivariate analysis, controlling for confounders assessed during the quality evaluation. Only peer-reviewed journal articles published in English were included.

Articles were excluded if they focused on patient groups or institutionalized individuals unless analyses distinguished between community-dwelling and institutionalized participants. Studies assessing social network characteristics from earlier life stages, such as youth or adolescence, to evaluate current depression outcomes or those that solely examined online social networks were also excluded. Additional exclusions applied to editorials, study protocols, conference proceedings, comments, reviews, qualitative studies, grey literature, case studies, and intervention studies.

For the meta-analysis, additional exclusion criteria were applied: 1) studies had to regress depression on social network, 2) they needed to use network size, network scale, or contact frequency as indicators of social networks, 3) sufficient information had to be provided to calculate the effect size and measurement error (details are provided in the analytical strategy section); and 4) depression and social networks had to be measured as continuous or binary variables (further details are included below).

In their systematic review, Reiner & Steinhoff (2024) summarized studies that regressed either social network variables on depression or vice versa. However, due to the limited number of studies suitable for the second association, this meta-analysis focuses solely on studies that regressed depression on social network variables. We also excluded studies that used indicators other than size, scale, and contact frequency, as other indicators–such as proximity, density, and homogeneity–were only tested in a few studies, limiting statistical comparison. Moreover, the instruments used to measure network size, scale, and contact frequency were relatively homogenous, while indicators like network composition lacked consistent measurement tools.

Network size refers to the number of social relationships in an individual's network, while contact frequency measures how often individuals engage with their social ties. Network scales, which capture structural and functional aspects, typically combine measures such as marital status, the number and frequency of contacts with children, close relatives, and friends, and participation in community organizations (Berkman & Syme, 1979).

3.2.2 Search strategy

The systematic database search was conducted from the inception of each database until July 11, 2023. The search strategy used keywords related to "depression," "social networks," and "older adults" (see Appendix, Table A3-1). These keywords were informed by previous systematic reviews covering these three topics (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018).

We searched seven databases–APA PsycINFO, ProQuest, PSYINDEX, PubMed, Scopus, SocINDEX, and Web of Science–using consistent keywords and search strategies. Additionally, we manually searched the reference lists of relevant systematic reviews (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018) to identify any additional eligible studies.

3.2.3 Study selection

References from the seven databases were imported into Rayyan (Ouzzani et al., 2016) for management. After removing duplicates, two researchers (AR, PS) independently screened the titles and abstracts to identify potentially eligible studies for full-text review. Both researchers then independently evaluated the full texts of these studies against the eligibility criteria. Any disagreements or discrepancies were resolved through consensus.

To enhance the reliability and validity of the review, the study selection process was piloted twice using random samples of 100 studies from the overall dataset for each pilot. This piloting ensured that all reviewers had a consistent and accurate understanding of the selection process (Lefebvre et al., 2019). An overview of the studies that appeared to meet the inclusion criteria but were ultimately excluded, along with the reasons for this exclusion, can be found in the Appendix, Table A3-2.

3.2.4 Data collection

Data extraction was performed using a standardized data collection form informed by related reviews (Ayalon & Levkovich, 2019; Gariépy et al., 2016; Harandi et al., 2017; Kelly et al., 2017; Mohd et al., 2019; Piolatto et al., 2022; Santini et al., 2015; Schwarzbach et al., 2014; Tajvar et al., 2013; Visentini et al., 2018). Two researchers (ED, AR) conducted the data extraction independently.

For each article, we extracted bibliographic information, and for each model testing the association of interest, we collected information on the (a) sample (year of the data collection, percentage of men, mean age, size, type of dataset, subsample), (b) independent and dependent variables (type, instrument used), (c) analysis, (d) results (coefficient, error measure, mean, standard deviation, raw data on prevalence of depression within groups), and (e) model (number and type of control variables included). The outcomes of interest were depression scores among community-dwelling older adults. Any disagreement was resolved through discussion.

3.2.5 Quality appraisal

Quality assessment was conducted using the Newcastle-Ottawa Scale (NOS; Wells et al., 2014) for cross-sectional and longitudinal studies. One reviewer (AR) performed the initial evaluation, which was then double-checked by another reviewer (PS). The NOS, widely used in previous systematic reviews (Hakeem et al., 2019; Mohd et al., 2019; Shamsrizi et al., 2020; Vivekanantham et al., 2019), assigns stars across three domains, with more stars indicating a higher-quality study (Wells et al., 2014). These domains evaluate study design, participant selection, comparability, and exposure and outcome assessment.

Following the methodology of several prior reviews (Hakeem et al., 2019; Mohd et al., 2019; Shamsrizi et al., 2020; Vivekanantham et al., 2019), we implemented a rigorous approach to quality assessment, using predefined thresholds to convert NOS scores to standards set by the Agency for Health Research and Quality. The detailed quality assessment of the studies can be found in the Appendix, Table A3-3.

3.2.6 Analytical strategy

There was heterogeneity in how the studies computed the indicators for social networks (network size, contact frequency, network scales) and depression. While the instruments used were similar, the resulting variables were sometimes treated as continuous, while others were manipulated to be binary and, in a few cases, transformed into categorical variables. This variation is relevant for both the type of effect size and comparability.

To address this, we decided to conduct two separate meta-analyses: one in which depression was treated as a continuous variable (with the effect size represented as standardized beta) and another in which depression was treated as a binary variable (with the effect size represented as log odds). Furthermore, we excluded studies that measured depression as a categorical variable due to the insufficient number of studies to conduct a meta-analysis. We also excluded studies where social networks were represented as categorical variables because of comparability issues.

Finally, we excluded studies that either did not directly report the effect size or the error measure or did not provide sufficient information to compute them. For instance, in the case of standardized beta, studies reporting the unstandardized coefficient without the standard deviation of X and Y were excluded because it was impossible to derive the standardized version of the coefficient and the standard error.

Regarding log odds, some studies reported other effect sizes, such as prevalence or hazard ratios. While it is possible to convert these measures into odds ratios (Grant, 2014), this conversion requires additional information that was not consistently reported, such as the raw numbers of participants with and without depression among those with low and high social networks.

For studies that did not directly report the effect size of interest and its standard error, we computed these values using the information extracted. The formulas used to calculate the standard error from either the 95% confidence interval or the *p*value are those reported in the *Cochrane Handbook for Systematic Reviews* (Higgins et al., 2023).

Regarding asterisks and *p*value, we adopted a conservative approach. When the authors did not provide the exact *p*value (or used asterisks), we transformed it using the following criteria: >0.05 = 0.55, <0.10 = 0.075, <0.05 = 0.025, <0.01 = 0.005, <0.001 = 0.0005.

In the case of a continuous outcome, the standardized beta was computed as the unstandardized coefficient multiplied by the ratio of the standard deviations (SD_x/SD_y). The same formula was applied to obtain the standardized standard error. For binary outcomes, ratio measures were converted into log odds using the formula suggested by both Grant (2014) and the *Cochrane Handbook* (Schünemann et al., 2023). Additionally, when the independent or dependent variables ranged from high to low, the effect sizes were inverted to maintain homogeneity (i.e. transforming from low to high values).

There was also heterogeneity in how studies computed the indicators for both social networks and depression. While the instruments used were similar, the resulting variables were sometimes treated as continuous, while others were manipulated to be binary and, in a few cases, transformed into categorical variables. This variation is relevant for both the type of effect size and comparability. Therefore, we decided to conduct two separate meta-analyses: one in which depression was treated as a continuous variable (with the effect size represented as standardized beta) and another in which depression was treated as a binary variable (with the effect size represented as log odds).

The data analysis was performed separately for the continuous and binary outcomes, in Stata (StataCorp, 2023). Model regressions with a robust variance estimator were estimated in R (R Core Team, 2022) using the robumeta package (Tanner-Smith & Tipton, 2013). To answer RQ1, we first conducted a meta-analysis, distinguishing among the three indicators of social networks. To answer RQ2 and RQ3, we estimated a meta-regression model.

Previous research typically used bivariate and multivariate random effects models (Holt-Lunstad et al., 2010; Piolatto et al., 2022). While the multivariate model is more complex and preferred for accounting for the influence of multiple moderators on the effect size (Jackson et al., 2011), it is constrained by sparse data.

In this study, we adopted a two-step approach. First, we applied a bivariate meta-regression model to assess the contribution of each factor to the variance in effect size. In the second step, we used a multivariate meta-regression to examine whether study characteristics influenced the effect size for the continuous depression variable. The second step was not conducted for the binary outcome due to insufficient data, as the number of studies was lower than the number of regressors, which would have led to an overfitted model and unreliable estimates.

Given that most articles included multiple model estimates varying in control variables or sample composition (total sample versus subgroups), we could not assume that the effect sizes were independent. To account for the hierarchical structure of the data–where multiple estimates within the same study may be correlated–we employed a robust variance estimator (RVE; Hedges et al., 2010).

Importantly, additional analysis showed that not accounting for the dependencies of effect sizes often led to a statistically significant association between study characteristics and the magnitude of the effect. This suggests that heterogeneity was more driven by differences within studies, such as varying control variables or model specifications, than between studies. These findings underscore the critical importance of accounting for the hierarchical nature of the data to avoid misleading conclusions.

Furthermore, to address potential bias due to sample size in the case of the binary outcome, we also estimated a model using the correction for small samples (Lin, 2018). Finally, since the effect size was derived not from raw data but from estimates, and the regression models varied in the number and type of control variables included, the assumption of homogeneity did not hold. Therefore, the meta-analysis and meta-regression employed a random effects model (REML estimator).

3.2.7 Risk of bias

We evaluated publication bias using funnel plots and Egger's test. The first are scatters showing treatment effects on the horizontal axis and the measure of the studies precision on the vertical axis. The potential presence of bias can be detected by looking at the symmetry of the plot. The plot should resemble a symmetrical inverted funnel. However, in the case of publication bias, i.e. smaller studies with no statistically significant effects remain unpublished, the plot will appear asymmetrical (Sterne & Egger, 2001). The Egger's test regresses the standardized effect sizes on their precisions. In the absence of publication bias, the regression intercept should be equal to zero (Lin & Chu, 2018).

3.3 Results

3.3.1 Study selection

Starting from the initial sample of 127 articles from the systematic review, 22 were excluded due to their measurement of networks, and eight were excluded for the causal direction of depression on social network. Of the remaining 97 eligible articles, 21 did not provide sufficient information to compute both the effect size and the error measure, and 14 measured depression or networks as categorical variables. Thus, we ended up with 62 articles, of which 18 were used in the analysis of the binary outcome (*n* models = 43) and 48 in the continuous outcome analysis (*n* models = 214)–four articles included both types of outcomes. Figure 3-1 visualizes the PRISMA flowchart of the selection process, and Table 3-1 provides an overview of the included articles.

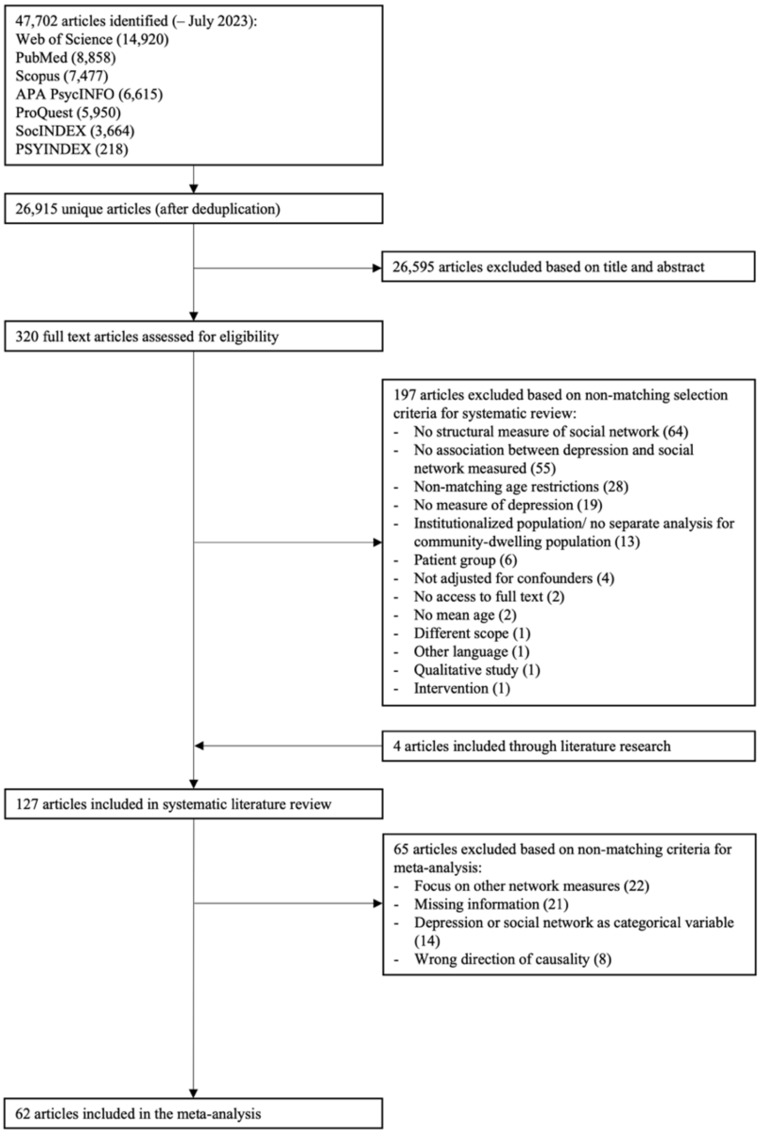


Figure 3-1 Selection flowchart

The included articles were published between 1990 and 2023, with half published after 2016, highlighting the substantial research conducted on this association, particularly in the last decade. Sample sizes ranged from 74 to 60,918, with a median of 1,563 respondents. Most studies were conducted in North America ($n = 25$), followed by Asian countries ($n = 21$). Fifteen studies occurred in European countries (including Israel), and only one was from South America.

The quality appraisal for each NOS domain and the overall evaluation are provided in the Appendix, Table A3-3. Most studies ($n = 48$) were classified as good quality, seven as fair quality, and seven as poor quality.

The majority used validated instruments to assess depression, with 30 using the Center for Epidemiologic Studies Depression Scale (CES-D) and 18 using the Geriatric Depression Scale. Other studies employed the EURO-D scale ($n = 7$) or other validated instruments ($n = 7$).

Table 3-1 Overview of included articles

Articles	Depression measure	Social network measure	N[a]	Quality
Antonucci et al., 1997	CES-D	Size (people who are important to them)	3777	Good
Bae et al., 2020	GDS-15	Scale (NCGG Social Network Scale)	2445	Good
Bisschop et al., 2004	CES-D (20)	Size (people in important and frequent contact, except partner)	2278	Good
Boey & Chiu, 2005	GDS-15	Scale (LSNS, family subscale, friend subscale)	1034	Good
Braam et al., 1997	CES-D (20)	Size (Number of people named in the seven categories: persons living in the same household, children and children in-law, other relatives, neighbors, people with whom one is working or studying, contacts in organizations and other contacts)	2817	Good
Bui, 2020	CES-D (11)	Size (total network size, confidant network size) Contact (less than once a year to every day)	2200	Good
Castro-Costa et al., 2008	GHQ-12	Contact (Weekly frequency of visits from offspring, relatives and friends)	1510	Poor
Chan & Zeng, 2009	GDS-15	Scale (SNS)	1042	Good
Chan & Zeng, 2011	GDS-15	Scale (LSNS)	839	Good
Chan et al., 2011	CES-D (11)	Scale (LSNS, friends and relatives)	4489	Good
Chi & Chou, 2001	CES-D (20)	Size (Relatives/Kin size, Number of relatives seen once a month, Number of relatives felt close to, Number of friends seen once a month, Number of friends felt close to)	1106	Good
Cho et al., 2019	CES-D (10)	Size (number of close friends and close relatives: 0, 1–2, 3–5, 6–9, 10 +)	2541	Good
Chou & Chi, 2001	CES-D (20)	Scale (LSNS)	411	Good
Domènech-Abella et al., 2017	CIDI 3.0	Size (Berkman-Syme Social Network Index) Contact (Contact with network members at least once per month in the previous 12 months)	3535	Good
Dorrance Hall et al., 2019	CES-D (9)	Size (persons with whom they talk about important matters and regularly interact)	2249	Good
Ermer & Proulx, 2022	CES-D (11)	Size (social network roster) Contact (contact with network member: every day, several times a week, once a week, once every two weeks,	865	Fair

Articles	Depression measure	Social network measure	N[a]	Quality
		once a month, a couple times a year, once a year, and less than once a year)		
Forsman et al., 2012	GDS-4	Contact (contact frequency with friends, contact frequency with neighbors: frequent vs. Infrequent contact)	6838	Good
Fredriksen-Goldsen et al., 2013	CES-D (10)	Size (Interaction with friends, family members, colleagues, and neighbors in a typical month; calculated and summarized by quartiles)	2439	Good
Fuller-Iglesias et al., 2008	CES-D (20)	Size (Hierarchical mapping technique)	99	Poor
Gao et al., 2022	CES-D (10)	Scale (LSNS, family subscale, friend subscale)	5934	Good
Hajek et al., 2016	CES-D (15)	Size (Number of important people regular in contact)	2201	Good
Hamid, 2019	GDS-15	Scale (LSNS)	594	Good
Han et al., 2007	KDSKA	Size (number of living parents, spouse, children, grandchildren, and other relatives)	205	Fair
Harada et al., 2023	GDS-15	Size (number of siblings, cousins, grandchildren or other relatives with whom respondent or respondent's spouse interacts on a regular basis (except household members))	739	Good
Harlow et al., 1991	CES-D (20)	Size (Total network, family network, friendship network, confidant network; Number of friends and family members outside of the household with whom the respondent had been in touch during the 6 months before interview and total size of the network which additionally included family and friends who lived with the respondent)	545	Fair
Holwerda et al., 2023	CES-D (10)	Size (Number of network members (≥ 18 years) with whom respondent had important/frequent contact)	899	Good
Jang et al., 2002	GDS-15	Scale (LSNS)	406	Good
Jiang et al., 2022	GDS-15	Scale (LSNS)	3769	Good
Kim & Lee, 2015	SGDS-K	Scale (LSNS, family subscale, friend subscale)	949	Good
Kim et al., 2012	GDS-15	Scale (LSNS)	210	Good
Kim et al., 2015	GDS-15	Scale (LSNS)	147	Fair
La Gory & Fitpatrick, 1992	CES-D (20)	Contact (Contact scale: visiting friends and relatives, being visited by them, phoning or writing them and meeting them in a social setting)	725	Poor
Lee & Chou, 2019	GDS-15	Size (Number of children, family members, and friends they felt close to)	850	Good
Lee et al., 1996	CES-D (20)	Size (Total Network Size: numbers of living parents, children, and friends)	162	Poor
Lee et al., 2017	GDS-30	Scale (LSNS)	200	Good
Litwin & Levinsky, 2022	Euro-D	Contact (In person contact; electronic contact: daily, several times a week, about once a week, less often, never)	33403	Good
Litwin & Levinsky, 2023	Euro-D	Size (Total Network Size: up to 6 persons with whom they discuss personal matters; one additional person who was important for any reason) Contact (Contact to confidants: 7-point scale: 1 = never; 7 = daily)	35145	Good
Litwin et al., 2015	Euro-D	Size (Total Network Size: up to 6 persons with whom they discuss personal matters; one additional person who was important for any reason) Contact (Contact frequency: never to daily)	25245	Good
Marshall & Rue, 2012	CES-D (20)	Contact (Index of contact frequency to family members/ friends/ church members: never to nearly every day)	1108	Good

Articles	Depression measure	Social network measure	N[a]	Quality
Marshall-Fabien & Miller, 2016	CES-D (12)	Contact (contact frequency with friends, contact frequency with neighbors: frequent vs. Infrequent contact)	1108	Good
Okwumabua et al., 1997	CES-D (20)	Scale (LSNS)	110	Poor
Oxman et al., 1992	CES-D (20)	Size (Number of close relatives phoning/writing yearly; Number of close friends phoning/writing yearly; Relatives/Kin size; Number of children/Children seen weekly)	1962	Poor
Palinkas et al., 1990	BDI (18)	Size (Friendship network size; Relatives/Kin size)	1615	Poor
Park & Roh, 2013	GDS-30	Scale (LSNS)	200	Good
Park et al., 2013	GDS-15	Scale (SNI)	374	Good
Park et al., 2019	CES-D (10)	Scale (LSNS, family subscale, friend subscale)	353	Good
Pavlidis et al., 2023	Euro-D	Size (Small network (1–2 members) vs. large network (3 + members))	60918	Fair
Reynolds et al., 2020	CES-D	Size (Number of important people regular in contact)	3005	Good
Roh et al., 2015	GDS-30	Scale (LSNS)	200	Good
Ruan et al., 2022	CES-D (9)	Scale (LSNS)	4466	Good
Santini et al., 2021	Euro-D	Size (number of close relations in the social network; up to 7 persons)	38300	Fair
Schwartz & Litwin, 2017	Euro-D	Size (up to 7 persons with whom they discuss important matters) Contact (contact frequency to people with whom they discuss important matters: daily to never)	14101	Good
Stringa et al., 2020	CES-D	Size (number of people in important and regular contact)	2279	Fair
Tang & Xie, 2021	CES-D	Scale (LSNS, family subscale, friend subscale)	2484	Good
Tang et al., 2020	CES-D (9)	Scale (LSNS, family subscale, friend subscale)	7662	Good
Tang et al., 2023a	PHQ-9	Size (Total number of network members with whom respondent could discuss important things)	1970	Good
Tang et al., 2023b	CES-D	Scale (LSNS, family subscale, friend subscale)	7601	Good
Tanikaga et al., 2023	GDS-15	Scale (LSNS)	74	Good
Taylor, 2021	CES-D (7)	Scale (SNI)	2323	Good
Tsai et al., 2005	GDS-15	Scale (LSNS)	1200	Good
Werneck et al., 2023	Euro-D	Size (number of people in network)	10569	Good
Zhang et al., 2023	DASS-21 (depression subscale)	Scale (LSNS)	634	Good

[a] *n: Sample size, baseline sample was used in longitudinal studies*

***Depression measures:** BDI Beck Depression Inventory, CES-D Centre of Epidemiologic Studies Depression Scale, CIDI Composite International Diagnostic Interview (Short Form), DASS-21 Depression Anxiety Stress Scale, EURO-D EURO geriatric depression scale, GDS Geriatric Depression Scale, GHQ General Health Questionnaire, KDSKA Kim Depression Scale for Korean Americans, PHQ-9 Patient Health Questionnaire, SGDS-K Geriatric Depression Scale Short Form Korean Version*

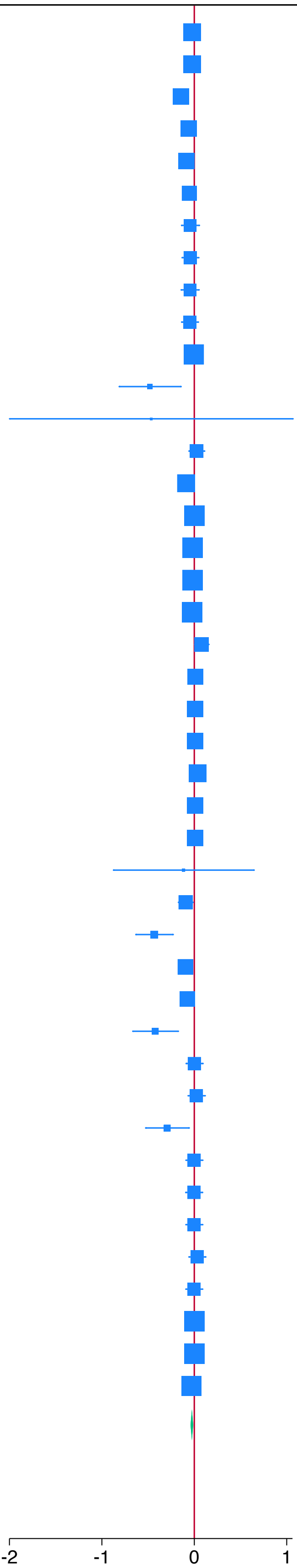
***Social network measures:** LSNS Lubben Social Network Scale, NCGG Social Network Scale National Center for Geriatrics and Gerontology Social Network Scale, SNI Social Network Index*

3.3.2 Continuous outcome

We examined 214 models testing the association between social networks and depression as a continuous variable. These models covered network scale (109 models), network size (70 models), and contact frequency (43 models).

The overall effect size (n = 214) was –0.078 (95% CI: [–0.094, –0.062], se = 0.0081, $p < 0.001$). Since this effect size represents a standardized beta, it indicates that social networks had a small but statistically significant influence on depression, with a one standard deviation increase in the network associated with a 0.078 decrease in depression (see Appendix, Table A3-4). However, the magnitude of the effect size varied across different network measures. Forest plots visually present the effect sizes and confidence intervals for each study, with larger squares indicating studies with greater weight in the meta-analysis (Deeks et al., 2019). The horizontal lines represent the confidence intervals, and the diamond at the bottom shows the overall estimated effect size, with its width reflecting the confidence interval. A confidence interval that does not cross zero (representing no effect) suggests statistical significance. As shown in the forest plots (see Figure 3-2, Figure 3-3, Figure 3-4), the effect size was larger for network scale (beta = –0.11, 95% CI: [–0.14, –0.08]) and smaller for both contact frequency (beta = –0.03, 95% CI: [–0.04, –0.01]) and network size (beta = –0.05, 95% CI: [–0.06, –0.03]).

Study	Standardized beta with 95% CI	Weight (%)
Bui, 2020	-0.02 [-0.07, 0.02]	3.11
Bui, 2020	-0.02 [-0.07, 0.02]	3.11
Chi & Chou, 2001	-0.15 [-0.20, -0.09]	2.59
Chi & Chou, 2001	-0.06 [-0.12, -0.00]	2.59
Chi & Chou, 2001	-0.09 [-0.14, -0.03]	2.60
Chi & Chou, 2001	-0.06 [-0.12, 0.01]	2.18
Ermer & Proulx, 2022	-0.04 [-0.14, 0.05]	1.52
Ermer & Proulx, 2022	-0.04 [-0.13, 0.04]	1.67
Ermer & Proulx, 2022	-0.05 [-0.14, 0.05]	1.52
Ermer & Proulx, 2022	-0.05 [-0.14, 0.04]	1.66
Jeon & Lubben, 2016	-0.00 [-0.02, 0.01]	4.22
Jeon & Lubben, 2016	-0.48 [-0.81, -0.15]	0.18
Jeon & Lubben, 2016	-0.47 [-2.00, 1.06]	0.01
Jeon & Lubben, 2016	0.03 [-0.06, 0.11]	1.81
La Gory & Fitpatrick, 1992	-0.09 [-0.13, -0.05]	3.27
La Gory & Fitpatrick, 1992	0.00 [-0.00, 0.01]	4.36
Litwin & Levinsky, 2023	-0.02 [-0.02, -0.01]	4.35
Litwin & Levinsky, 2023	-0.02 [-0.02, -0.01]	4.35
Litwin & Levinsky, 2023	-0.02 [-0.03, -0.02]	4.35
Litwin et al., 2015	0.08 [0.00, 0.15]	2.02
Litwin et al., 2015	0.01 [-0.05, 0.07]	2.48
Litwin et al., 2015	0.01 [-0.04, 0.06]	2.68
Litwin et al., 2015	0.01 [-0.04, 0.06]	2.68
Litwin et al., 2015	0.04 [-0.01, 0.08]	3.19
Litwin et al., 2015	0.01 [-0.04, 0.06]	2.68
Litwin et al., 2015	0.01 [-0.04, 0.06]	2.68
Marshall & Rue, 2012	-0.12 [-0.87, 0.64]	0.04
Marshall & Rue, 2012	-0.09 [-0.17, -0.02]	1.95
Marshall & Rue, 2012	-0.43 [-0.63, -0.23]	0.46
Marshall & Rue, 2012	-0.10 [-0.16, -0.03]	2.37
Marshall & Rue, 2012	-0.08 [-0.14, -0.01]	2.34
Marshall & Rue, 2012	-0.42 [-0.67, -0.18]	0.32
Marshall-Fabien & Miller, 2016	0.00 [-0.09, 0.09]	1.65
Marshall-Fabien & Miller, 2016	0.02 [-0.07, 0.11]	1.62
Marshall-Fabien & Miller, 2016	-0.29 [-0.53, -0.06]	0.35
Marshall-Fabien & Miller, 2016	-0.00 [-0.09, 0.09]	1.65
Marshall-Fabien & Miller, 2016	-0.00 [-0.09, 0.08]	1.65
Marshall-Fabien & Miller, 2016	-0.00 [-0.09, 0.09]	1.65
Marshall-Fabien & Miller, 2016	0.03 [-0.06, 0.12]	1.65
Marshall-Fabien & Miller, 2016	-0.00 [-0.09, 0.09]	1.65
Schwartz & Litwin, 2017	0.00 [-0.01, 0.01]	4.32
Schwartz & Litwin, 2017	0.00 [-0.01, 0.01]	4.32
Schwartz & Litwin, 2017	-0.03 [-0.05, -0.01]	4.15
Overall	-0.03 [-0.04, -0.01]	



Heterogeneity: $\tau^2 = 0.00$, $I^2 = 95.12\%$, $H^2 = 20.49$

Test of $\theta_i = \theta_j$: $Q(42) = 217.57$, $p = 0.00$

Test of $\theta = 0$: $z = -3.55$, $p = 0.00$

Random-effects REML model

Figure 3-2 Forest plot for frequency of contact (continuous outcome)

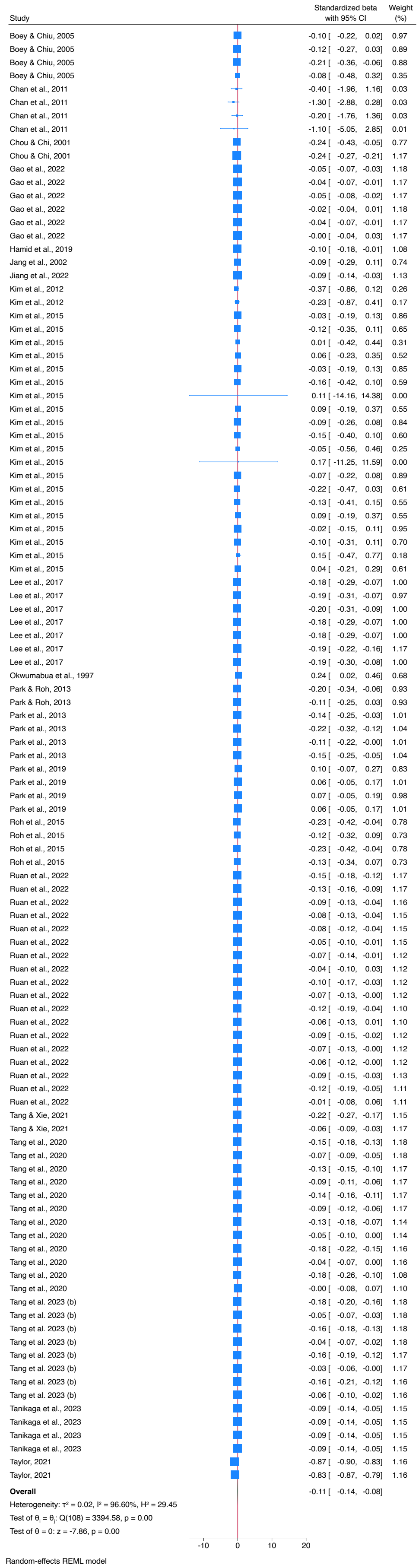


Figure 3-3 Forest plot for network scale (continuous outcome)

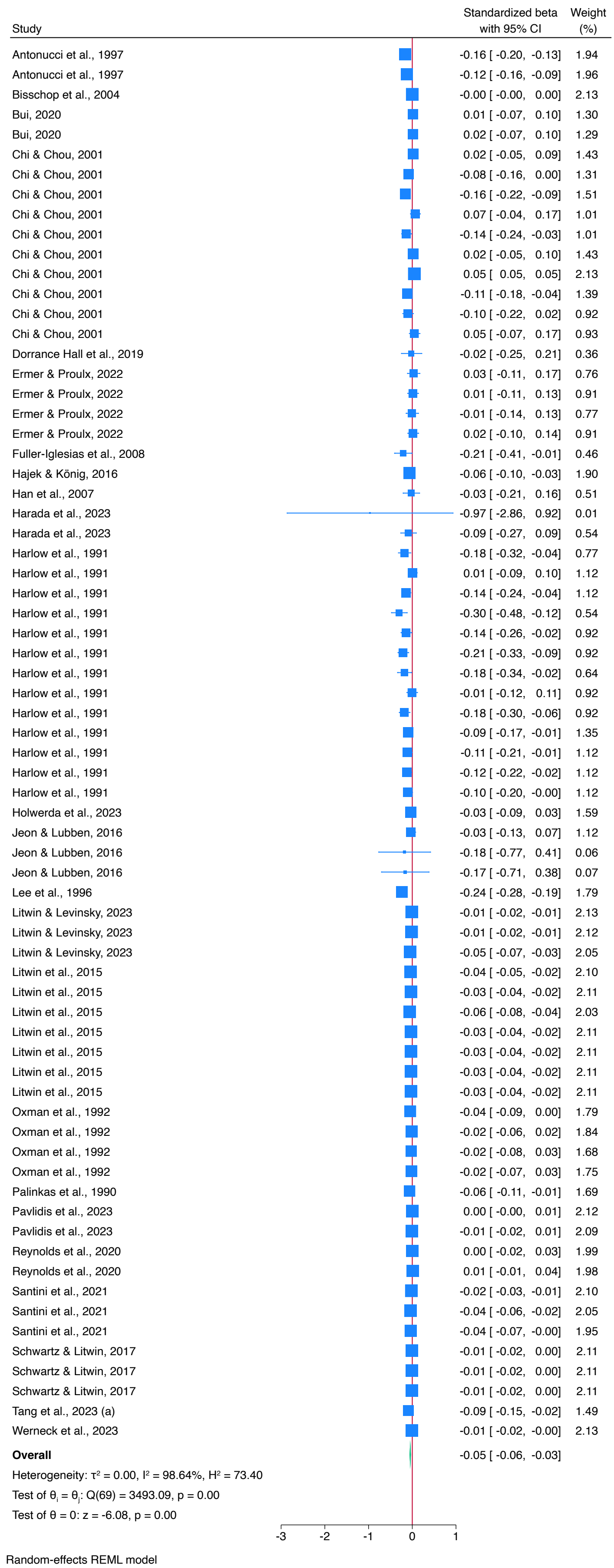


Figure 3-4 Forest plot for network size (continuous outcome)

3.3.3 Binary outcome

We examined 43 models testing the association between social networks and depression as a binary variable, focusing on network size (18 models), network scale (13 models), and contact frequency (12 models).

The overall effect size for studies measuring depression as a binary variable (n = 43) was log odds -0.31 (95% CI: [-0.43, -0.19]), confirming the negative relationship. Individuals with lower values in network indicators were less likely to be depressed than those with higher values (see Appendix,

Table A3-5). The effect size was similar for both contact frequency (log odds = -0.55, 95% CI: [-0.92, -0.19]) and network size (log odds = -0.22, 95% CI: [-0.36, -0.09], but stronger for network scale (log odds = -0.20, 95% CI: [-0.30, -0.10]), as shown in the forest plots (see Figure 3-5, Figure 3-6, Figure 3-7).

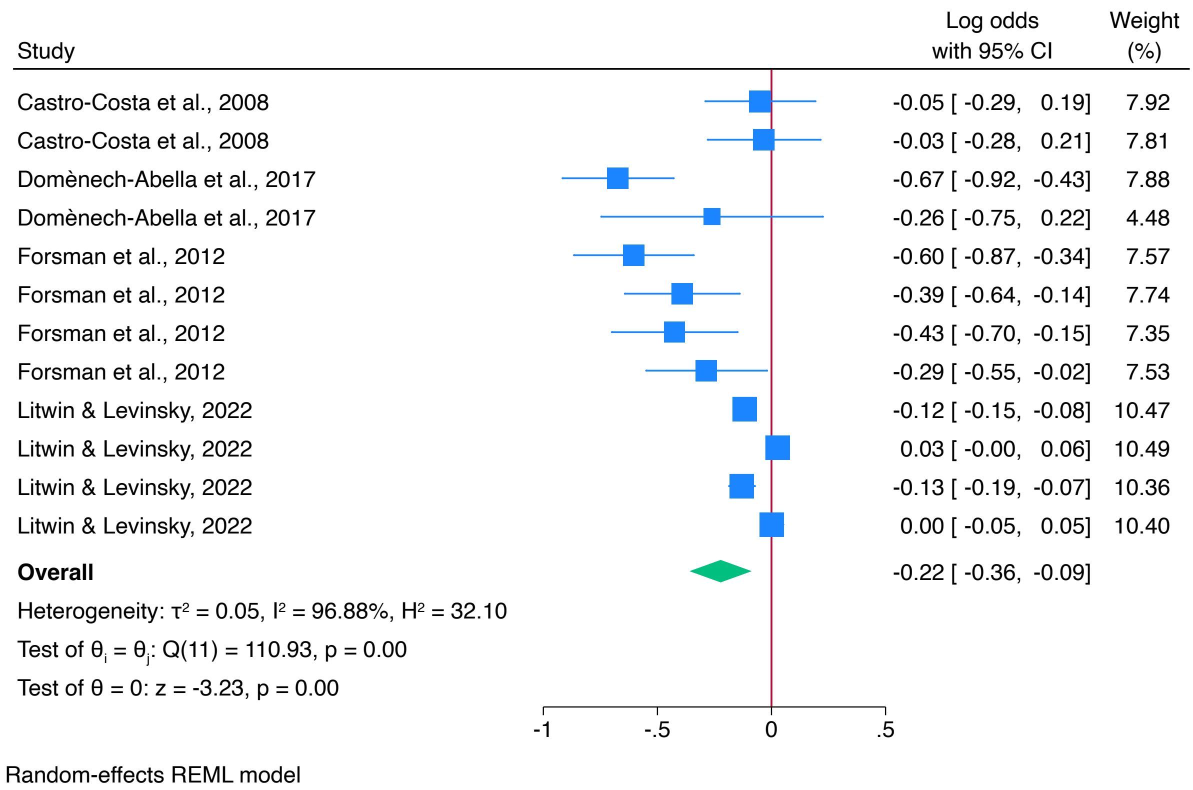


Figure 3-5 Forest plot for contact frequency (binary outcome)

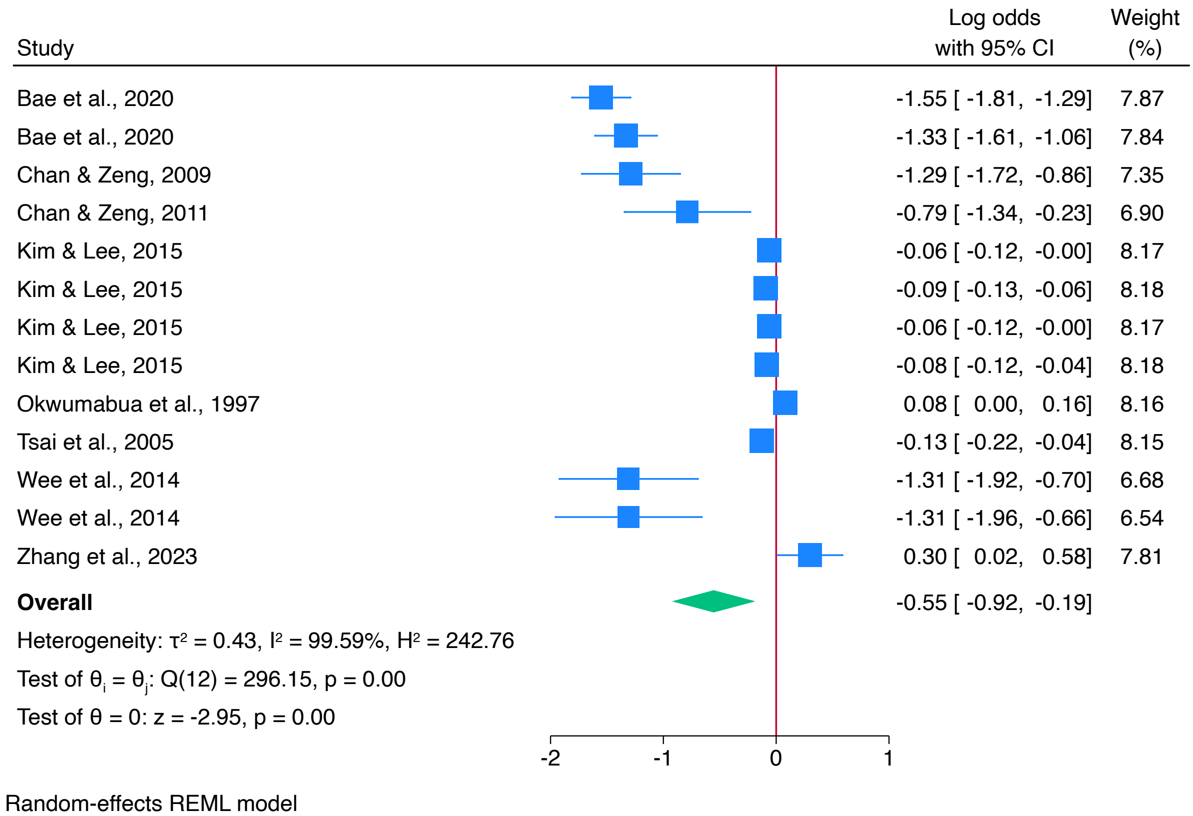


Figure 3-6 Forest plot for network scale (binary outcome)

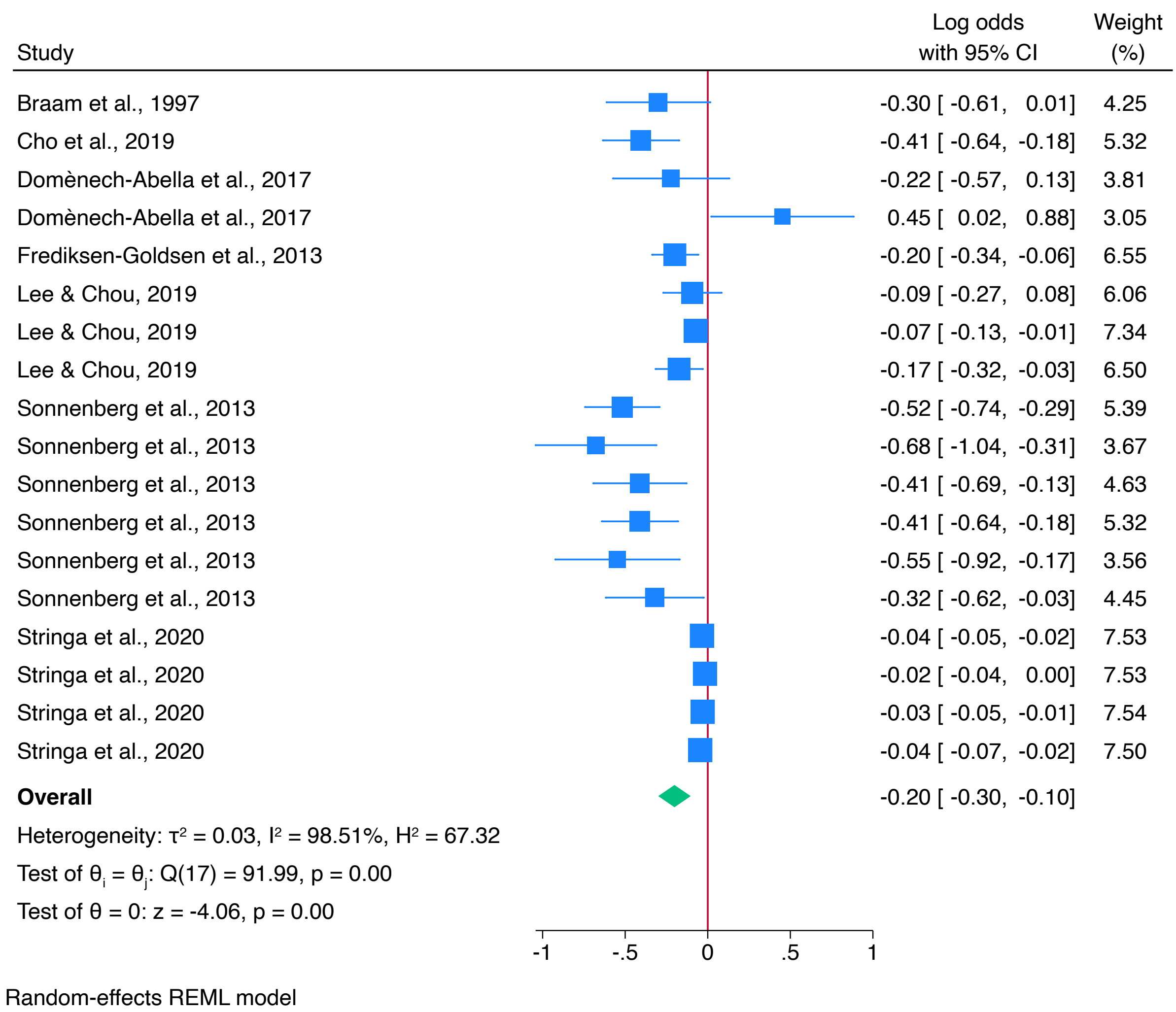


Figure 3-7 Forest plot for network size (binary outcome)

3.3.4 Results from the bivariate meta-regression

Heterogeneity was extremely high for both the continuous ($I^2 = 99.44$) and the binary outcome ($I^2 = 98.92$), even when distinguishing between the three network indicators, as shown in Table A3-4 and

Table A3-5 in the Appendix. This aligns with the heterogeneity commonly found in meta-analyses (Migliavaca et al., 2022). However, examining whether and to what extent study characteristics influenced this heterogeneity was essential. Table 3-2 presents the bivariate meta-regression results for the continuous outcomes and Table 3-3 those for the binary outcome. Each factor was regressed separately on the effect size, with the coefficient and standard error reported for each model.

Table 3-2 Bivariate meta-regression with robust variance estimator (RVE) - continuous outcome

Covariate	Estimate	SE	CI Lower	CI Upper	p-value
Network indicator (ref. scale)					
Contact	0.06	0.03	-0.01	0.14	0.100

Covariate	Estimate	SE	CI Lower	CI Upper	p-value
Size	0.06	0.03	-0.01	0.12	0.072
Region (ref. North America)					
Asia	0.03	0.03	-0.04	0.09	0.385
Europe	0.09*	0.03	0.02	0.15	0.017
Year	0.00	0.00	0.00	0.00	0.862
Self-collected data	-0.02	0.03	-0.08	0.03	0.412
Mean age	0.00	0.01	-0.02	0.02	0.764
Percentage of men	0.00	0.00	0.00	0.00	0.316
Type of alters (ref. Mixed)					
Family	0.00	0.03	-0.06	0.07	0.874
Friend	0.03	0.03	-0.03	0.09	0.292
Neighbor	-0.02	0.02	-0.13	0.10	0.592
Type of tie					
Important (ref: all other types)	0.03	0.06	-0.24	0.30	0.688
Discuss (ref: all other types)	0.07*	0.02	0.02	0.11	0.011
Interact (ref: all other types)	-0.06**	0.02	-0.11	-0.02	0.008
Support (ref: all other types)	0.00	0.07	-0.60	0.61	0.965
Close (ref: all other types)	-0.01	0.03	-0.07	0.04	0.592
Depression instrument (ref. CES-D)					
Euro-D	0.08*	0.02	0.03	0.13	0.011
GDS	-0.03	0.04	-0.11	0.05	0.426
Other	0.06	0.03	-0.05	0.16	0.169
Longitudinal (ref. cross-sectional)	-0.02	0.04	-0.10	0.06	0.606
Number of control variables	0.00	0.00	0.00	0.01	0.066
Type of control variable					
Age (ref. no)	-0.05	0.02	-0.10	0.00	0.067
Gender (ref. no)	0.01	0.02	-0.03	0.06	0.549
Health (ref. no)	0.04	0.05	-0.07	0.15	0.432
Network (ref. no)	0.05	0.02	0.00	0.09	0.064
Country (ref. no)	0.07*	0.01	0.01	0.12	0.037
Marital status (ref. no)	0.01	0.02	-0.03	0.06	0.599
Educational level (ref. no)	-0.01	0.02	-0.05	0.03	0.461
SES (ref. no)	-0.01	0.03	-0.06	0.05	0.832
Children (ref. no)	0.00	0.02	-0.06	0.05	0.843
Personality (ref. no)	0.03	0.04	-0.14	0.20	0.544
Interaction (ref. no)	0.02	0.02	-0.03	0.08	0.319
Religion (ref. no)	-0.07*	0.03	-0.15	0.00	0.047
Ethnicity (ref. no)	0.05	0.02	-0.01	0.12	0.075
Living condition (ref. no)	-0.01	0.02	-0.06	0.04	0.688
Social activities (ref. no)	0.03	0.03	-0.28	0.34	0.521
Other (ref. no)	-0.02	0.03	-0.15	0.11	0.536
Culture (ref. no)	-0.10	0.11	-1.46	1.27	0.536
Immigration (ref. no)	-0.03	0.04	-0.15	0.09	0.510

Covariate	Estimate	SE	CI Lower	CI Upper	p-value
N = 222, except for year (N = 191), mean age (N = 169) and percentage of men (N = 206).					

For the continuous outcome (see Table 3-2), several characteristics significantly influenced the effect size. Studies conducted in Europe had higher effect sizes than those from North America. There were also differences based on the type of ties. Studies where the interaction examined involved a discussion about important matters between the ego and alters yielded stronger effect sizes, while those involving interactions with nominated individuals resulted in weaker effect sizes. The measure of depression also mattered, with studies using the EURO-D scale showing larger effect sizes compared to those using the CES-D scale. The number or type of control variables generally did not significantly impact the effect size, with two exceptions. Studies controlling for religion showed smaller effect sizes, while those controlling for country showed slightly larger effects. Other study characteristics did not significantly influence effect size.

For the binary outcome (see Table 3-3), longitudinal studies on average found higher effect sizes than those conducted on cross-sectional data. Furthermore, a few control variables seem to have influenced the effect size, i.e. those models controlling for age, gender, or other controls found stronger effect sizes than those who did not control for those variables. In contrast, the models that controlled for the participation to social activities found lower effect sizes. However, when we apply the correction for small sample size, only the effect of gender is confirmed.

Table 3-3 Bivariate meta-regression with robust variance estimator (RVE) - binary outcome

Covariate	Estimate	SE	CI lower	CI upper	p-value	p-value*
Network indicator (ref. scale)						
Contact	0.22	0.29	-0.40	0.83	0.469	0.510
Size	0.23	0.29	-0.38	0.84	0.432	0.469
Region (ref. North America)						
Asia	-0.20	0.24	-0.72	0.32	0.425	0.464
Europe	-0.08	0.14	-0.37	0.21	0.583	0.606
South America	0.10	0.09	-0.10	0.29	0.314	0.382
Year	0.02	0.02	-0.04	0.07	0.451	0.490
Self-collected data	-0.11	0.19	-0.51	0.29	0.557	0.584
Mean age	0.00	0.01	-0.04	0.03	0.822	0.891
Percentage of men	0.00	0.00	-0.01	0.00	0.261	0.369
Type of alters (ref. Mixed)						
Family	0.17	0.11	-0.07	0.41	0.143	0.301
Friend	0.04	0.17	-0.32	0.41	0.806	0.832
Neighbor	-0.09	0.11	-0.32	0.15	0.450	0.432
Type of tie						
Important (ref: all other types)	-0.07	0.08	-0.24	0.09	0.359	0.531

Covariate	Estimate	SE	CI lower	CI upper	p-value	p-value*
Discuss (ref: all other types)	-0.07	0.08	-0.23	0.10	0.393	0.651
Interact (ref: all other types)	0.07	0.17	-0.30	0.43	0.708	0.819
Support (ref: all other types)	-0.07	0.08	-0.23	0.10	0.393	0.651
Close (ref: all other types)	0.15	0.13	-0.14	0.43	0.281	0.311
Depression instrument (ref. CES-D)						
Euro-D	0.19	0.13	-0.09	0.47	0.171	0.287
GDS	-0.21	0.24	-0.72	0.31	0.397	0.420
Other	0.16	0.17	-0.20	0.52	0.354	0.450
Longitudinal (ref. cross-sectional)	0.32*	0.11	0.08	0.55	0.011	0.217
Number of control variables	0.01	0.01	0.00	0.02	0.087	0.146
Type of control variable						
Age (ref. no)	0.36*	0.16	0.03	0.69	0.033	0.051
Gender (ref. no)	0.45*	0.17	0.09	0.82	0.019	0.042
Health (ref. no)	0.10	0.13	-0.18	0.39	0.447	0.491
Network (ref. no)	0.09	0.16	-0.24	0.42	0.584	0.601
Country (ref. no)	0.07	0.16	-0.28	0.41	0.692	0.785
Marital status (ref. no)	0.20	0.16	-0.13	0.54	0.217	0.242
Educational level (ref. no)	0.16	0.17	-0.20	0.52	0.353	0.414
SES (ref. no)	0.22	0.15	-0.10	0.53	0.161	0.183
Interaction (ref. no)	0.07	0.13	-0.20	0.34	0.583	0.671
Religion (ref. no)	-0.08	0.08	-0.25	0.08	0.280	0.288
Ethnicity (ref. no)	0.02	0.08	-0.14	0.18	0.810	0.811
Living condition (ref. no)	0.01	0.16	-0.33	0.35	0.954	0.961
Social activities (ref. no)	-0.89***	0.19	-1.30	-0.48	0.000	0.173
Other (ref. no)	0.23*	0.10	0.02	0.44	0.036	0.228

N = 43, except for year (N = 34), mean age (N = 28), percentage of men (N = 42).
** p-values with small-sample correction*

3.3.5 Results from the multivariate meta-regression

Table 3-4 presents the results of the multivariate meta-regression using RVE, where all variables were regressed on the effect size for the continuous outcome. The coefficients show the association between study characteristics and effect size while controlling for other variables. It is important to mention that control variables indicate whether studies accounted for a particular factor, but do not provide insights into specific group comparisons. Instead, the analysis assesses whether including a given control variable is significantly associated with variations in effect sizes across studies. Due to missing values, the meta-regression was estimated using 127 cases.

Regarding variability in effect sizes, within-study variation was estimated to be zero (omega-squared = 0), and between-study variation was small (tau-squared = 0.0073). The results from the bivariate regression were not confirmed. After controlling for all covariates, no statistically significant association (at the 5% significance level) was found between effect size and study characteristics. This is particularly important since the effect sizes were derived from model coefficients rather than raw data.

For network indicators, results suggest that contact frequency and network size are associated with an increased effect size compared to studies using network scales. These effects approached marginal significance at the 10% level. The inclusion of health as a control variable also showed marginal significance, suggesting stronger effect sizes. Additionally, no differences were found in the case of type of alters when "mixed" was used as the reference category. However, further analysis using family as a reference category revealed that the effect size was significantly higher among friends, suggesting family ties may have a greater buffering effect on depression than friends do. However, these effects were only marginally significant.

Table 3-4 Multivariate meta-regression with robust variance estimator (RVE) - continuous outcome

Covariate	**Estimate**	**SE**	**CI lower**	**CI upper**	**p-value**
Network indicator (ref. scale)					
Contact	0.30	0.16	-0.05	0.65	0.086
Size	0.30	0.14	0.00	0.61	0.052
Region (ref. North America)					
Asia	0.09	0.09	-0.13	0.31	0.378
Europe	-0.03	0.13	-0.33	0.27	0.804
Year	0.00	0.00	-0.01	0.01	0.595
Self-collected data	0.15	0.35	-0.77	1.07	0.682
Mean age	0.01	0.01	-0.01	0.04	0.161
Percentage of men	0.00	0.00	0.00	0.00	0.614
Type of alters (ref. Mixed)					
Family	-0.29	0.45	-0.65	5.33	0.545
Friend	-0.23	0.45	-0.51	5.29	0.631
Type of tie					
Important (ref: all other types)	-0.03	0.16	-0.41	0.35	0.854
Discuss (ref: all other types)	-0.04	0.05	-0.19	0.10	0.398
Interact (ref: all other types)	0.09	0.12	-0.27	0.45	0.476
Support (ref: all other types)	0.04	0.17	-0.37	0.44	0.840
Close (ref: all other types)	0.08	0.13	-0.27	0.44	0.542
Depression instrument (ref. CES-D)					
Euro-D	0.12	0.12	-0.18	0.42	0.368
GDS	-0.17	0.46	-1.36	1.03	0.733
Other	0.16	0.20	-0.41	0.73	0.467
Longitudinal (ref. cross-sectional)	-0.11	0.09	-0.30	0.09	0.261
Number of control variables	0.00	0.00	-0.01	0.01	0.684
Type of control variable					
Age (ref. no)	-0.19	0.17	-0.72	0.35	0.357
Gender (ref. no)	-0.03	0.03	-0.12	0.07	0.452

Covariate	Estimate	SE	CI lower	CI upper	p-value
Health (ref. no)	0.23	0.11	-0.02	0.48	0.065
Network (ref. no)	0.04	0.03	-0.03	0.11	0.222
Country (ref. no)	0.24	0.13	-0.10	0.57	0.129
Marital status (ref. no)	0.12	0.09	-0.11	0.34	0.237
Educational level (ref. no)	-0.07	0.09	-0.29	0.15	0.494
SES (ref. no)	0.00	0.06	-0.14	0.14	0.998
Children (ref. no)	0.14	0.40	-0.90	1.19	0.733
Personality (ref. no)	0.06	0.14	-0.37	0.48	0.697
Interaction (ref. no)	0.04	0.02	-0.02	0.09	0.169
Religion (ref. no)	0.01	0.07	-0.22	0.24	0.913
Ethnicity (ref. no)	0.13	0.08	-0.08	0.34	0.165
Living condition (ref. no)	0.04	0.06	-0.10	0.19	0.495
Social activities (ref. no)	0.06	0.04	-0.05	0.17	0.182
Other (ref. no)	0.06	0.07	-0.10	0.22	0.403
Culture (ref. no)	-0.47	0.29	-1.13	0.18	0.137
Immigration (ref. no)	0.05	0.06	-0.14	0.25	0.449
N = 127					

3.3.6 Asymmetry, heterogeneity and publication bias

We examined asymmetry using both graphical representation and Egger's test. Funnel plots show the distribution of studies included in the meta-analysis, with effect sizes plotted against their standard errors (Deeks et al., 2019). A symmetrical distribution suggests no major publication bias, while asymmetry may indicate potential bias or small-study effects. Here, the funnel plots (Appendix, Figure A3-1 and Figure A3-2) suggested the presence of asymmetry. For continuous outcomes, most studies reported a standard error between 0 and 0.4, clustering around zero, with more studies showing a negative rather than positive effect size. For binary outcomes, there was less variation in the standard error (none exceeding 0.4) but greater heterogeneity in effect size, skewed toward negative values, with few studies reporting a positive effect.

Egger's test was used to check for a systematic relationship between effect size and standard error in the meta-analysis. In both cases, the negative beta1 and statistically significant p-value indicated that smaller studies tended to report stronger (or more negative) effect sizes, potentially skewing the overall results (continuous outcome: beta1 = –0.45, SE = 0.195, z = –2.29, Prob > |z| = 0.022; binary outcome: beta1 = –3.05, SE = 0.642, z = –4.75, Prob > |z| = 0.000). As noted by Egger, this asymmetry could be attributed to factors such as publication bias, methodological quality, or heterogeneity (Sterne et al., 2011).

3.4 Discussion

Older adults are particularly vulnerable to depression due to a reduction in social relationships and a shrinking social network over the life course (Wrzus et al., 2013). Depression levels worsened significantly among older adults following the Covid-19 pandemic (Gaggero et al., 2022), underscoring the importance of social ties as a buffer for depression in this population. Research on the relationship between social networks and depression in older adults has expanded considerably, and this meta-analysis provides valuable insights by systematically examining multiple aspects of social networks.

Consistent with the main effect model (Kawachi & Berkman, 2001) and previous literature reviews (Reiner & Steinhoff, 2024; Schwarzbach et al., 2014), our findings confirm that larger social networks, more frequent contact, and higher social network scale scores are associated with lower levels of depression. However, while the association was statistically significant and consistent, the effect sizes across all social network indicators were small. This suggests that depression is a complex issue, where even strong social ties may not fully shield older adults from depressive symptoms due to other life challenges such as physical health decline (Blazer, 2003), bereavement (Stroebe et al., 2007), or financial difficulties (Fiske et al., 2009). Nonetheless, the consistent association across different measures highlights social networks' meaningful role in mitigating depression, particularly when combined with other protective factors.

Although there appeared to be differences in the strength of the association depending on the type of network indicator, these were not confirmed in the more statistically stringent analysis. However, the results suggest that network scales–including both structural and functional aspects of social networks–were the strongest predictor of reduced depression, while contact frequency and network size had smaller effects. Notably, this effect is only marginally significant and thus merely indicative of a trend. This tentative trend aligns with the main effect model (Kawachi & Berkman, 2001), which proposes that the psychological benefits of social networks arise not only from their size but also from their functional roles, such as offering emotional support and promoting health-related behaviors.

Our findings align with Schwarzbach et al. (2014), who reported a consistent association between social relations and depression in later life, yet also found variability depending on relationship type. This aligns with our observation that network scales incorporating both structural and functional aspects had the strongest effect, while contact frequency and network size had smaller effects. Furthermore, comparisons with meta-analyses across different age groups suggest that younger populations may benefit more from network size, whereas older adults prioritize emotionally meaningful relationships (Gariépy et al., 2016). This shift in social priorities with age may partly explain why effect sizes in our study were small but consistent.

Additionally, cross-cultural comparisons highlight possible contextual influences. While Gariépy et al. (2016) found social support to be protective against depression in Western countries, studies in Middle Eastern (Tajvar et al., 2013) and Asian populations (Tengku Mohd et al., 2019) suggest that cultural norms shape how social ties influence mental health. These differences may also explain why Fasihi Harandi et al. (2017) found a moderate effect of social support on mental health in Iran, whereas our findings suggest a smaller, albeit significant, effect of social networks. Such variations underscore the importance of considering both structural (network size, contact frequency) and functional (emotional and instrumental support) aspects when assessing the impact of social ties on depression.

Consistent with earlier studies highlighting family as a key source of good health (Antonucci et al., 2011) and research suggesting that diverse networks—comprising both family and friends—are particularly beneficial for health outcomes (Chao, 2011; Choi & Jeon, 2021), our results suggest that the positive effect of networks on depression is similar for both mixed and family networks. However, studies focusing exclusively on friend networks showed stronger effect sizes than those focusing solely on family networks. Nevertheless, while our results point to a potential trend favoring family over mixed or friend-centered networks, the effect does not reach the conventional 5% significance threshold required for statistical confirmation. This aligns with the broader literature, which presents varying perspectives on the relative importance of family and friendships for mental health in later life. While some studies emphasize the unique protective role of family due to its long-term stability and greater likelihood of providing instrumental and emotional support (Antonucci et al., 2011; Litwin, 2011), others suggest that friendships–particularly those characterized by high quality and minimal stress –may be equally or even more beneficial for emotional well-being (Huxhold et al., 2014).

Contrary to our expectations, gender did not significantly affect the relationship between social networks and depression. Neither the percentage of men in the sample nor the inclusion of gender as a control variable in the regression model influenced the effect size, except in models using a binary measure for depression. One possibility is that age-related factors reduce traditional gender differences in social networks as people age. For example, older men may become more dependent on social networks later in life, particularly after retirement or bereavement, narrowing the gender gap in the mental health benefits of social ties (Cornwell & Schafer, 2016). However, to draw firm conclusions about gender differences, subgroup analyses would be necessary. Unfortunately, we lacked the statistical power to conduct such analyses.

Notably, there were differences between binary and continuous outcome variables in the bivariate meta-regressions. These discrepancies may arise from variations in statistical power due to differing sample sizes. Additionally, the lack of consensus among studies on the cutoff for diagnosing depression could explain some of the variability in the results. Binary measures of depression, commonly used to assess clinical prevalence, may oversimplify the relationship compared to continuous measures, which provide a more nuanced understanding of mental health. For studies seeking to explore the subtleties of mental health, continuous measures appear more appropriate than binary ones.

On average, further exploration of the heterogeneity in the results suggests that the way studies on the association of interest were conducted did not significantly affect the estimated effect size. While a few characteristics were initially found to be significantly associated with the effect size, these results were not confirmed when controlling for all identified study characteristics. This is particularly relevant given that the effect sizes were derived from model estimates rather than raw data. Neither the number nor type of control variables were significantly associated with effect size. The lack of association between study characteristics and effect size suggests that the impact of social networks on depression is relatively robust, regardless of the specific measures or strategies used in the studies.

3.4.1 Limitations and future research

While this meta-analysis provides valuable insights into the relationship between social networks and depression in older adults, several limitations must be acknowledged. The relationship is bidirectional, but due to limited evidence on how depression affects social networks, we were unable to account for this in our analysis. As a result, the effect sizes may overemphasize the protective role of social networks and underestimate the impact of depression on social withdrawal. Future research should explore both directions simultaneously using methods like cross-lagged panel models or longitudinal designs to more accurately capture the bidirectional effects.

Second, the analysis is limited by the scope of the studies included in the systematic review by Reiner & Steinhoff (2024). Any gaps in their review, such as limited geographic diversity or the omission of specific social network measures, are therefore reflected in this meta-analysis. Additionally, the heterogeneity across studies was notably high, which is common in meta-analyses, particularly those using regression coefficients instead of raw data (Migliavaca et al., 2022). This variability likely stems from differences in study design, sample characteristics, measurement instruments, and statistical methods, making it difficult to generalize findings across all populations (Harrer et al., 2022). Despite meta-regression efforts to address this, residual heterogeneity remains, suggesting that unmeasured factors may still contribute to the variability in effect sizes.

A third limitation involves the discrepancy between binary and continuous measures of depression, which may explain some of the variability in results. Binary measures, often used to assess clinical prevalence, can oversimplify the relationship between social networks and depression. These measures typically rely on arbitrary cutoffs to classify individuals as depressed or not, resulting in inconsistencies across studies when different thresholds are applied. This lack of consensus complicates cross-study comparisons and may distort the strength of the observed association (Karlsson et al., 2010). In contrast, continuous measures provide a more nuanced understanding by capturing a spectrum of depressive symptoms, offering greater sensitivity to variations in mental health. Future research should prioritize continuous measures, particularly in studies exploring subtler, subclinical aspects of depression. For studies continuing to use binary outcomes, establishing standardized cutoffs in line with validated recommendations for each depression scale would improve consistency and comparability across studies.

Fourth, publication bias is another limitation. Although statistical methods were used to detect and account for this bias, it is possible that studies showing stronger associations between social networks and depression were more likely to be published, potentially leading to an overestimation of the actual effects. The growing adoption of open data practices and prospective registration of observational studies (Heymann, 2020) will be vital in mitigating such biases in future research.

Fifth, the restricted sample size and lack of relevant information prevented detailed subgroup analyses, particularly regarding gender differences and the relative importance of family versus friends. Future research with larger, more diverse datasets is needed to investigate these potentially significant distinctions.

However, this meta-analysis offers important contributions. It is the first to provide statistical evidence on the association between structural social network characteristics and depression in older adults. Our results highlight that network scales are particularly strongly associated with reducing depressive symptoms. Future research should consider this when designing studies or interventions. For example, interventions should not only focus on increasing the frequency of social contacts but also consider the nature of these relationships and the perceived quality of the interactions.

Moreover, future research should pursue more nuanced subgroup analyses, especially regarding gender differences and types of social ties, and further explore the longitudinal impact of social networks on depression. Unifying cutoff thresholds in studies using binary depression measures would also enhance comparability and reduce variability, leading to more reliable conclusions in future research.

In conclusion, while the overall effect of social networks on depression is modest, its consistency across different indicators underscores the importance of fostering strong, supportive social ties among older adults to improve mental health. These findings emphasize both the need and the opportunity to develop interventions that address depression in older adults, ultimately improving their health and quality of life.

3.5 References

Antonucci, T. C., Birditt, K. S., Sherman, C. W., & Trinh, S. (2011). Stability and change in the intergenerational family: A convoy approach. *Ageing and Society*, *31*(7), 1084–1106. https://doi.org/10.1017/S0144686X1000098X

Antonucci, T. C., Fuhrer, R., & Dartigues, J.-F. (1997). Social relations and depressive symptomatology in a sample of community-dwelling French older adults. *Psychology and Aging*, *12*(1), 189–195. https://doi.org/10.1037/0882-7974.12.1.189

Appelbaum, M., Cooper, H., Kline, R. B., Mayo-Wilson, E., Nezu, A. M., & Rao, S. M. (2018). Journal article reporting standards for quantitative research in psychology: The APA Publications and Communications Board task force report. *American Psychologist*, *73*(1), 3–25. https://doi.org/10.1037/amp0000191

Ayalon, L., & Levkovich, I. (2019). A systematic review of research on social networks of older adults. *The Gerontologist*, *59*(3), e164–e176. https://doi.org/10.1093/geront/gnx218

Bae, S., Harada, K., Chiba, I., Makino, K., Katayama, O., Lee, S., Shinkai, Y., & Shimada, H. (2020). A new social network scale for detecting depressive symptoms in older Japanese adults. *International Journal of Environmental Research and Public Health*, *17*(23), 8874. https://doi.org/10.3390/ijerph17238874

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social Science & Medicine*, *51*(6), 843–857. https://doi.org/10.1016/S0277-9536(00)00065-4

Berkman, L. F., & Syme, S. L. (1979). Social networks, host resistance, and mortality: A nine-year follow-up study of Alameda County residents. *Social Networks, 109*(2), 186–204. https://doi.org/10.1093/oxfordjournals.aje.a112674

Bisschop, M. I., Kriegsman, D. M. W., Beekman, A. T. F., & Deeg, D. J. H. (2004). Chronic diseases and depression: The modifying role of psychosocial resources. *Social Science & Medicine*, *59*(4), Article 4. https://doi.org/10.1016/j.socscimed.2003.11.038

Blazer, D. G. (2003). Depression in Late Life: Review and Commentary. *The Journals of Gerontology: Series A*, *58*(3), 249–265. https://doi.org/10.1093/gerona/58.3.M249

Boey, K. W., & Chiu, H. F. K. (2005). Life strain and psychological distress of older women and older men in Hong Kong. *Aging & Mental Health*, *9*(6), 555–562. https://doi.org/10.1080/13607860500193351

Braam, A. W., Beekman, A. T. F., van Tilburg, T. G., Deeg, D. J. H., & van Tilburg, W. (1997). Religious involvement and depression in older Dutch citizens. *Social Psychiatry and Psychiatric Epidemiology*, *32*(5), 284–291. https://doi.org/10.1007/BF00789041

Bui, B. K. H. (2020). The relationship between social network characteristics and depressive symptoms among older adults in the United States: Differentiating between network structure and network function. *Psychogeriatrics*, *20*(4), 458–468. https://doi.org/10.1111/psyg.12530

Castro-Costa, É., Lima-Costa, M. F., Carvalhais, S., Firmo, J. O. A., & Uchoa, E. (2008). Factors associated with depressive symptoms measured by the 12-item General Health

Questionnaire in community-dwelling older adults (The Bambuí Health Aging Study). *Revista Brasileira de Psiquiatria*, *30*(2), 104–109. https://doi.org/10.1590/S1516-44462008005000007

Chan, A., Malhotra, C., Malhotra, R., & Østbye, T. (2011). Living arrangements, social networks and depressive symptoms among older men and women in Singapore. *International Journal of Geriatric Psychiatry*, *26*(6), 630–639. https://doi.org/10.1002/gps.2574

Chan, M. F., & Zeng, W. (2009). Investigating factors associated with depression of older women in Macau. *Journal of Clinical Nursing*, *18*(21), 2969–2977. https://doi.org/10.1111/j.1365-2702.2009.02867.x

Chan, M. F., & Zeng, W. (2011). Exploring risk factors for depression among older men residing in Macau. *Journal of Clinical Nursing*, *20*(17–18), 2645–2654. https://doi.org/10.1111/j.1365-2702.2010.03689.x

Chao, S. F. (2011). Assessing social support and depressive symptoms in older Chinese adults: A longitudinal perspective. *Aging & Mental Health*, *15*(6), 765–774. https://doi.org/10.1080/13607863.2011.562182

Chi, I., & Chou, K.-L. (2001). Social support and depression among elderly Chinese people in Hong Kong. *The International Journal of Aging and Human Development*, *52*(3), 231–252. https://doi.org/10.2190/V5K8-CNMG-G2UP-37QV

Cho, J. H.-J., Olmstead, R., Choi, H., Carrillo, C., Seeman, T. E., & Irwin, M. R. (2019). Associations of objective versus subjective social isolation with sleep disturbance, depression, and fatigue in community-dwelling older adults. *Aging & Mental Health*, *23*(9), 1130–1138. https://doi.org/10.1080/13607863.2018.1481928

Choi, K.-W., & Jeon, G.-S. (2021). Social Network Types and Depressive Symptoms among Older Korean Men and Women. *International Journal of Environmental Research and Public Health*, *18*(21), 11175. https://doi.org/10.3390/ijerph182111175

Chou, K.-L., & Chi, I. (2001). Stressful life events and depressive symptoms: Social support and sense of control as mediators or moderators? *The International Journal of Aging and Human Development*, *52*(2), 155–171. https://doi.org/10.2190/9C97-LCA5-EWB7-XK2W

Cohen, S. (2004). Social relationships and health. *American Psychologist*, *59*(8), 676–684. https://doi.org/10.1037/0003-066X.59.8.676

Cohen, S., Underwood, L. G., Gottlieb, B. H., & Fetzer Institute (Eds.). (2000). *Social support measurement and intervention: A guide for health and social scientists*. Oxford University Press.

Cornwell, B., & Schafer, M. H. (2016). Social Networks in Later Life. In *Handbook of Aging and the Social Sciences* (pp. 181–201). Elsevier. https://doi.org/10.1016/B978-0-12-417235-7.00009-3

Deeks, J. J., Higgins, J. P., Altman, D. G., & on behalf of the Cochrane Statistical Methods Group. (2019). Analysing data and undertaking meta-analyses. In J. P. T. Higgins, J.

Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), *Cochrane Handbook for Systematic Reviews of Interventions* (1st ed., pp. 241–284). Wiley. https://doi.org/10.1002/9781119536604.ch10

Domènech-Abella, J., Lara, E., Rubio-Valera, M., Olaya, B., Moneta, M. V., Rico-Uribe, L. A., Ayuso-Mateos, J. L., Mundó, J., & Haro, J. M. (2017). Loneliness and depression in the elderly: The role of social network. *Social Psychiatry and Psychiatric Epidemiology*, *52*(4), 381–390. https://doi.org/10.1007/s00127-017-1339-3

Dorrance Hall, E., Meng, J., & Reynolds, R. M. (2019). Confidant network and interpersonal communication associations with depression in older adulthood. *Health Communication*, *35*(7), 872–881. https://doi.org/10.1080/10410236.2019.1598616

Ermer, A. E., & Proulx, C. M. (2022). The association between relationship strain and emotional well-being among older adult couples: The moderating role of social connectedness. *Aging & Mental Health*, *26*(6), 1198–1206. https://doi.org/10.1080/13607863.2021.1910786

Fiske, A., Wetherell, J. L., & Gatz, M. (2009). Depression in Older Adults. *Annual Review of Clinical Psychology*, *5*(1), 363–389. https://doi.org/10.1146/annurev.clinpsy.032408.153621

Forsman, A. K., Nyqvist, F., Schierenbeck, I., Gustafson, Y., & Wahlbeck, K. (2012). Structural and cognitive social capital and depression among older adults in two Nordic regions. *Aging & Mental Health*, *16*(6), 771–779. https://doi.org/10.1080/13607863.2012.667784

Fredriksen-Goldsen, K. I., Emlet, C. A., Kim, H.-J., Muraco, A., Erosheva, E. A., Goldsen, J., & Hoy-Ellis, C. P. (2013). The physical and mental health of lesbian, gay male, and bisexual (LGB) older adults: The role of key health indicators and risk and protective factors. *The Gerontologist*, *53*(4), 664–675. https://doi.org/10.1093/geront/gns123

Fuller-Iglesias, H., Sellars, B., & Antonucci, T. C. (2008). Resilience in old age: Social relations as a protective factor. *Research in Human Development*, *5*(3), 181–193. https://doi.org/10.1080/15427600802274043

Gaggero, A., Fernández-Pérez, Á., & Jiménez-Rubio, D. (2022). Effect of the COVID-19 pandemic on depression in older adults: A panel data analysis. *Health Policy (Amsterdam, Netherlands)*, *126*(9), 865–871. https://doi.org/10.1016/j.healthpol.2022.07.001

Gao, J., Hu, H., & He, H. (2022). Household indebtedness and depressive symptoms among older adults in China: The moderating role of social network and anticipated support. *Journal of Affective Disorders*, *298*(Part A), 173–181. https://doi.org/10.1016/j.jad.2021.10.133

Gariépy, G., Honkaniemi, H., & Quesnel-Vallée, A. (2016). Social support and protection from depression: Systematic review of current findings in Western countries. *British Journal of Psychiatry*, *209*(4), 284–293. https://doi.org/10.1192/bjp.bp.115.169094

Grant, R. L. (2014). Converting an odds ratio to a range of plausible relative risks for better communication of research findings. *BMJ*, *348*, f7450. https://doi.org/10.1136/bmj.f7450

Hajek, A., Brettschneider, C., Lange, C., Posselt, T., Wiese, B., Steinmann, S., Weyerer, S., Werle, J., Pentzek, M., Fuchs, A., Stein, J., Luck, T., Bickel, H., Mösch, E., Wolfsgruber, S., Heser, K., Maier, W., Scherer, M., Riedel-Heller, S. G., & König, H.-H. (2016). Gender differences in the effect of social support on health-related quality of life: Results of a population-based prospective cohort study in old age in Germany. *Quality of Life Research*, *25*(5), 1159–1168. https://doi.org/10.1007/s11136-015-1166-5

Hakeem, F. F., Bernabé, E., & Sabbah, W. (2019). Association between oral health and frailty: A systematic review of longitudinal studies. *Gerodontology*, *36*(3), 205–215. https://doi.org/10.1111/ger.12406

Hamid, T. A. (2019). The role of social network, social support, religiosity and depression among elderly Malaysians who had experienced major life events. *The Medical Journal of Malaysia*, *74*(3), 198–204.

Han, H.-R., Kim, M., Lee, H. B., Pistulka, G., & Kim, K. B. (2007). Correlates of depression in the Korean American elderly: focusing on personal resources of social support. *Journal of Cross-Cultural Gerontology*, *22*(1), 115–127. https://doi.org/10.1007/s10823-006-9022-2

Harada, K., Sugisawa, H., Sugihara, Y., Yanagisawa, S., & Shimmei, M. (2023). Big five personality traits, social networks, and depression among older adults in Japan: A multiple mediation analysis. *The International Journal of Aging and Human Development*, *97*(1), 111–128. https://doi.org/10.1177/00914150221109893

Harandi, T. F., Mohammad Taghinasab, M., & Dehghan Nayeri, T. (2017). The correlation of social support with mental health: A meta-analysis. *Electronic Physician*, *9*(9), 5212–5222. https://doi.org/10.19082/5212

Harlow, S. D., Goldberg, E. L., & Comstock, G. W. (1991). A longitudinal study of risk factors for depressive symptomatology in elderly widowed and married women. *American Journal of Epidemiology*, *134*(5), 526–538. https://doi.org/10.1093/oxfordjournals.aje.a116125

Harrer, M., Cuijpers, P., Furukawa, T. A., & Ebert, D. D. (2022). *Doing meta-analysis with R: A hands-on guide* (First edition). CRC Press.

Hedges, L., Tipton, E., & Johnson, M. (2010). Robust variance estimation in meta-regression with dependent effect size estimates. *Research Synthesis Methods*, *1*(1), 39–65. https://doi.org/10.1002/jrsm.5

Heymann, D. L. (2020). Data sharing and outbreaks: Best practice exemplified. *The Lancet*, *395*(10223), 469–470. https://doi.org/10.1016/S0140-6736(20)30184-7

Higgins, J. P. T., Li, T., & Deeks, J. J. (2023). Chapter 6: Choosing effect measures and computing estimates of effect. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T.

Li, M. Page, & V. Welch (Eds.), *Cochrane Handbook for Systematic Reviews of Interventions*. https://training.cochrane.org/handbook/current/chapter-06

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *PLoS Medicine*, *7*(7), e1000316. https://doi.org/10.1371/journal.pmed.1000316

Holwerda, T. J., Jaarsma, E., Van Zutphen, E. M., Beekman, A. T. F., Pan, K.-Y., Van Vliet, M., Stringa, N., Van Den Besselaar, J. H., MacNeil-Vroomen, J. L., Hoogendijk, E. O., & Kok, A. A. L. (2023). The impact of COVID-19 related adversity on the course of mental health during the pandemic and the role of protective factors: A longitudinal study among older adults in The Netherlands. *Social Psychiatry and Psychiatric Epidemiology*, *58*(7), 1109–1120. https://doi.org/10.1007/s00127-023-02457-5

Huxhold, O., Miche, M., & Schuz, B. (2014). Benefits of having friends in older ages: Differential effects of informal social activities on well-being in middle-aged and older adults. *The Journals of Gerontology: Series B*, *69*(3), 366–375. https://doi.org/10.1093/geronb/gbt029

Jackson, D., Riley, R., & White, I. R. (2011). Multivariate meta-analysis: Potential and promise. *Statistics in Medicine*, *30*(20), 2481–2498. https://doi.org/10.1002/sim.4172

Jang, Y., Haley, W. E., Small, B. J., & Mortimer, J. A. (2002). The role of mastery and social resources in the associations between disability and depression in later life. *The Gerontologist*, *42*(6), 807–813. https://doi.org/10.1093/geront/42.6.807

Jiang, F., Kuper, H., Zhou, C., Qin, W., & Xu, L. (2022). Relationship between hearing loss and depression symptoms among older adults in China: The mediating role of social isolation and loneliness. *International Journal of Geriatric Psychiatry*, *37*(6), 1–8. https://doi.org/10.1002/gps.5729

Karlsson, L., Marttunen, M., Karlsson, H., Kaprio, J., & Hillevi, A. (2010). Minor change in the diagnostic threshold leads into major alteration in the prevalence estimate of depression. *Journal of Affective Disorders*, *122*(1–2), 96–101. https://doi.org/10.1016/j.jad.2009.06.025

Kawachi, I., & Berkman, L. F. (2001). Social ties and mental health. *Journal of Urban Health*, *78*(3), 458–467. https://doi.org/10.1093/jurban/78.3.458

Kelly, M. E., Duff, H., Kelly, S., McHugh Power, J. E., Brennan, S., Lawlor, B. A., & Loughrey, D. G. (2017). The impact of social activities, social networks, social support and social relationships on the cognitive functioning of healthy older adults: A systematic review. *Systematic Reviews*, *6*(1), 259. https://doi.org/10.1186/s13643-017-0632-2

Kim, B. J., Sangalang, C. C., & Kihl, T. (2012). Effects of acculturation and social network support on depression among elderly Korean immigrants. *Aging & Mental Health*, *16*(6), 787–794. https://doi.org/10.1080/13607863.2012.660622

Kim, K., & Lee, M. (2015). Depressive symptoms of older adults living alone: The role of community characteristics. *The International Journal of Aging and Human Development*, *80*(3), 248–263. https://doi.org/10.1177/0091415015590315

Kim, T., Nguyen, E. T., Yuen, E. J., Nguyen, T., Sorn, R., & Nguyen, G. T. (2015). Differential role of social connectedness in geriatric depression among southeast Asian ethnic groups. *Progress in Community Health Partnerships: Research, Education, and Action*, *9*(4), 483–493. https://doi.org/10.1353/cpr.2015.0075

Kuiper, J. S., Zuidersma, M., Oude Voshaar, R. C., Zuidema, S. U., van den Heuvel, E. R., Stolk, R. P., & Smidt, N. (2015). Social relationships and risk of dementia: A systematic review and meta-analysis of longitudinal cohort studies. *Ageing Research Reviews*, *22*, 39–57. https://doi.org/10.1016/j.arr.2015.04.006

Kuiper, J. S., Zuidersma, M., Zuidema, S. U., Burgerhof, J. G. M., Stolk, R. P., Oude Voshaar, R. C., & Smidt, N. (2016). Social relationships and cognitive decline: A systematic review and meta-analysis of longitudinal cohort studies. *International Journal of Epidemiology, 45*(4), 1169–1206. https://doi.org/10.1093/ije/dyw089

La Gory, M., & Fitpatrick, K. (1992). The effects of environmental context on elderly depression. *Journal of Aging and Health*, *4*(4), 459–479. https://doi.org/10.1177/089826439200400401

Lee, M. S., Crittenden, K. S., & Yu, E. (1996). Social support and depression among elderly Korean immigrants in the United States. *The International Journal of Aging and Human Development*, *42*(4), 313–327. https://doi.org/10.2190/2VHH-JLXY-EBVG-Y8JB

Lee, S., & Chou, K. (2019). Assessing the relative contribution of social exclusion, income-poverty, and financial strain on depressive symptoms among older people in Hong Kong. *Aging & Mental Health*, *23*(11), 1487–1495. https://doi.org/10.1080/13607863.2018.1506740

Lee, Y.-S., Park, S.-Y., Roh, S., Koenig, H. G., & Yoo, G. J. (2017). The role of religiousness/spirituality and social networks in predicting depressive symptoms among older Korean Americans. *Journal of Cross-Cultural Gerontology*, *32*(2), 239–254. https://doi.org/10.1007/s10823-017-9317-5

Lefebvre, C., Glanville, J., Briscoe, S., Littlewood, A., Marshall, C., Metzendorf, M., Noel-Storr, A., Rader, T., Shokraneh, F., Thomas, J., Wieland, L. S., & on behalf of the Cochrane Information Retrieval Methods Group. (2019). Searching for and selecting studies. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), *Cochrane Handbook for Systematic Reviews of Interventions* (1st ed., pp. 67–107). Wiley. https://doi.org/10.1002/9781119536604.ch4

Lin, L. (2018). Bias caused by sampling error in meta-analysis with small sample sizes. *PLOS ONE*, *13*(9), e0204056. https://doi.org/10.1371/journal.pone.0204056

Lin, L., & Chu, H. (2018). Quantifying Publication Bias in Meta-Analysis. *Biometrics*, *74*(3), 785–794. https://doi.org/10.1111/biom.12817

Litwin, H. (2011). The association between social network relationships and depressive symptoms among older Americans: What matters most? *International Psychogeriatrics*, *23*(6), 930–940. https://doi.org/10.1017/S1041610211000251

Litwin, H. (2012). Physical activity, social network type, and depressive symptoms in late life: An analysis of data from the National Social Life, Health and Aging Project. *Aging & Mental Health*, *16*(5), 608–616. https://doi.org/10.1080/13607863.2011.644264

Litwin, H., & Levinsky, M. (2022). Social networks and mental health change in older adults after the Covid-19 outbreak. *Aging & Mental Health*, *26*(5), 925–931. https://doi.org/10.1080/13607863.2021.1902468

Litwin, H., & Levinsky, M. (2023). The interplay of personality traits and social network characteristics in the subjective well-being of older adults. *Research on Aging*, *45*(7–8), 538–549. https://doi.org/10.1177/01640275221113048

Litwin, H., Stoeckel, K. J., & Schwartz, E. (2015). Social networks and mental health among older Europeans: Are there age effects? *European Journal of Ageing*, *12*(4), 299–309. https://doi.org/10.1007/s10433-015-0347-y

Marshall, G. L., & Rue, T. C. (2012). Perceived discrimination and social networks among older African Americans and Caribbean Blacks. *Family & Community Health*, *35*(4), 300–311. https://doi.org/10.1097/FCH.0b013e318266660f

Marshall-Fabien, G. L., & Miller, D. B. (2016). Exploring ethnic variation in the relationship between stress, social networks, and depressive symptoms among older black Americans. *Journal of Black Psychology*, *42*(1), 54–72. https://doi.org/10.1177/0095798414562067

Migliavaca, C. B., Stein, C., Colpani, V., Barker, T. H., Ziegelmann, P. K., Munn, Z., Falavigna, M., & Prevalence Estimates Reviews-Systematic Review Methodology Group (PERSyst). (2022). Meta-analysis of prevalence: I2 statistic and how to deal with heterogeneity. *Research Synthesis Methods*, *13*(3), 363–367. https://doi.org/10.1002/jrsm.1547

Mohd, T., Yunus, R., Hairi, F., Hairi, N., & Choo, W. (2019). Social support and depression among community dwelling older adults in Asia: A systematic review. *BMJ OPEN*, *9*(7). https://doi.org/10.1136/bmjopen-2018-026667

Okwumabua, J. O., Baker, F. M., Wong, S. P., & Pilgram, B. O. (1997). Characteristics of depressive symptoms in elderly urban and rural African Americans. *The Journals of Gerontology: Series A*, *52A*(4), M241–M246. https://doi.org/10.1093/gerona/52A.4.M241

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan—A web and mobile app for systematic reviews. *Systematic Reviews*, *5*(1), 210. https://doi.org/10.1186/s13643-016-0384-4

Oxman, T. E., Berkman, L. F., Kasl, S., Freeman, D. H., & Barrett, J. (1992). Social support and depressive symptoms in the elderly. *American Journal of Epidemiology*, *135*(4), 356–368. https://doi.org/10.1093/oxfordjournals.aje.a116297

Palinkas, L. A., Wingard, D. L., & Barrett-Connor, E. (1990). The biocultural context of social networks and depression among the elderly. *Social Science & Medicine*, *30*(4), 441–447. https://doi.org/10.1016/0277-9536(90)90346-T

Park, J., & Roh, S. (2013). Daily spiritual experiences, social support, and depression among elderly Korean immigrants. *Aging & Mental Health*, *17*(1), 102–108. https://doi.org/10.1080/13607863.2012.715138

Park, N. S., Jang, Y., Lee, B. S., Haley, W. E., & Chiriboga, D. A. (2013). The mediating role of loneliness in the relation between social engagement and depressive symptoms among older Korean Americans: Do men and women differ? *The Journals of Gerontology: Series B*, *68*(2), 193–201. https://doi.org/10.1093/geronb/gbs062

Park, N. S., Lee, B. S., Chiriboga, D. A., & Chung, S. (2019). Loneliness as a mediator in the relationship between social engagement and depressive symptoms: Age differences among community-dwelling Korean adults. *Health & Social Care in the Community*, *27*(3), 706–716. https://doi.org/10.1111/hsc.12687

Pavlidis, G., Motel-Klingebiel, A., & Aartsen, M. (2023). Exclusion from social relations in later life: On the gendered associations of social networks with mental wellbeing. *Aging & Mental Health*, *27*(7), 1313–1321. https://doi.org/10.1080/13607863.2022.2116397

Piolatto, M., Bianchi, F., Rota, M., Marengoni, A., Akbaritabar, A., & Squazzoni, F. (2022). The effect of social relationships on cognitive decline in older adults: An updated systematic review and meta-analysis of longitudinal cohort studies. *BMC Public Health*, *22*(1), 278. https://doi.org/10.1186/s12889-022-12567-5

R Core Team. (2022). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Reiner, A., & Steinhoff, P. (2024). The association of social networks and depression in community-dwelling older adults: A systematic review. *Systematic Reviews*, *13*(1), 161. https://doi.org/10.1186/s13643-024-02581-6

Reynolds, R. M., Meng, J., & Dorrance Hall, E. (2020). Multilayered social dynamics and depression among older adults: A 10-year cross-lagged analysis. *Psychology and Aging*, *35*(7), 948–962. https://doi.org/10.1037/pag0000569

Roh, S., Lee, Y.-S., Kim, Y., Park, S.-Y., & Chaudhuri, A. (2015). Gender differences in the roles of religious support and social network support in reducing depressive symptoms among older Korean Americans. *Journal of Social Service Research*, *41*(4), 484–497. https://doi.org/10.1080/01488376.2015.1037041

Ruan, H., Shen, K., & Chen, F. (2022). Negative life events, social ties, and depressive symptoms for older adults in China. *Frontiers in Public Health*, *9*, 774434. https://doi.org/10.3389/fpubh.2021.774434

Santini, Z. I., Jose, P. E., Koyanagi, A., Meilstrup, C., Nielsen, L., Madsen, K. R., Hinrichsen, C., Dunbar, R. I. M., & Koushede, V. (2021). The moderating role of social network size in the temporal association between formal social participation and mental health: A longitudinal analysis using two consecutive waves of the Survey of Health, Ageing and Retirement in Europe (SHARE). *Social Psychiatry and Psychiatric Epidemiology*, *56*(3), 417–428. https://doi.org/10.1007/s00127-020-01961-2

Santini, Z. I., Koyanagi, A., Tyrovoloas, S., Mason, C., & Haro, J. M. (2015). The association between social relationships and depression: A systematic review. *Journal of Affective Disorders*, *175*, 53–65. http://dx.doi.org/10.1016/j.jad.2014.12.049

Schünemann, H. J., Vist, G. E., Higgins, J. P. T., Santesso, N., Deeks, J. J., Glasziou, P., Akl, E. A., & Guyatt, G. H. (2023). Chapter 15: Interpreting results and drawing conclusions. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. Page, & V. Welch (Eds.), *Cochrane Handbook for Systematic Reviews of Interventions*. https://training.cochrane.org/handbook/current/chapter-06

Schwartz, E., & Litwin, H. (2017). Are newly added and lost confidants in later life related to subsequent mental health? *International Psychogeriatrics*, *29*(12), 2047–2057. https://doi.org/10.1017/S1041610217001338

Schwarzbach, M., Luppa, M., Forstmeier, S., König, H.-H., & Riedel-Heller, S. G. (2014). Social relations and depression in late life-A systematic review. *International Journal of Geriatric Psychiatry*, *29*(1), 1–21. https://doi.org/10.1002/gps.3971

Shamsrizi, P., Gladstone, B. P., Carrara, E., Luise, D., Cona, A., Bovo, C., & Tacconelli, E. (2020). Variation of effect estimates in the analysis of mortality and length of hospital stay in patients with infections caused by bacteria-producing extended-spectrum beta-lactamases: A systematic review and meta-analysis. *BMJ Open*, *10*(1), e030266. https://doi.org/10.1136/bmjopen-2019-030266

Siette, J., Pomare, C., Dodds, L., Jorgensen, M., Harrigan, N., & Georgiou, A. (2021). A comprehensive overview of social network measures for older adults: A systematic review. *Archives of Gerontology and Geriatrics*, *97*, 104525. https://doi.org/10.1016/j.archger.2021.104525

StataCorp. (2023). *Stata Statistical Software: Release 18* [Computer software]. College Station, TX: StataCorp LLC.

Sterne, J. A. C., & Egger, M. (2001). Funnel plots for detecting bias in meta-analysis: Guidelines on choice of axis. *Journal of Clinical Epidemiology*, *54*(10), 1046–1055. https://doi.org/10.1016/S0895-4356(01)00377-8

Sterne, J. A. C., Sutton, A. J., Ioannidis, J. P. A., Terrin, N., Jones, D. R., Lau, J., Carpenter, J., Rucker, G., Harbord, R. M., Schmid, C. H., Tetzlaff, J., Deeks, J. J., Peters, J., Macaskill, P., Schwarzer, G., Duval, S., Altman, D. G., Moher, D., & Higgins, J. P. T. (2011). Recommendations for examining and interpreting funnel plot asymmetry in meta-analyses of randomised controlled trials. *BMJ*, *343*(jul22 1), d4002–d4002. https://doi.org/10.1136/bmj.d4002

Stringa, N., Milaneschi, Y., van Schoor, N. M., Suanet, B., van der Lee, S., Holstege, H., Reinders, M. J. T., Beekman, A. T. F., & Huisman, M. (2020). Genetic liability for depression, social factors and their interaction effect in depressive symptoms and depression over time in older adults. *The American Journal of Geriatric Psychiatry*, *28*(8), 844–855. https://doi.org/10.1016/j.jagp.2020.02.011

Stroebe, M., Schut, H., & Stroebe, W. (2007). Health outcomes of bereavement. *The Lancet*, *370*(9603), 1960–1973. https://doi.org/10.1016/S0140-6736(07)61816-9

Tajvar, M., Fletcher, A., Grundy, E., & Arab, M. (2013). Social support and health of older people in Middle Eastern countries: A systematic review. *Australasian Journal on Ageing*, *32*(2), 71–78. https://doi.org/10.1111/j.1741-6612.2012.00639.x

Tang, D., Lin, Z., & Chen, F. (2020). Moving beyond living arrangements: The role of family and friendship ties in promoting mental health for urban and rural older adults in China. *Aging & Mental Health*, *24*(9), 1523–1532. https://doi.org/10.1080/13607863.2019.1602589

Tang, D., Mair, C. A., & Hu, Q. (2023b). Widowhood, social networks, and mental health among Chinese older adults: The moderating effects of gender. *Frontiers in Psychology*, *14*, 1142036. https://doi.org/10.3389/fpsyg.2023.1142036

Tang, D., & Xie, L. (2021). Whose migration matters? The role of migration in social networks and mental health among rural older adults in China. *Ageing and Society, 43*(6), 1389–1408. https://doi.org/10.1017/S0144686X21001197

Tang, F., Jiang, Y., Li, K., & Rosso, A. L. (2023a). Residential segregation and depressive symptoms in older Chinese immigrants: The mediating role of social processes. *The Gerontologist*, *63*(8), 1376–1384. https://doi.org/10.1093/geront/gnad027

Tanikaga, M., Uemura, J., Hori, F., Hamada, T., & Tanaka, M. (2023). Changes in community-dwelling elderly's activity and participation affecting depression during Covid-19 pandemic: A cross-sectional study. *International Journal of Environmental Research and Public Health*, *20*(5), 4228. https://doi.org/10.3390/ijerph20054228

Tanner-Smith, E. E., & Tipton, E. (2013). Robust variance estimation with dependent effect sizes: Practical considerations including a software tutorial in Stata and SPSS. *Research Synthesis Methods, 5*(1), 1-85. https://doi.org/10.1002/jrsm.1091

Taylor, H. (2021). Social isolation, loneliness, and physical and mental health among black older adults. *Annual Review of Gerontology and Geriatrics*, *41*(1), 123–144. https://doi.org/10.1891/0198-8794.41.123

Tengku Mohd, T. A. M., Yunus, R. M., Hairi, F., Hairi, N. N., & Choo, W. Y. (2019). Social support and depression among community dwelling older adults in Asia: A systematic review. *BMJ Open*, *9*(7), e026667. https://doi.org/10.1136/bmjopen-2018-026667

Tsai, Y.-F., Yeh, S.-H., & Tsai, H.-H. (2005). Prevalence and risk factors for depressive symptoms among community-dwelling elders in Taiwan. *International Journal of Geriatric Psychiatry*, *20*(11), 1097–1102. https://doi.org/10.1002/gps.1413

Visentini, C., Cassidy, M., Bird, V. J., & Priebe, S. (2018). Social networks of patients with chronic depression: A systematic review. *Journal of Affective Disorders*, *241*, 571–578. https://doi.org/10.1016/j.jad.2018.08.022

Vivekanantham, A., Edwin, C., Pincus, T., Matharu, M., Parsons, H., & Underwood, M. (2019). The association between headache and low back pain: A systematic review. *The Journal of Headache and Pain*, *20*(1), 82. https://doi.org/10.1186/s10194-019-1031-y

Wells, G. A., Shea, B., O'Connell, D., Peterson, J., Welch, V., Losos, M., & Tugwell, P. (2014). *The Newcastle-Ottawa Scale (NOS) for assessing the quality of nonrandomised studies in meta-analyses*. https://www.ohri.ca/programs/clinical_epidemiology/oxford.asp

Werneck, A. O., Cunha, P. M., & Silva, D. R. (2023). The mediation role of social network size and perception in the association between physical activity and depressive symptoms: A prospective analysis from the SHARE study. *Aging & Mental Health*, *27*(9), 1738–1743. https://doi.org/10.1080/13607863.2023.2177831

World Health Organization. (2020). Ageing. *World Health Organization – Health Topics*. https://www.who.int/health-topics/ageing

World Health Organization. (2023). *Depressive disorder (depression)*. https://www.who.int/news-room/fact-sheets/detail/depression

Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: A meta-analysis. *Psychological Bulletin*, *139*(1), 53–80. https://doi.org/10.1037/a0028601

Zhang, Y., Kuang, J., Xin, Z., Fang, J., Song, R., Yang, Y., Song, P., Wang, Y., & Wang, J. (2023). Loneliness, social isolation, depression and anxiety among the elderly in Shanghai: Findings from a longitudinal study. *Archives of Gerontology and Geriatrics*, *110*, 104980. https://doi.org/10.1016/j.archger.2023.104980

During the preparation of this work the author(s) used Cambridge Proofreading, ChatGPT and DeepL in order to refine the manuscript's language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

3.6 Appendix

Table A3-1 Search strategy: keywords and Boolean operators

Boolean operator	Concept
	Social network
	"social support" OR "social network*" OR "social relation*" OR "social contact*" OR "social isolation" OR "social capital" OR "lonel*" OR "social engagement" OR "social integration" OR "social activit*" OR "social withdrawal" OR "social participation" OR "social disengagement" OR "personal network*" OR "social tie*" OR "social interaction" OR "social embeddedness" OR "family relation*" OR "kinship relation*" OR "friendship*" OR "social influence*" OR "social vulnerability" OR "peer support" OR "emotional support" OR "social connectedness" OR "belongingness" OR "socially isolated" OR "social environment" OR "tangible support" OR "emotional closeness"
	Older adults
AND	"aging" OR "ageing" OR "old* adult*" OR "late* life" OR "elder*" OR "geriatric*" OR "old* people" OR "old* male*" OR "old* female*" OR "late-life" OR "old* patient*" OR "old* age" OR "late adulthood" OR "life span" OR "life course" OR "second half of life" OR "life-span" OR "life-course" OR "aged" OR "old* person*" OR

	"lifespan" OR "old* population*" OR "HRS" OR "MHAS" OR "ELSA" OR "SHARE" OR "CRELES" OR "KLoSA" OR "JSTAR" OR "TILDA" OR "CHARLS" OR "LASI" OR "MARS" OR "IFLS" OR "SAGE" OR "HAALSI" OR "HAGIS" OR "NICOLA" OR "ELSI" OR "HART" OR "AHEAD" OR "Health and Retirement Study" OR "Mexican Health and Aging Study" OR "English Longitudinal Study of Ageing" OR "Survey of Health, Ageing and Retirement in Europe" OR "Costa Rican Longevity and Healthy Aging Study" OR "Korea Employment Information Service" OR "Japanese Study of Aging and Retirement" OR "Irish Longitudinal Study on Ageing" OR "China Health and Retirement Longitudinal Study" OR "Longitudinal Aging Study in India" OR "Malaysia Ageing and Retirement Survey" OR "Indonesia Family Life Survey" OR "Study on global Ageing and adult health" OR "The Health and Aging Study in Africa" OR "Healthy Ageing in Scotland" OR "Northern Ireland Cohort for the Longitudinal Study of Ageing" OR "Brazilian Longitudinal Study of Aging" OR "Health, Aging, and Retirement in Thailand" OR "Asset and Health Dynamics Among the Oldest Old"
	Depression
AND	"depression*" OR "psychiatric disorder" OR "mood" OR "affective disorder" OR "MDD" OR "psychological distress" OR "CES-D" OR "DSM IV" OR "depressive*" OR "DSM V"

Table A3-2 Excluded articles

Author(s), Year	Title	Reason for exclusion
Ali et al., 2022	Multidimensional Social Network Types and Their Correlates in Older Americans	causality
Aung et al., 2016	The social network index and its relation to laterlife depression among the elderly aged >=80 years in northern Thailand	categorical variable
Becker et al., 2019	Marriage, parenthood and social network: Subjective well-being and mental health in old age	missing information
Bincy et al., 2022	Social network and its effect on selected dimension of health and quality of life among community dwelling urban and rural geriatric population in India	causality
Bisconti & Bergeman, 1999	Perceived Social Control as a Mediator of the Relationships Among Social Support, Psychological Weil-Being, and Perceived Health	missing information
Blumstein et al., 2004	The Effect of a Communal Lifestyle on Depressive Symptoms in Late Life	missing information
Byers et al., 2012	Twenty-Year Depressive Trajectories Among Older Women	categorical variable
Cao et al., 2015	Social capital and depression: evidence from urban elderly in China	other network measure
Chao, 2011	Assessing social support and depressive symptoms in older Chinese adults: A longitudinal perspective	missing information
Cheng et al., 2014	Childlessness and Subjective Well-being in Chinese Widowed Persons	missing information
Choi & Jeon, 2021	Social Network Types and Depressive Symptoms among Older Korean Men and Women	other network measure
Coleman et al., 2022	What kinds of social networks protect older adults' health during a pandemic? The tradeoff between preventing infection and promoting mental health	missing information: only AME
Domènech-Abella et al., 2019	Anxiety, depression, loneliness and social network in the elderly: longitudinal associations from The Irish Longitudinal Study on Ageing (TILDA)	categorical variable
Fernández & Rosell, 2022	An Analysis of the Relationship Between Religiosity and Psychological Well-Being in Chilean Older People Using Structural Equation Modeling	missing information
Fiori et al., 2006	Social Network Typologies and Mental Health Among Older Adults	other network measure
Förster et al., 2018	Loss experiences in old age and their impact on the social network and depression– results of the Leipzig Longitudinal Study of the Aged (LEILA 75+)	other network measure
Förster et al., 2021	The Role of Social Isolation and the Development of Depression. A Comparison of the Widowed and Married Oldest Old in Germany	missing information
Gan & Best, 2021	Prior Social Contact and Mental Health Trajectories during COVID-19: Neighborhood Friendship Protects Vulnerable Older Adults	missing information
Goldberg et al., 1985	Depressive symptoms social networks and social support of elderly women	categorical variable
Golden et al., 2009	Loneliness, social support networks, mood and well-being in community-dwelling elderly	other network measure
Gu et al., 2023	Comparing the role of social connectivity with friends and family in depression among older adults in China: evaluating the moderating effect of urban–rural status	missing information
Gumà & Fernández-Carro, 2021	Life goes on: The influence of the perceived quality of social relations on older women's mental health after the loss of a partner in Europe	other network measure
Harasemiw et al., 2019	Is the association between social network types, depressive symptoms and life satisfaction mediated by the perceived availability of social support? A cross-	other network measure

Author(s), Year	Title	Reason for exclusion
	sectional analysis using the Canadian Longitudinal Study on Aging	
Houtjes et al., 2014	The impact of an unfavorable depression course on network size and loneliness in older people: a longitudinal study in the community: Depression, network size, and loneliness	causality
Husaini, 1997	Predictors of depression among the elderly: Racial differences over time.	missing information
Jang et al., 2011	Gender Differences in Depressive Symptoms Among Older Korean American Immigrants	missing information
Jeon & Lubben, 2016	The Influence of Social Networks and Supports on Depression Symptoms: Differential Pathways for Older Korean Immigrants and Non-Hispanic White Americans	missing information
Kim & Lee, 2019	Social Support Network Types and Depressive Symptoms Among Community-Dwelling Older Adults in South Korea	other network measure
Kim et al., 2016	Longitudinal changes in social networks, health and wellbeing among older Koreans	other network measure
Klug et al., 2014	Aging Without Depression: A Cross-Sectional Study	missing information: coefficients not reported
Kuchibhatla et al., 2012	Trajectory classes of depressive symptoms in a community sample of older adults	categorical variable
Li et al., 2019	Social Networks and Depressive Symptoms among Chinese Older Immigrants: Does Quantity, Quality, and Composition of Social Networks Matter?	missing information
Li et al., 2022	Construction of path analysis model on related factors of social isolation in older people	causality
Litwin & Levinsky, 2021	Always alone? Network transitions among detached older Europeans and their effects	other network measure
Litwin et al., 2020	Network type, transition patterns and well-being among older Europeans	other network measure
Litwin, 2011	The association between social network relationships and depressive symptoms among older Americans: what matters most?	other network measure
Litwin, 2012	Physical activity, social network type, and depressive symptoms in late life: An analysis of data from the National Social Life, Health and Aging Project	other network measure
Liu et al., 2016	Family Relationships, Social Connections, and Depressive Symptoms Among Chinese Older Adults in International Migrant Families	categorical variable
Mechakra-Tahiri et al., 2010	Gender, social relationships and depressive disorders in adults aged 65 and over in Quebec	other network measure
Merchant et al., 2020	Factors associated with social isolation in community-dwelling older adults: a cross-sectional study	causality
Merhabi & Béland, 2021	Frailty as a Moderator of the Relationship between Social Isolation and Health Outcomes in Community-Dwelling Older Adults	categorical variable
Miller & Lago, 1990	The Well-Being of Older Women: The Importance of Pet and Human Relations	missing information
Minicuci et al., 2002	Prevalence Rate and Correlates of Depressive Symptoms in Older Individuals: The Veneto Study	missing information: coefficients not reported
Murayama et al., 2014	Are neighborhood bonding and bridging social capital protective against depressive mood in old age? A multilevel analysis in Japan	other network measure
Park et al., 2014	Social network types and well-being among South Korean older adults	other network measure
Park et al., 2018	Associations of a social network typology with physical and mental health risks among older adults in South Korea	other network measure

Author(s), Year	Title	Reason for exclusion
Pilehvari et al., 2023	Retirement's impact on health: what role does social network play?	missing information
Santini et al., 2015	The association of relationship quality and social networks with depression, anxiety, and suicidal ideation among older married adults: Findings from a cross-sectional analysis of the Irish Longitudinal Study on Ageing (TILDA)	categorical variable
Santini et al., 2016	Social relationships, loneliness, and mental health among older men and women in Ireland: A prospective community-based study	missing information
Santini et al., 2017	The protective properties of Act-Belong-Commit indicators against incident depression, anxiety, and cognitive impairment among older Irish adults: Findings from a prospective community-based study	categorical variable
Shouse et al., 2013	Depression and Cognitive Functioning as Predictors of Social Network Size	causality
Sicotte et al., 2008	Social networks and depressive symptoms among elderly women and men in Havana, Cuba	other network measure
Singh et al., 2016	Social Network and Mental Health Among Older Adults in Rural Uttar Pradesh, India: A Cross-Sectional Study	categorical variable
Sohn et al., 2017	Social network types among older Korean adults: Associations with subjective health	other network measure
Sonnenberg et al., 2013	Gender differences in the relation between depression and social support in later life	missing information
Stoeckel & Litwin, 2016	The impact of social networks on the relationship between functional impairment and depressive symptoms in older adults	other network measure
Sugie et al., 2022	Prevalence, overlap, and interrelationships of physical, cognitive, psychological, and social frailty among community-dwelling older people in Japan	missing information: no error measure
Taylor et al., 2018	Social Isolation, Depression, and Psychological Distress among Older Adults	categorical variable
Vicente & Guadalupe, 2022	Childlessness, personal social networks and wellbeing at advanced ages: a cross-sectional study in a Southern European familistic welfare state	categorical variable
Voils et al., 2007	Five-year trajectories of social networks and social support in older adults with major depression	causality
Webster et al., 2015	Social Networks and Health Among Older Adults in Lebanon: The Mediating Role of Support and Trust	other network measure
Wee et al., 2014	Individual and area-level socioeconomic status and their association with depression amongst community-dwelling elderly in Singapore	categorical variable
Wendel et al., 2022	Social Network and Participation in Elderly Primary Care Patients in Germany and Associations with Depressive Symptoms—A Cross-Sectional Analysis from the AgeWell.de Study	causality
Wu et al., 2017	Prevalence of and risk factors for minor and major depression among community-dwelling older adults in Taiwan	categorical variable
Ye & Zhang, 2019	Social Network Types and Health among Older Adults in Rural China: The Mediating Role of Social Support	other network measure

Table A3-3 NOS quality evaluation for each domain and overall

Author, Year	Selection	Comparability	Outcome	Evaluation
Cross-sectional studies				
Antonucci et al., 1997	4	2	2	*Good*
Bae et al., 2020	3	2	2	*Good*
Boey & Chiu, 2005	4	2	2	*Good*
Braam et al., 1997	4	2	2	*Good*
Castro-Costa et al., 2008	0	1	2	*Poor*
Chan & Zeng, 2009	5	2	2	*Good*
Chan & Zeng, 2011	4	2	2	*Good*
Chan et al., 2011	4	2	2	*Good*
Chi & Chou, 2001	3	2	2	*Good*
Cho et al., 2018	4	2	2	*Good*
Chou & Chi, 2001	4	2	2	*Good*
Domènech-Abella et al., 2017	3	2	2	*Good*
Dorrance Hall et al., 2019	3	2	2	*Good*
Ermer & Proulx, 2022	2	2	2	*Fair*
Forsman et al., 2012	4	2	2	*Good*
Frediksen-Goldsen et al., 2013	3	2	2	*Good*
Fuller-Iglesias et al., 2008	4	2	1	*Poor*
Gao et al., 2022	4	2	2	*Good*
Hamid et al., 2019	3	1	2	*Good*
Han et al., 2007	2	2	2	*Fair*
Harada et al., 2023	3	2	2	*Good*
Jang et al., 2002	4	2	2	*Good*
Jiang et al., 2022	3	2	2	*Good*
Kim & Lee, 2015	4	2	2	*Good*
Kim et al., 2012	3	2	2	*Good*
Kim et al., 2015	2	2	2	*Fair*
La Gory & Fitpatrick, 1992	2	2	1	*Poor*
Lee & Chou, 2019	3	2	2	*Good*
Lee et al., 1996	2	1	1	*Poor*
Lee et al., 2017	3	2	2	*Good*
Litwin & Levinsky, 2022	3	2	2	*Good*
Litwin & Levinsky, 2023	3	2	2	*Good*
Litwin et al., 2015	4	2	2	*Good*
Marshall & Rue, 2012	3	2	2	*Good*
Marshall-Fabien & Miller, 2016	3	2	2	*Good*
Okwumabua et al., 1997	3	2	1	*Poor*
Palinkas et al., 1990	1	2	2	*Poor*
Park & Roh, 2013	3	2	2	*Good*
Park et al., 2013	3	2	2	*Good*
Park et al., 2019	3	2	2	*Good*
Pavlidis et al., 2023	2	2	2	*Fair*
Roh et al., 2015	3	2	2	*Good*
Tang & Xie, 2021	4	2	2	*Good*
Tang et al., 2020	5	2	2	*Good*
Tang et al., 2023b	4	2	2	*Good*
Tanikaga et al., 2023	3	2	2	*Good*
Taylor, 2021	3	2	2	*Good*
Tsai et al., 2005	3	1	2	*Good*
Longitudinal studies				
Bisschop et al., 2004	3	2	3	*Good*
Bui, 2020	4	2	2	*Good*
Hajek & König, 2016	3	2	2	*Good*
Harlow et al., 1991	2	1	3	*Fair*
Holwerda et al., 2023	3	2	2	*Good*
Oxman et al., 1992	2	0	3	*Poor*
Reynolds et al., 2020	3	2	3	*Good*
Ruan et al., 2022	4	2	3	*Good*
Santini et al., 2021	2	1	2	*Fair*

Author, Year	Selection	Comparability	Outcome	Evaluation
Schwartz & Litwin, 2017	3	2	3	*Good*
Stringa et al., 2020	2	1	2	*Fair*
Tang et al., 2023a	3	2	2	*Good*
Werneck et al., 2023	4	2	2	*Good*
Zhang et al., 2023	4	2	3	*Good*

Table A3-4 Subgroup meta-analysis summary (continuous outcome)

Study	Effect size	[95% conf. interval]		Weight (%)
Group: Contact				
bui_m2	-0.022	-0.066	0.021	0.58
bui_m4	-0.022	-0.066	0.021	0.58
chi_m6	-0.146	-0.203	-0.089	0.56
chi_m7	-0.062	-0.119	-0.005	0.56
chi_m13	-0.087	-0.144	-0.03	0.56
chi_m14	-0.055	-0.124	0.014	0.54
ermer_m2	-0.044	-0.138	0.051	0.5
ermer_m4	-0.044	-0.131	0.043	0.51
ermer_m6	-0.047	-0.141	0.047	0.5
ermer_m8	-0.049	-0.137	0.039	0.51
jeon_m2	-0.004	-0.017	0.009	0.6
jeon_m4	-0.48	-0.812	-0.148	0.18
jeon_m6	-0.468	-1.998	1.063	0.01
jeon_m8	0.025	-0.057	0.107	0.52
lagory_m1	-0.089	-0.129	-0.049	0.58
lagory_m2	0.002	-0.002	0.006	0.6
litwin23_m2	-0.018	-0.023	-0.013	0.6
litwin23_m4	-0.019	-0.024	-0.014	0.6
litwin23_m4	-0.024	-0.03	-0.018	0.6
litwin15_m2	0.079	0.005	0.153	0.53
litwin15_m4	0.011	-0.049	0.071	0.56
litwin15_m10	0.01	-0.045	0.065	0.56
litwin15_m11	0.01	-0.045	0.065	0.56
litwin15_m12	0.036	-0.006	0.078	0.58
litwin15_m13	0.01	-0.045	0.065	0.56
litwin15_m14	0.01	-0.045	0.065	0.56
marshall_m1	-0.116	-0.874	0.642	0.04
marshall_m2	-0.095	-0.171	-0.018	0.53
marshall_m3	-0.433	-0.632	-0.233	0.32
marshall_m4	-0.097	-0.16	-0.034	0.55
marshall_m5	-0.076	-0.14	-0.012	0.55
marshall_m6	-0.422	-0.665	-0.178	0.26
marshallfabien_m1	0.001	-0.088	0.089	0.51
marshallfabien_m2	0.023	-0.066	0.113	0.51
marshallfabien_m3	-0.293	-0.525	-0.06	0.27
marshallfabien_m4	-0.001	-0.09	0.087	0.51
marshallfabien_m5	-0.004	-0.092	0.085	0.51
marshallfabien_m6	-0.002	-0.09	0.087	0.51
marshallfabien_m7	0.031	-0.057	0.119	0.51
marshallfabien_m8	-0.003	-0.091	0.086	0.51
schwartz_m1	0	-0.008	0.008	0.6
schwartz_m2	0	-0.008	0.008	0.6
schwartz_m3	-0.03	-0.046	-0.014	0.6
theta	-0.026	-0.04	-0.012	
Group: scale				
boey_m1	-0.1	-0.223	0.023	0.45
boey_m2	-0.12	-0.269	0.029	0.4
boey_m3	-0.21	-0.362	-0.058	0.4
boey_m4	-0.08	-0.484	0.324	0.13
chan11_m1	-0.4	-1.956	1.156	0.01
chan11_m2	-1.3	-2.881	0.281	0.01
chan11_m3	-0.2	-1.756	1.356	0.01
chan11_m4	-1.1	-5.053	2.853	0
chou_m1	-0.24	-0.43	-0.05	0.33
chou_m2	-0.24	-0.269	-0.211	0.59
gao_m1	-0.052	-0.071	-0.032	0.59
gao_m2	-0.039	-0.069	-0.009	0.59

Study	Effect size	[95% conf. interval]		Weight (%)
gao_m3	-0.048	-0.075	-0.02	0.59
gao_m4	-0.017	-0.043	0.009	0.59
gao_m5	-0.041	-0.072	-0.01	0.59
gao_m6	-0.001	-0.035	0.034	0.58
hamid_m1	-0.095	-0.178	-0.012	0.52
jang02_m1	-0.09	-0.292	0.112	0.32
jiang_m1	-0.086	-0.141	-0.03	0.56
kim12_m1	-0.37	-0.858	0.118	0.1
kim12_m2	-0.23	-0.868	0.408	0.06
kim15_m1	-0.03	-0.189	0.129	0.39
kim15_m2	-0.12	-0.354	0.114	0.27
kim15_m3	0.01	-0.425	0.445	0.12
kim15_m4	0.06	-0.233	0.353	0.21
kim15_m5	-0.03	-0.192	0.132	0.38
kim15_m6	-0.16	-0.422	0.102	0.24
kim15_m7	0.11	-14.155	14.375	0
kim15_m8	0.09	-0.188	0.368	0.22
kim15_m9	-0.09	-0.256	0.076	0.37
kim15_m10	-0.15	-0.405	0.105	0.25
kim15_m11	-0.05	-0.558	0.458	0.09
kim15_m12	0.17	-11.247	11.587	0
kim15_m13	-0.07	-0.221	0.081	0.4
kim15_m14	-0.22	-0.471	0.031	0.25
kim15_m15	-0.13	-0.407	0.147	0.22
kim15_m16	0.09	-0.188	0.368	0.22
kim15_m17	-0.02	-0.151	0.111	0.44
kim15_m18	-0.1	-0.315	0.115	0.3
kim15_m19	0.15	-0.47	0.77	0.06
kim15_m20	0.04	-0.211	0.291	0.25
lee17_m1	-0.18	-0.293	-0.067	0.47
lee17_m2	-0.19	-0.312	-0.068	0.45
lee17_m3	-0.2	-0.313	-0.087	0.47
lee17_m4	-0.18	-0.293	-0.067	0.47
lee17_m5	-0.18	-0.293	-0.067	0.47
lee17_m6	-0.19	-0.225	-0.155	0.58
lee17_m7	-0.19	-0.303	-0.077	0.47
okwumabua_m1	0.24	0.018	0.462	0.29
parkroh13_m1	-0.2	-0.336	-0.064	0.43
parkroh13_m2	-0.11	-0.246	0.026	0.43
park13_m1	-0.14	-0.248	-0.032	0.48
park13_m2	-0.22	-0.318	-0.122	0.49
park13_m3	-0.11	-0.218	-0.002	0.48
park13_m4	-0.15	-0.248	-0.052	0.49
park19_m1	0.1	-0.069	0.269	0.37
park19_m2	0.06	-0.049	0.169	0.47
park19_m3	0.07	-0.048	0.188	0.46
park19_m4	0.06	-0.049	0.169	0.47
roh_m1	-0.231	-0.419	-0.042	0.34
roh_m2	-0.119	-0.323	0.085	0.31
roh_m3	-0.231	-0.419	-0.042	0.34
roh_m4	-0.134	-0.338	0.07	0.31
ruan_m1	-0.15	-0.182	-0.118	0.59
ruan_m2	-0.126	-0.162	-0.091	0.58
ruan_m3	-0.086	-0.128	-0.044	0.58
ruan_m4	-0.084	-0.129	-0.039	0.57
ruan_m5	-0.079	-0.122	-0.036	0.58
ruan_m6	-0.055	-0.1	-0.009	0.57
ruan_m7	-0.071	-0.136	-0.006	0.55
ruan_m8	-0.038	-0.103	0.026	0.55
ruan_m9	-0.1	-0.166	-0.035	0.55
ruan_m10	-0.068	-0.133	-0.002	0.55

Study	Effect size	[95% conf. interval]		Weight (%)
ruan_m11	-0.118	-0.191	-0.045	0.54
ruan_m12	-0.057	-0.128	0.014	0.54
ruan_m13	-0.085	-0.148	-0.022	0.55
ruan_m14	-0.066	-0.13	-0.001	0.55
ruan_m15	-0.062	-0.123	-0.001	0.55
ruan_m16	-0.094	-0.154	-0.034	0.56
ruan_m17	-0.123	-0.191	-0.054	0.54
ruan_m18	-0.007	-0.076	0.062	0.54
tang21_m1	-0.221	-0.268	-0.174	0.57
tang21_m2	-0.06	-0.094	-0.026	0.58
tang20_m1	-0.153	-0.176	-0.131	0.59
tang20_m2	-0.069	-0.089	-0.049	0.59
tang20_m3	-0.125	-0.153	-0.098	0.59
tang20_m4	-0.086	-0.114	-0.058	0.59
tang20_m5	-0.137	-0.163	-0.11	0.59
tang20_m6	-0.091	-0.117	-0.064	0.59
tang20_m7	-0.127	-0.182	-0.071	0.56
tang20_m8	-0.049	-0.102	0.004	0.56
tang20_m9	-0.185	-0.223	-0.146	0.58
tang20_m10	-0.035	-0.073	0.002	0.58
tang20_m11	-0.179	-0.259	-0.099	0.53
tang20_m12	-0.004	-0.076	0.068	0.54
tang23b_m1	-0.179	-0.201	-0.157	0.57
tang23b_m2	-0.047	-0.067	-0.027	0.57
tang23b_m3	-0.158	-0.184	-0.132	0.57
tang23b_m4	-0.045	-0.071	-0.019	0.57
tang23b_m5	-0.156	-0.189	-0.123	0.56
tang23b_m6	-0.034	-0.065	-0.003	0.56
tang23b_m7	-0.164	-0.207	-0.121	0.55
tang23b_m8	-0.06	-0.101	-0.019	0.55
tanikaga_m1	-0.091	-0.137	-0.046	0.57
tanikaga_m2	-0.091	-0.137	-0.046	0.57
tanikaga_m3	-0.091	-0.137	-0.046	0.57
tanikaga_m4	-0.091	-0.137	-0.046	0.57
taylor21_m1	-0.867	-0.904	-0.829	0.58
taylor21_m2	-0.833	-0.875	-0.792	0.58
theta	-0.113	-0.141	-0.085	
Group: size				
antonucci_m1	-0.164	-0.197	-0.131	0.59
antonucci_m2	-0.124	-0.155	-0.093	0.59
bisschop_m1	-0.001	-0.004	0.002	0.6
bui_m1	0.013	-0.069	0.096	0.52
bui_m3	0.017	-0.066	0.101	0.52
chi_m1	0.022	-0.05	0.094	0.54
chi_m2	-0.079	-0.16	0.002	0.52
chi_m3	-0.157	-0.223	-0.091	0.55
chi_m4	0.066	-0.043	0.175	0.48
chi_m5	-0.136	-0.245	-0.027	0.48
chi_m8	0.023	-0.049	0.095	0.54
chi_m9	0.047	0.046	0.048	0.6
chi_m10	-0.11	-0.185	-0.035	0.53
chi_m11	-0.101	-0.219	0.017	0.46
chi_m12	0.05	-0.067	0.167	0.46
dorrance_m1	-0.02	-0.249	0.209	0.28
ermer_m1	0.028	-0.11	0.166	0.42
ermer_m3	0.013	-0.106	0.132	0.46
ermer_m5	-0.005	-0.142	0.132	0.42
ermer_m7	0.017	-0.102	0.136	0.46
fuller_m1	-0.21	-0.406	-0.014	0.33
hajek_m1	-0.062	-0.099	-0.026	0.58

Study	Effect size	[95% conf. interval]		Weight (%)
han_m1	-0.026	-0.21	0.158	0.34
harada_m1	-0.97	-2.864	0.924	0.01
harada_m2	-0.09	-0.266	0.086	0.36
harlow_m1	-0.18	-0.317	-0.043	0.42
harlow_m2	0.007	-0.091	0.105	0.5
harlow_m3	-0.14	-0.238	-0.042	0.5
harlow_m4	-0.3	-0.476	-0.124	0.36
harlow_m5	-0.14	-0.258	-0.022	0.46
harlow_m6	-0.21	-0.328	-0.092	0.46
harlow_m7	-0.18	-0.337	-0.023	0.39
harlow_m8	-0.007	-0.125	0.111	0.46
harlow_m9	-0.18	-0.298	-0.062	0.46
harlow_m10	-0.09	-0.168	-0.012	0.53
harlow_m11	-0.11	-0.208	-0.012	0.5
harlow_m12	-0.12	-0.218	-0.022	0.5
harlow_m13	-0.1	-0.198	-0.002	0.5
holwerda_m1	-0.03	-0.09	0.03	0.56
jeon_m1	-0.03	-0.128	0.068	0.49
jeon_m3	-0.18	-0.769	0.409	0.07
jeon_m7	-0.165	-0.705	0.375	0.08
lee96_m1	-0.239	-0.284	-0.194	0.57
litwin23_m1	-0.013	-0.02	-0.006	0.6
litwin23_m3	-0.014	-0.021	-0.007	0.6
litwin23_m3	-0.05	-0.07	-0.03	0.59
litwin15_m1	-0.037	-0.051	-0.023	0.6
litwin15_m3	-0.031	-0.042	-0.02	0.6
litwin15_m5	-0.062	-0.085	-0.039	0.59
litwin15_m6	-0.031	-0.042	-0.02	0.6
litwin15_m7	-0.031	-0.042	-0.02	0.6
litwin15_m8	-0.031	-0.042	-0.02	0.6
litwin15_m9	-0.031	-0.042	-0.02	0.6
oxman_m1	-0.044	-0.089	0.001	0.57
oxman_m2	-0.019	-0.06	0.022	0.58
oxman_m3	-0.024	-0.077	0.029	0.56
oxman_m4	-0.019	-0.068	0.029	0.57
palinkas_m1	-0.06	-0.113	-0.007	0.56
pavlidis_m1	0.003	-0.005	0.011	0.6
pavlidis_m2	-0.007	-0.023	0.009	0.6
reynolds_m1	0.004	-0.024	0.031	0.59
reynolds_m2	0.015	-0.014	0.043	0.59
santini21_m1	-0.022	-0.035	-0.009	0.6
santini21_m2	-0.036	-0.057	-0.016	0.59
santini21_m3	-0.036	-0.068	-0.005	0.59
schwartz_m4	-0.01	-0.022	0.002	0.6
schwartz_m5	-0.01	-0.022	0.002	0.6
schwartz_m6	-0.01	-0.022	0.002	0.6
tang23a_m1	-0.086	-0.153	-0.019	0.55
werneck_m1	-0.009	-0.015	-0.004	0.6
theta	-0.047	-0.062	-0.032	
Overall theta	-0.078	-0.094	-0.062	

Study			**Effect size**	**[95% conf. interval]**	**Weight (%)**
Heterogeneity summary					
Group	df	Q (P > Q)	tau2	% I2	H2
Contact	42	217.57 (0.000)	0.001	95.12	20.49
Scale	108	3394.58 (0.000)	0.017	96.60	29.45
Size	69	3493.09 (0.000)	0.003	98.64	73.4
Overall	221	11162.06 (0.000)	0.012	99.44	179.6
Test of group differences: Q_b = chi2(2) = 29.13			*Prob > Q_b = 0.000*		

Table A3-5 Subgroup meta-analysis summary (binary outcome)

Study	**Log-odds**	**[95% conf. interval]**		**Weight (%)**
Group: Contact				
castro_m1	-0.05	-0.29	0.191	2.35
castro_m2	-0.033	-0.28	0.214	2.34
domenech17_m2	-0.673	-0.916	-0.431	2.35
domenech17_m4	-0.261	-0.746	0.224	1.84
forsman_m1	-0.604	-0.866	-0.343	2.31
forsman_m2	-0.392	-0.643	-0.141	2.33
forsman_m3	-0.425	-0.7	-0.15	2.29
forsman_m4	-0.285	-0.549	-0.021	2.31
litwin22_m1	-0.118	-0.153	-0.082	2.58
litwin22_m2	0.027	-0.004	0.057	2.59
litwin22_m3	-0.13	-0.186	-0.074	2.58
litwin22_m4	0.001	-0.048	0.05	2.58
theta	-0.223	-0.358	-0.088	
Group: scale				
bae_m1	-1.552	-1.809	-1.294	2.32
bae_m2	-1.332	-1.605	-1.059	2.29
chan09_m1	-1.289	-1.723	-0.855	1.95
chanzeng11_m1	-0.788	-1.344	-0.233	1.68
kimlee15_m1	-0.062	-0.121	-0.003	2.57
kimlee15_m2	-0.094	-0.134	-0.055	2.58
kimlee15_m3	-0.062	-0.121	-0.003	2.57
kimlee15_m4	-0.083	-0.123	-0.044	2.58
okwumabua_m2	0.08	0.003	0.157	2.56
tsai_m1	-0.128	-0.217	-0.039	2.55
wee_m1	-1.309	-1.921	-0.697	1.57
wee_m2	-1.309	-1.956	-0.663	1.5
zhang_m1	0.3	0.016	0.584	2.27
theta	-0.554	-0.922	-0.186	
Group: size				
braam_m2	-0.3	-0.613	0.013	2.21
cho_m3	-0.405	-0.635	-0.176	2.37
domenech17_m1	-0.223	-0.574	0.128	2.13
domenech17_m3	0.451	0.021	0.881	1.96
frediksen_m1	-0.198	-0.337	-0.06	2.51
lee19_m1	-0.094	-0.27	0.081	2.46
lee19_m2	-0.073	-0.132	-0.013	2.57
lee19_m3	-0.174	-0.316	-0.032	2.5
sonnenberg_m1	-0.519	-0.743	-0.294	2.38
sonnenberg_m2	-0.678	-1.043	-0.314	2.1
sonnenberg_m3	-0.412	-0.693	-0.131	2.28
sonnenberg_m4	-0.412	-0.642	-0.182	2.37
sonnenberg_m5	-0.548	-0.923	-0.173	2.08

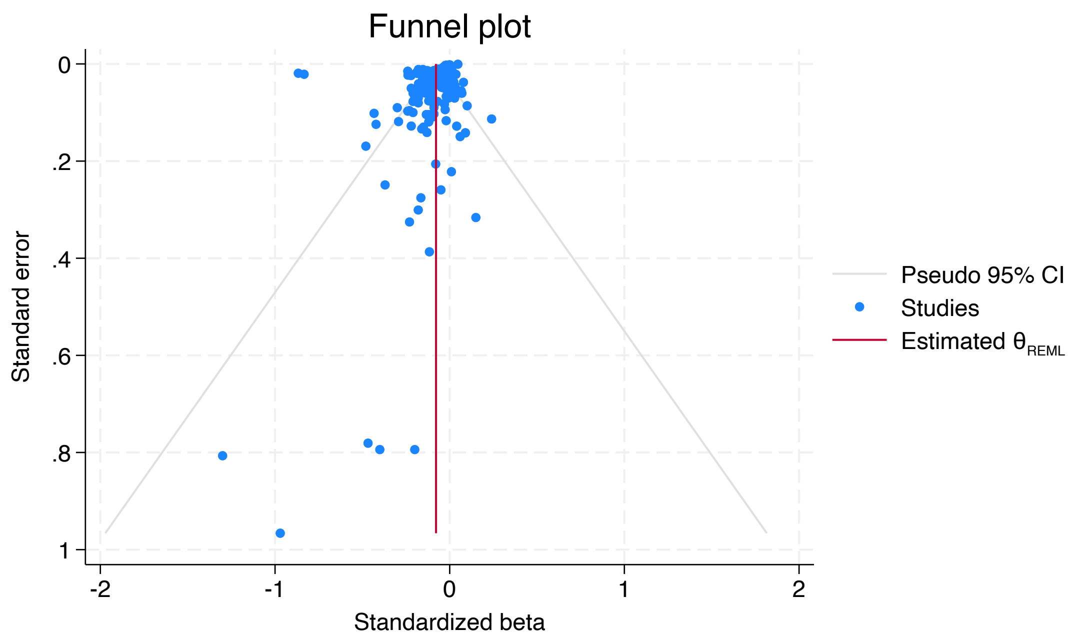
Study	Log-odds	[95% conf. interval]		Weight (%)	
sonnenberg_m6	-0.322	-0.618	-0.027	2.25	
stringa_m5	-0.036	-0.053	-0.018	2.59	
stringa_m6	-0.017	-0.036	0.001	2.59	
stringa_m7	-0.03	-0.046	-0.015	2.59	
stringa_m8	-0.045	-0.073	-0.017	2.59	
theta	-0.202	-0.299	-0.104		
Overall theta	-0.308	-0.430	-0.186		

Heterogeneity summary

Group	df	Q (P> Q)	tau2	% I2	H2
Contact	11	110.93 (0.000)	0.045	96.88	32.10
Scale	12	296.15 (0.000)	0.430	99.59	242.76
Size	17	91.99 (0.000)	0.033	98.51	67.32
Overall	42	523.10 (0.000)	0.149	99.50	201.25

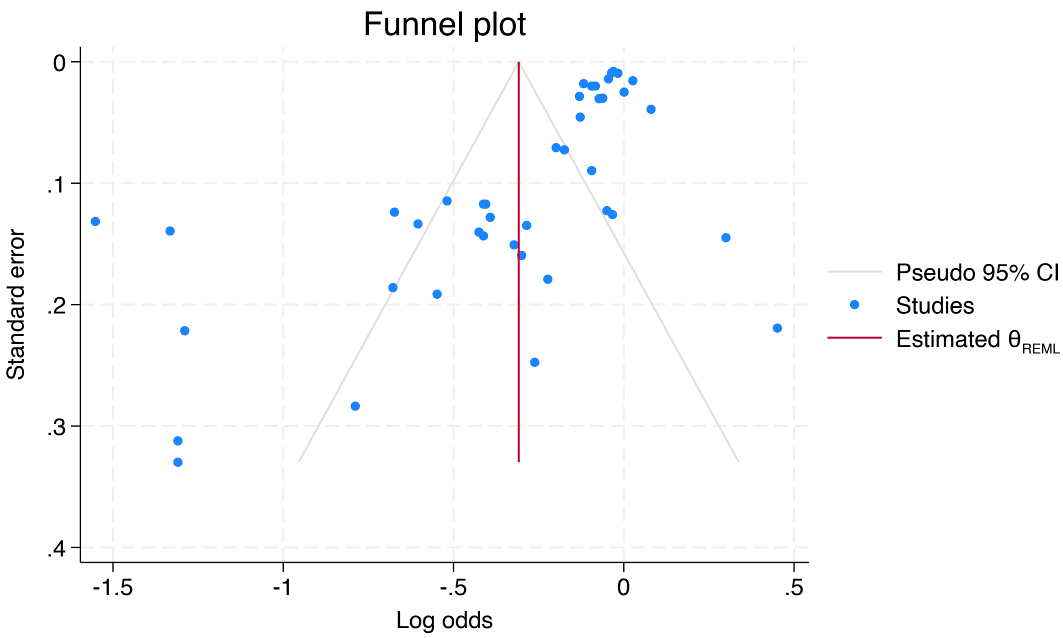
Test of group differences: Q_b = chi2(2) = 3.29 *Prob > Q_b = 0.193*

Figure A3-1 Funnel plot (continuous outcome)



Note: To improve the readability of the graph, two studies with larger standard errors were excluded from the plot.

Figure A3-2 Funnel plot (binary outcome)



CHAPTER 4. WHO WOULD ASK WHOM FOR HEALTH ADVICE? THE STRUCTURAL ANATOMY OF HEALTH ADVICE NETWORKS AMONG MIDDLE-AGED AND OLDER ADULTS

Amelie Reiner, Mark Wittek & Lea Ellwardt

Abstract

Social relationships provide opportunities to exchange and obtain health advice. Not only close confidants may be perceived as health advice sources, but also acquaintances that people meet in places outside a closed circle of family and friends, e.g., voluntary organizations. This study is the first to analyze the structure of complete health advice networks in three voluntary organizations and compare them with more commonly studied close relationships. To this end, we collected data on multiple networks and health outcomes among 143 middle-aged and older adults (mean age = 53.9 years) in three carnival clubs in Germany. Our analyses demonstrate that perceived health advice and close relationships overlap only by 34%. Moreover, recent advances in exponential random graph models (ERGMs) allow us to illustrate that the network structure of perceived health advice differs starkly from that of close relationships. For instance, we found that networks centered around health advice exhibited lower transitivity and greater segregation by gender and age as compared with close relationship networks. We also found that actors with poor physical health perceive less individuals as health advisors than those with good physical health. Our findings suggest that community settings, such as voluntary associations, provide a unique platform for exchanging health advice and information among both close and distant network members.

Keywords: health advice; perceived social support; whole networks; health; older adults; ERGM

4.1 Introduction

Previous research has highlighted the significance of social networks not only for the transmission of communicable diseases, but also for non-communicable health outcomes, including lower risk of cognitive decline (Kuiper et al., 2016), dementia (Kuiper et al., 2015), depression (Reiner & Steinhoff, 2024), and premature mortality (Holt-Lunstad et al., 2010). A key mechanism linking social networks to health is the mobilization of resources embedded in social relationships that support the prevention of and recovery from illness. These resources include various forms of social support, such as advice, information, emotional support, affirmation, and attitudes from others with regard to managing individual health issues (Abbott et al., 2012; Schafer, 2013). Thereby, communication about health issues is a central mechanism through which social networks exert their influence on health outcomes, and communication often leads to the activation of social support and the transmission of valuable information. People routinely share concerns, seek advice, and shape one another's health decisions through everyday conversations (Berkman et al., 2000; K. P. Smith & Christakis, 2008). Seeking health-related advice becomes particularly important with aging, as morbidity progresses (Thoits, 2011).

Previous research on health advice among middle-aged and older adults primarily investigated egocentric network data and found that it is mainly exchanged within close relationships, such as family, friends, but also others, like coworkers (Perry & Pescosolido, 2010, 2015). However, less attention has been paid to social settings that encompass both close and more distant relationships despite the potential benefits of the latter in providing nonredundant information (Granovetter, 1973). As it is notoriously difficult to record conversations among participants in real time (for a rare exception, see McFarland et al., 2013), survey studies usually ask respondents who they confine in related to personal matters (e.g., Marsden, 1987). However, only asking for instances of seeking advice overlocks dormant social capital in social ties that might only get activated if a problematic situation, such as a health issue arises (Small, 2017).

Rather, the belief that social support, such as advice, is available if needed has continuously shown to be more predictive of positive health outcomes than the actual support received (Uchino, 2009; Wills & Shinar, 2000). The perception of available advice shapes an individual's willingness to seek advice or support during times of acute illness (Thoits, 2011). Accordingly, we examine the perceived structural opportunities for obtaining health advice. In addition, most previous work lacks complete network data, which prevents researchers from disentangling the interplay between health advice and close relationships in bounded settings for interaction, such as voluntary associations. Our study complements existing literature by investigating how health advice networks (HANs), particularly those of older adults, are structured and extend beyond immediate social circles.

To address this gap, we aim to present a first case study analyzing HANs outside the family or institutional context, more specifically within voluntary associations. Similar to urban communes (e.g., Martin et al., 2001), voluntary associations represent a naturally bounded, yet informal social setting where social ties form and evolve organically. Formal volunteering is frequently used by older adults as an active strategy to expand their networks, and combat social isolation and loneliness (Donnelly & Hinterlong, 2010; Jongenelis et al., 2022). Studying voluntary associations present a suitable research site to study the interplay between health and multiple types of networks as they include—but are not restricted to—family, close friends, and colleagues in addition to health advice networks. Importantly, beyond their primary purpose, such associations may serve as sites where individuals gain access to unanticipated social capital (Small, 2009), including valuable health-related information and support. We argue that voluntary associations are a fruitful breeding ground for health advice and that HANs exhibit a distinct structure in comparison to close ties.

We draw on two parallel streams of literature. The first investigates the effects of HANs on individuals' health outcomes, largely independent of social context (Perry & Pescosolido, 2010, 2015; Schafer, 2013). A growing number of studies have used statistical network models to examine the spread of health information in specific domains, such as HIV prevention (Young et al., 2020), vaccination attitudes (Salathé & Bonhoeffer, 2008) or misinformation (Dunn et al., 2017; Surian et al., 2016), treating health advice as an implicit transmission mechanism. However, this work tends to focus on specific behaviors, online settings or only implicitly model health advice and rarely examines the structural features of complete HANs in naturally bounded offline environments. In line with a growing stream of network research, we argue that studying network endogenous processes, such as transitivity and reciprocity, is crucial to better understanding how social networks shape the life outcomes of individuals (Christakis & Fowler, 2007; Perkins et al., 2015).

The second stream investigates the structure of complete networks, particularly in naturally bounded contexts, such as schools (Bearman et al., 2004; Moody, 2001) or science (Newman, 2001; Wittek et al., 2023). Even though there exists some research on specific types of ties, such as negative (Berger & Dijkstra, 2013; Isakov et al., 2019), gossip (Ellwardt et al., 2012) or romantic ties (Bearman et al., 2004), much of this work has emphasized close relationships, which are typically represented as strong ties, defined by frequent contact, emotional intensity, and mutual investment (Granovetter, 1973). However, this emphasis should not obscure the growing recognition of the important role that weaker ties can play in structured social environments. Recent research has continued to explore the role of weak ties in social networks, noting their potential relevance for information diffusion and access to diverse resources under certain conditions (Aral, 2016; Kim & Fernandez, 2023), as well as their occasional presence within individuals' core discussion networks (Small, 2013). This underscores that function-specific relationships, like health advice ties, need not align neatly with close relationships. Rather, such networks may rely on a mix of strong and weak connections, depending on trust, accessibility, and expertise (Perry & Pescosolido, 2010). Despite this, function-specific ties, particularly those involving the exchange of health-related advice, have received far less attention. Yet, there are no studies investigating the structure of HANs with statistical network models, which limits our understanding of the structural conditions that shape how individuals identify potential health advisors within social environments beyond the family context—an essential process for effectively addressing health-related challenges.

We address this lacuna by analyzing complete networks of health advice and close relationships embedded in three voluntary associations with exponential random graph models (ERGMS, Lusher et al., 2013) for the first time. Recent advances in ERGMs allow us to build models taking into account how health advisors and close ties are intertwined, and to compare the presence and strength of social processes in these tie types by using average marginal effects (Duxbury, 2023).

Our results indicate that, on average, individuals identify two health advisors in their voluntary organization. Crucially, health advice and close relationships overlap only by 33%, and the network structure of health advice differs starkly from that of close relationships. This indicates that voluntary associations play a vital role in broadening access to diverse health information beyond the individual's immediate social circles. Additionally, we observed that homophily in sociodemographic traits and individual health status influences the likelihood of seeking health-related advice. As a result, individuals' efforts to seek health advice are shaped not only by their personal characteristics but also by the social dynamics of their relationships and local communities.

We argue that combining insights on HANs with a social network lens to study networks and health in voluntary associations offers a fruitful extension of the existing literature. If researchers and practitioners are better able to understand the self-organizing principles of HANs that shape an individual's opportunities to receive, share, and exchange health advice with others, more effective interventions can be tailored toward the promotion of health information exchange and, consequently, toward the improvement of community and public health (cf. Small, 2013, 2017).

4.2 Study context: Voluntary associations

Prior research on HANs has mostly taken an egocentric approach and found that HANs are comprised of family and other close individuals (Perry & Pescosolido, 2010, 2015). Less attention has been paid to broader contexts that include both close and distant ties, with the latter offering access to nonredundant information (Granovetter, 1973). Particularly in contexts beyond the family, people may unintendedly access information that offer unanticipated gains

(Small, 2009). For middle-aged and older adults, local voluntary social settings—distinct from family, close friends, and work—are particularly relevant. These settings become increasingly important as aging, retirement, and health changes lead to shrinking social networks (Wrzus et al., 2013).

Older adults often engage in formal social activities, particularly volunteering, as a way to combat social isolation, strengthen their networks, and reduce loneliness (Donnelly & Hinterlong, 2010; Jongenelis et al., 2022). Defined as unpaid and non-mandatory work for a community or organization (Donnelly & Hinterlong, 2010) volunteering is widely recognized for its role in supporting healthy aging. Studies have associated it with numerous health advantages, such as improved self-rated health, enhanced life satisfaction, a lower risk of mortality, reduced depressive symptoms, and greater functional independence (Greenfield & Marks, 2004; Webster et al., 2021).

Here, we examine HANs within the contexts of voluntary associations, specifically carnival clubs in a metropolitan region in Germany. These clubs are responsible for organizing cultural festivities during Carnival season, a vibrant and long-standing tradition marked by parades, music, costumes, and social gatherings leading up to Lent. Strongly intertwined with the region's cultural identity, these festivities celebrate local dialects, customs, and community ties.

However, carnival clubs serve a purpose beyond the seasonal celebrations, as they facilitate year-round engagement. Members participate in various social activities, including summer festivals, monthly informal gatherings, and charitable initiatives, fostering continuous interaction within the group. Prior qualitative research on carnival club members (Steinhoff et al., 2024), suggests that participation is driven more by the sense of community than by the festival itself. Members find it easy to establish and maintain social ties within the clubs, as active participation is not a strict requirement. For retirees, these clubs serve as a means to regain a sense of purpose and mitigate the loss of role and status often associated with retirement. The sense of being needed and valued through involvement in the club contributes positively to overall well-being (Steinhoff et al., 2024).

Unlike institutional settings—such as workplaces or retirement homes—where social ties are often shaped by structural constraints and limited choice, carnival clubs are characterized by self-selection and greater individual agency in forming social connections (Rawlings et al., 2023). This makes carnival clubs an ideal case for studying HANs of middle-aged and older adults exceeding the family context. First, these associations provide a voluntary leisure setting in which informal socializing takes place in a heterogeneous group, exceeding the contexts of family, neighborhood, and work organizations (cf. Granovetter, 1973). Second, they often include a disproportionate share of adults in the second half of life. Third, because membership is formally defined, they offer a clearly demarcated network boundary, a crucial requirement for employing sociometric social network analysis. Furthermore, these associations remained active during Covid-19-related social distancing measures and are open to all individuals, with no prerequisites for joining.[2] Unlike other voluntary settings such as sports clubs or retirement homes, these clubs are less selective regarding members' health. The health demographics of our study sample closely reflect those of the general German population (Robert Koch-Institut, 2018), reducing the likelihood of selection bias related to health and making them a valuable context for studying health-related network effects.

4.3 Theory

Close relationship networks and HANs are not mutually exclusive, rather they coevolve. For example, in their study on clients using mental health services for the first time, Perry and Pescosolido (2010) found HANs to be particularly comprised of close, strong, and frequently contacted relationships, in additional to more specialized associates. Given the sensitivity of health-related topics, individuals may be reluctant to share medical experiences or seek advice from those with whom they lack emotional closeness and thus, prefer close confidants. From the long research tradition on close relationships in other domains, such as school settings (Coleman, 1968; McFarland et al., 2014; Moody, 2001), universities (Vörös et al., 2021; Wimmer & Lewis, 2010), and workplaces (Ellwardt et al., 2012; Kilduff & Krackhardt, 1994), we know that networks of close relationships are typically structured by multiple organizational principles, such as transitive closure and segregation along social categories. Based on their coevolution, we expect that some of these principles will also apply to HANs. Additionally, as Small (2017) highlights, individuals do not always anticipate the sources of support, e.g., advisors, they will rely on. More recent findings further suggest that individuals commonly and intentionally avoid confiding in close friends and family depending on the conjunction of network member and topic (Small et al., 2024). Conversely, they may seek advice from more distant or even unexpected ties (Small, 2013, 2017). These patterns underscore the importance to consider the possible conditions across a range of stronger and weaker ties that make such discussions more likely. Voluntary associations create opportunities for unanticipated gains by exposing individuals to diverse social interactions, including weak ties that may become crucial for health-related exchanges. In the following sections, we discuss organizational principles for networks of close relationships and present hypotheses regarding whether and to what extent we expect to

[2] In some of these clubs, women cannot be members. Here, club 1 comprise only men, whereas club 2 is mixed-gender.

observe these principles in HANs. Thereby, we look at the structural mechanisms (e.g., transitivity and homophily) that shape how health-related advice unfold, as well as the conditions that make health-related advice more likely—particularly when involving weak ties. Table 4-1 provides an overview of the hypotheses and the modelled terms.

4.3.1 Transitivity

Transitive closure or clustering is a common feature in many social networks, which is to say that actors with shared contacts tend to establish relationships (e.g., Granovetter, 1973), ranging from more emotionally-distant networks (e.g., work advice-seeking networks, Bunger et al., 2018) to emotionally-close networks, such as friendships (McFarland et al., 2014; Moody, 2001). This tendency can be explained by the fact that common contacts act as foci for interactions (Feld, 1981), and that actors prefer balanced social relationships (Heider, 1958; Yap & Harrigan, 2015). Theory and empirical studies suggest that trust, repeated interaction, and shared norms in close relationships often amplify transitive closure (McFarland et al., 2014; Moody, 2001). Close-tie networks are generally dense, and the alters in these networks are strongly interconnected (Granovetter, 1973). This density results in relationships that mutually reinforce one another (Small et al., 2015), which reflects a high level of transitive closure, or in quantitative terms, a greater number of closed relationship triangles.

In the context of voluntary associations, we expect to observe transitive closure in HANs as well, but to a lesser extent. Voluntary associations foster diverse interactions that include both strong and weak ties. While members may develop recurring interactions, their engagement is often structured around shared interests or group activities rather than deep, long-standing personal connections. Additionally, by definition, HANs can involve a broader and more heterogeneous range of social ties, often including instrumental, topic-specific interactions that may be less committed, more sporadic, more targeted, and less reciprocated than deeper, multifunctional connections characterized by long-standing emotional bonds and enduring relational histories. Because of these reasons, individuals do not necessarily prioritize balance to the same extent as in close relationship triangles (Kawachi & Berkman, 2001), especially in the setting of voluntary associations. Information flow in HANs should thus be less constrained by the need for balance, and information imbalance should be less disruptive to the stability of these ties. In short, imbalance seems more tolerable in HANs. In addition, individuals in HANs may actively seek advice from beyond their immediate ties to gain diverse perspectives and avoid redundancy (Perry & Pescosolido, 2010), resulting in greater numbers of open triangles with bridges to adjacent clusters.

Furthermore, advice exchanges are not confined to regular face-to-face interactions and can even flow between strangers (Small, 2017), although this seems to be more the exception than the rule when it comes to private conversations about sensitive health issues. Studies have demonstrated that discussion networks—with whom people discuss important matters with, which may include advice relationships—often form around immediate needs and availability, rather than preexisting strong ties. For example, in a series of studies, Small (2017) argued that the assumption that discussion networks closely mirror networks of close ties is likely to be incorrect. Through an extensive study of a cohort of graduate students at an elite university, Small (2017) illustrated that individuals seek out others who are readily available in their daily lives to discuss important matters, rather than solely turning to friends and family. In addition, discussion networks were found to adapt rapidly to new environments, due to the quick transformation of respondents' obligations and routine activities (Small et al., 2015). This observation underscores the fluid and dynamic nature of discussion networks, likely to be applicable to advice networks. This is particularly important in the health context, where lower transitive closure allows HANs to be more adaptable and responsive to changing health needs and information. Such networks can quickly disseminate important health information or advice without being constrained by the rigid structures of highly transitive networks.

H1: HANs in voluntary associations are characterized by transitive closure, but to a lesser extent than networks of close relationships.

4.3.2 Homophily

A second recurring structural feature of close relationships is network segregation along multiple social categories, such as gender, education, and age (McPherson et al., 2001). Wimmer and Lewis (2010) argue that network segregation is constituted by several factors, such as the opportunity structure for tie formation, network endogenous processes, and a genuine preference for others from the same social category (i.e., homophily). Previous studies have provided evidence for homophilous tie formation in various settings, for example, gender homophily in school children's friendships (Shrum et al., 1988; Stehlé et al., 2013), racial homophily in online dating platforms (Bruch & Newman, 2019), or educational homophily in parental networks (Lenkewitz & Wittek, 2022).

In general, homophilous ties are more likely to be activated for support and discussion because similarity facilitates communication, increases predictability, promotes trust and reciprocity, and reduces conflict (McPherson et al., 2001; Suitor & Keeton, 1997). Here, homophily is most beneficial when two individuals are similar in terms of characteristics that are relevant to the challenges or circumstances they are trying to overcome. Particularly with regard to health issues that are tied to social categories (e.g., age and gender), similarity may facilitate communication and promote trust in seeking health-related advice. For instance, in qualitative research, women were found to be more likely to turn to women than men to talk about menopause (Edwards et al., 2021). Similarly, network members of the same age are more likely to seek advice on the topic of an upcoming hip surgery—a relatively common treatment in aging adults.

We expect that both HANs and networks of close relationships in voluntary associations will exhibit homophily. Although voluntary associations bring together diverse individuals, health advice are likely to be more common among members who share relevant social characteristics. While some studies suggest that health advice in acute health crises may transcend social categories (Perry & Pescosolido, 2010), we test for homophilous tie formation in HANs within voluntary associations to assess its significance. As an important organizational principle of close relationship networks, homophily within voluntary associations may provide members with a sense of belonging and trust, further reinforcing the role of these institutions in facilitating health-related support and advice exchange.

H2: HANs and networks of close relationships in voluntary associations exhibit homophily with regard to gender, age, and education to a similar extent.

4.3.3 Network structure and health

In general, networks reflect competing preferences to associate with the most desirable individuals (e.g., Martin, 2009). Particularly in bounded settings, such as voluntary associations, such preferences may be directed towards the most successful, the most physically attractive, or the healthiest individuals (Centola & Van De Rijt, 2015), or more generally speaking, those with the highest status in a social group. Poor health is a stigmatized condition (Link & Phelan, 2001), and research has found that poor health—especially if a condition is both stigmatized and visible—influences friendship choices among adolescents (Ali et al., 2011; Crosnoe et al., 2008). Also, multiple studies report that older adults with depression have smaller networks (for a review, see Reiner & Steinhoff, 2024). For several reasons, this stigmatization may result in the social isolation of those who are perceived as unhealthy.

First, unhealthy individuals might not be desirable as friends, as they cannot participate regularly in group activities (Galenkamp & Deeg, 2016). Second, people may be reluctant to associate with those who are unhealthy and stigmatized, due to concerns about the potential impact on their own social reputation (Crosnoe et al., 2008; Haas et al., 2010). Third, people with poor health use strategies such as concealment and withdrawal to hide their medical condition which can also be a pathway into social isolation (Link, 1987; Link et al., 1989). Those in poor health may anticipate negative interactions and stigmatization, which makes them withdraw from social relationships (Link & Phelan, 2001). Whether driven by the avoidance of others or self-withdrawal, individuals with poor health are likely to both receive and send fewer nominations for close friends in voluntary associations.

However, voluntary associations also provide opportunities for seeking health-related advice and support, which conversely may lead individuals with poor health to perceive more health-related advice and receive more nominations as health advisors. According to the Network Episode Model, social ties are often activated during illness, providing both health-related attitudes and information, as well as access to health services (Perry & Pescosolido, 2010), possibly increasing their perception of available support. In addition, their experience with health issues may make them valuable sources of health advice, perhaps even facilitating expert status in the group. Thus, people in poor health are expected to be more engaged in HANs, both sending and receiving more health-related nominations as compared with close relationship nominations.

However, the sender and receiver effects in HANs and close-tie networks are likely to differ based on the type of health condition. Physical health limitations are expected to have a stronger influence on individuals' activity in both networks. Despite general reluctance to discuss poor health (Small et al., 2024), people with physical health problems may still be more inclined to seek advice or share experiences. In contrast, mental health conditions, often associated with stigma, withdrawal and a reduced ability to engage in social interactions (Cacioppo & Cacioppo, 2014; Link & Phelan, 2001) may lead to a diminished capacity or desire to seek advice or support from others. Moreover, the distorted thought patterns associated with poor mental health can lead to a systematic underestimation of available social support (Beck, 1967, 1979). Consequently, individuals with physical health issues are expected to be more active in HANs compared to those experiencing mental health challenges.

H3a: Individuals with poor health receive fewer nominations as close relationships, but more as health advisors, compared to those in good health. This effect is expected to be stronger among those with poor physical health than among those with poor mental health.

H3b: Individuals with poor health nominate fewer network partners as close relationships, but more as health advisors, compared to those in good health. This effect is expected to be stronger among those with poor physical health than among those with poor mental health.

Furthermore, several studies have demonstrated homophily in relation to health. Scholars have found that depressed adolescents often face peer avoidance, leaving them with limited friendship options aside from others who are experiencing similar mental health issues (Hogue & Steinberg, 1995; Schaefer et al., 2011). Researchers have observed similar patterns for obese adolescents (Crosnoe et al., 2008). In addition, Schafer (2016) provides evidence that retirement residents are more likely to interact with those who share similar health statuses.

Prior research has also found that homophily yields the most benefits when it involves characteristics directly relevant to the challenges or situations people are facing. In keeping with this notion, experiential homophily (i.e., having encountered similar difficulties or situations, such as cancer) plays a bigger role in the selection of discussion partners (Thoits, 1986). Perry and Pescosolido (2010) further support the idea of experiential homophily in HANs, finding that people are more likely to seek health advice from those who have faced similar mental health challenges.

H3c: Networks of close relationships and HANs show experiential homophily in voluntary associations. This effect should be more pronounced in HANs than in networks of close relationships.

Table 4-1 Overview of hypotheses

Hypotheses		**Model term in health advice network**	**Expected direction**	**Model term in network of close relationships**
H1	HANs in voluntary associations are characterized by transitive closure, but to a lesser extent than networks of close relationships.	GWESP	<	GWESP
H2	HANs and networks of close relationships in voluntary associations exhibit homophily with regard to gender, age, and education to a similar extent.	Same gender Same age group Same education	= = =	Same gender Same age group Same education
H3a	Individuals with poor health receive fewer nominations as close relationships, but more as health advisors, compared to those in good health. This effect is expected to be stronger among those with poor physical health than among those with poor mental health.	Poor physical health: receive Poor mental health: receive	>> >	Poor physical health: receive Poor mental health: receive
H3b	Individuals with poor health nominate fewer network partners as close relationships, but more as health advisors, compared to those in good health. This effect is expected to be stronger among those with poor physical health than among those with poor mental health.	Poor physical health: send Poor mental health: send	>> >	Poor physical health: send Poor mental health: send
H3c	Networks of close relationships and HANs show experiential homophily in voluntary associations. This effect should be more pronounced in HANs than in networks of close relationships.	Same physical health Same mental health	> >	Same physical health Same mental health

4.4 Methods

4.4.1 Data

We used sociometric survey data collected from three voluntary associations in a region in Germany. Research staff initially recruited professional contacts and further used snowball sampling to gain access to three voluntary associations. We deemed only active members eligible to ensure that every member had a nonzero chance of meeting and talking to every other member. Therefore, after debriefing the association's head of management, we excluded five permanently inactive members, as well as people who were living in institutions, far away, or abroad, and people who were unable to participate due to severe health condition. This resulted in a target sample of 143 members, ranging from 45–53 members per association. None of the participants were members of multiple participating associations, thus the sample yielded three entirely nonoverlapping networks.

After the manager of each voluntary association contacted the participants, we invited the respondents to complete an online questionnaire. A digital survey was feasible because the participating associations had shifted much of their correspondence to internet-mediated communication during the COVID-19 pandemic, and nearly all participants were experienced using computers or smartphones. We offered home visits for assistance where appropriate; one participant provided their answers in a Computer Assisted Personal Interview visit. Filling in the online survey took 25.8 min, on average.

High response rates are a prerequisite for social network analysis that investigates complete networks. Therefore, we incentivized study participation with a monetary donation to the voluntary association, contingent on its members' response rate. Specifically, each association could earn a maximum of 500 €: for an 80% response rate, an association would receive 80% of that maximum (i.e., 0.8 * 500 = 400 €). As an additional incentive, we offered to include several customized questions at the end of the survey that allowed associations to gather information regarding their topics of interest in an anonymized setting.

Data were collected between May and October 2023, with a total of 114 participants and a resulting mean response rate of 80%. Two of the three clubs consisted exclusively of men. Within the third club, 44% of the members were male. The mean age ranged from 50 to 58 years (total age range = 23–86 years), and 97% of the respondents were born in the territory of present-day Germany[3]. According to the CASMIN classification (Federal Institute for

[3] Only 3% of carnival club members were born outside present-day Germany, indicating that migrants are underrepresented compared to the general population (Zensus 2022, 2024). While ethnicity often shapes social networks (Glitz, 2014; Hu et al., 2022; Kroneberg & Wittek, 2023; Wittek et al., 2020), it appears to be a negligible factor within these carnival clubs.

Vocational Education and Training, 2024), 24% of the respondents had low education, 38% middle education, and 38% higher education. Most of the respondents (72%) were engaged in paid work for at least 19 hours per week, net of retirement status. 17% lived on their own. Others either lived with their (marital) partner, children, parents (or in-laws), and/or another nonrelated person.

We received a positive vote from the ethics committee (University of Cologne; reference: 220036LE) prior to our data collection. We followed strict data protection guidelines and ensured informed consent.

4.4.2 Measures

Network variables

All network variables used a roster design such that respondents could select individual members from a roster of all members. To reduce respondent burden and the time required to fill in the survey, respondents were initially asked to indicate those members with whom they had ever had contact. Only members selected in that initial question were then presented in a respondent's subsequent rosters; members who were not personally known to the respondent were filtered out. The composition of the *HAN* was assessed by asking respondents with whom they would be likely to talk if they had a health problem they were concerned about, or if they had to make an important decision about their own medical treatment. This is a validated item from the National Social Life, Health, and Aging Project (Waite et al., 2007). This was a directed network in which respondents could nominate others as advisors (i.e., they could send a tie), and they themselves could be nominated as an advisor by others (i.e., they could receive a tie).

Close relationships were operationalized as the presence of recent informal contact and positive emotion. Two binary network items were combined: respondents had also met each other outside of voluntary association events within the previous 6 months, and the other person brought them great joy or great happiness (Engstler et al., 2022). This was a directed network with sent and received nominations, as well. Even stricter measurements of close tie relationships—that were measured by combining the two network items of giving them great joy or great happiness *and* that they had had contact at least several times per month—did not yield to different results (see Table A4-5).

Kinship ties indicated whether network members were related by blood or married. Kinship was coded as present when at least one person indicated being related, hence it was coded as an undirected network.

Individual variables

Age was captured with three categories: less than 45 years, 45–64 years, and 65 years and older. *Gender* was constructed as a binary measure, with males as the reference category. *Education* consisted of three categories: low, middle, and high education, in keeping with the CASMIN classification (Federal Institute for Vocational Education and Training, 2024). *Poor physical health* was measured with a single item regarding whether respondents had, in the previous 6 months, experienced limitations on activities they usually engage in due to a health problem. We operationalized not being strongly restricted and being severely restricted as poor physical health, whereas not being restricted served as the reference category. *Poor mental health* was based on the index of the Negative Affect Subscale of the Positive and Negative Affect Schedule (Crawford & Henry, 2004). Scores ranged from 1 to 5, with higher values indicating poorer mental health. Individuals with scores of 3 or higher were classified as having poor mental health. We controlled for respondents' *occupation*, as working in the health sector and being perceived as a professional are likely to attract health advice partners. Respondents indicated whether they currently worked or had ever worked in healthcare. This resulted in a binary measure, with not having worked in healthcare being the reference category.

4.4.3 Analytic strategy

Exponential Random Graph Models (ERGMs)

Using the R-package statnet (Handcock et al., 2008), we modelled the structure of HANs and networks of close relationships with ERGMs, which compare the relational patterns in a network with those found in a set of simulated random networks (Lusher et al., 2013), and we tested the interplay of these two networks through entrainment effects (Yap & Harrigan, 2015). In ERGMs, the more an observed network structure deviates from what would be expected by chance, the larger the effect and the higher its significance. These models provide a valuable method for dissecting the global structure of networks, offering insights into the underlying generative processes for individual ties, while considering the influence of related factors (Lusher et al., 2013). In our study, this method allowed us to examine the formation of health advice ties while taking into account other network-structural characteristics, such as transitivity or the mutual nomination to be a health advice partner, as well as individual-level characteristics, such as gender.

Recall that our sample comprised three voluntary associations with their respective HANs and close relationship networks. The use of ERGMs for multilayer networks led to problems with convergence. Also, modelling separate ERGMs for each voluntary association was difficult due to poor model convergence[4]. Similarly, fitting separate ERGMs and combining the results in a meta-regression was not suitable, because the group-level sample size of three was small. We therefore combined the three respective networks into a single block diagonal adjacency matrix prior to fitting one ERGM. This facilitated the estimation of a pooled ERGM, with the added benefit of greater statistical power (Duxbury & Wertsching, 2023; Vega Yon et al., 2021) and ease of interpretation. To account for missing data, we applied multiple imputation techniques throughout all analytic steps, using chained equations (van Buuren & Groothuis-Oudshoorn, 2011).

Average Marginal Effects (AMEs)

We used Average Marginal Effects (AMEs) to increase statistical power and to reduce bias induced by scaling (Duxbury & Wertsching, 2023). Crucially, AMEs ensure a valid comparison of estimates of HANs with networks of close relationships and allow for a substantial interpretation of coefficients on an absolute probability scale (Duxbury, 2023). To accurately compare effect sizes between HANs and networks of close ties, we interpreted AMEs in relation to the baseline probability of forming a tie. Kreager (2021, p. 59) recently pointed out that "AMEs differ from odds ratios in that they are on a probability scale and so their magnitudes should be interpreted relative to the baseline tie probability (i.e., network density)". Here, we used the average density weighted by network size, as the block diagonal estimation underestimates the overall density. Consequently, we present AMEs that have been adjusted by dividing them by the baseline probability of forming a tie, which can be interpreted as the change in the baseline tie probability when a network variable increases by one unit.

Goodness of fit and sensitivity analyses

We examined the goodness of fit (GOF) using statnet's built-in GOF command for ERGMs. This procedure simulates networks based on the modelled coefficients and compares the simulated values for the edgewise-shared partner, degree distribution, and geodesic distance statistics with the respective observed values.

Further sensitivity analyses include other operationalizations of health variables and the network of close relationships. We alternatively operationalized physical health as self-rated health. Further, we built an index of emotional and social loneliness as an alternative measure for mental health. Similar to the procedure used for the mental health variable in the main analyses, we combined information on whether respondents miss the pleasure of the company of

[4] When estimating the models separately, we found the results to be similar for the converging models. However, due to high standard errors and the skewed distribution of some variables, we decided not to report the separate estimations. The results are available upon request.

others, miss emotional security and warmth, often feel rejected, whether there are many people they can trust completely, whether there are plenty of people they can rely on when they have a problem, and whether there are enough people they feel close to. To effectively capture lonely people, we dichotomized the index, ranging from 1 to 4, using 2 as a cut-off point. We alternatively used a stricter definition of close ties that required respondents to indicate that the other person brought them great joy or great happiness (Engstler et al., 2022) *and* that they had to have contact at least several times per month, whether in person, by phone, mail, email, or other means. In the sensitivity analyses, we also explored the effect of being employed at least 19 hours a week, testing for incoming and outgoing ties across both networks (M8, see Table A4-4 and Table A4-5). All sensitivity analyses suggested that the results were generally robust; these are discussed in the Appendix (see Appendix, Sensitivity analyses, Table A4-1, Table A4-2, Table A4-3).

Model specifications

Following an iterative modeling strategy (Wimmer & Lewis, 2010, p. 625), we estimated a variety of specifications under different settings for the estimation process. Through this iterative procedure, we aimed to find convergence for a given specification and aimed to achieve satisfactory GOF. Table 4-2 provides an overview of the different model specifications we estimated to study the structural anatomy of HANs and close tie networks. Generally, the model with the smallest Bayesian Information Criterion (BIC) should be preferred. Ultimately, we chose M1 for both networks, as it demonstrates the best convergence and model fit, given the inclusion of all theoretically relevant parameters. The results of the other models are displayed in the Appendix, Table A4-4 for HANs and Table A4-5 for close tie networks.

Table 4-2 Summary of exponential random graph model specifications

Model terms	**Hypotheses**	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**
Edges		x	x	x	x	x	x	x	x
Mutual		x	x	x	x	x		x	x
GWESP	H1	x	x	x	x	x		x	x
GWDSP		x	x	x	x	x		x	x
GWIDEG			x						
Entrainment: Health advice/ Network of close ties		x	x	x	x	x			x
Entrainment: Kin		x	x	x	x	x			x
Same age	H2	x	x			x	x		x
Same education	H2	x	x			x	x		x
Same gender	H2	x	x			x	x		x
Poor physical health: send	H3b	x	x		x		x		x

Model terms	**Hy-poth eses**	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**
Poor physical health: re-ceive	H3a	x	x		x		x		x
Same physical health	H3c	x	x		x		x		x
Poor mental health: send	H3b	x	x		x		x		x
Poor mental health: receive	H3a	x	x		x		x		x
Same mental health	H3c	x	x		x		x		x
Employment health sector: receive		x	x						x
Employed									x
BIC: Health advice		1741	1746	1645	1687	1709	2948	2375	1770
BIC: Close Ties		2477	2485	2318	2374	2415	4449	-	2483
Table		Table 4-5	Table A4-4 Table A4-5	Table A4-4 Table A4-5	Table A4-4 Table A4-5	Table A4-4 Table A4-5	Table A4-4 Table A4-5	Table A4-4	Table A4-4 Table A4-5

Note. —X signifies whether a term was included in the respective model specification; - signifies that the model did not converge under the given specification.

Structural effects are part of every model and control for endogenous compositions. The *edges* term models the general tendency of respondents to nominate network members. This term counted all ties present in a network, thus representing the network's density (cf. S. Smith et al., 2016). Because most close relationships are marked by a preference for reciprocity (Gould, 2002), all models included the *mutual* term, which captured the general tendency of respondents to reciprocate the nominations they received from others. In addition, we included the geometrically weighted edgewise shared partner (*gwesp*) term and the geometrically weighted dyadic shared partner (*gwdsp*) term. The gwesp term captured transitivity, which is the tendency of actors to befriend their friends' friends (Hunter, 2007). The gwdsp term captured how often pairs of nodes shared connections to the same other nodes in the network. The likelihood of a tie increased with each additional edgewise/dyadic shared partner, but the magnitude of this increase diminished with each additional shared partner. This diminishing return of additionally shared friends is represented by the gwesp/gwdsp *alpha* term, both of which we fix to 0.5. Throughout our iterative modeling procedure, we included the geometrically weighted indegree effect (*gwideg*) for all tie types to account for different activity levels between actors.

Entrainment effects modelled exogeneous effects of other tie characteristics on tie formation (i.e., whether a tie of one type predicted ties of another type; Robins & Pattison, 2006). To address the coevolving relationship between networks of close relationships and HANs, we introduced a *close relationship entrainment effect* into our model of HANs and vice versa. These effects quantified the extent to which close relationships and health advice ties co-occurred by counting directed ties of one type that coincided with nominations of another type between two actors. Furthermore, all models included a *kin entrainment effect* to account for being related by blood or marriage.

Node-level characteristics (dyad) modelled exogeneous effects of individual attributes on dyadic tie formation (i.e., whether the attributes combined from two individuals predicted a tie between them). Homophily included a count statistic that enumerated all same-attribute ties, with all cross-attribute ties serving as reference categories (e.g., same-gender ties vs. cross-gender ties). We included homophily terms for education, age, gender, poor physical health, and poor mental health.

Node-level characteristics (individual) modelled exogeneous effects of individual attributes on tie formation in general (i.e., whether an attribute was associated with the individual's activity and popularity in the network). To test our theoretical expectations of individual health status, we included terms that captured whether members with poor health sent and received more or fewer nominations. These main effects were included for physical health and mental health. Furthermore, we included the same terms for each level of age, gender, and education to test for the overrepresentation of possible ties between nodes that shared an attribute (i.e., homophily). Finally, we controlled for the received nominations for those who were, at the time of data collection, or had been employed in the health sector.

4.5 Results

4.5.1 Descriptives

Table 4-3 presents the individual level descriptive statistics for our analysis sample. Education and age were roughly equally distributed across clubs. Only the second voluntary association had a mixed-gender network.

Table 4-3 Summary statistics for analysis sample

	Voluntary association 1		**Voluntary association 2**		**Voluntary association 3**		**All**	
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
N	53		45		45		143	
Participated	47	89	34	76	33	73	114	80
Gender (female)	0	0	25	56	0	0	25	17
Age								
>45	17	32	14	31	6	13	37	26
45-64	19	36	23	51	21	47	63	44
65+	17	32	8	18	18	40	43	30
Education								
Low	20	38	6	13	8	18	34	24
Middle	21	40	23	51	10	22	54	38
High	12	23	16	36	27	60	55	38
Poor physical health	23	43	24	53	16	36	63	44
Poor mental health	18	34	23	50	8	18	49	34

Our descriptive results (see Table 4-4) provide the first evidence for the notion that health advice and close relationships are distinct relational processes: the overlap between both network types was modest, with a Jaccard index of 0.34 (n = 188). Whereas 51% (n = 284) of all ties were exclusively close ties, 16% (n = 90) of all ties were characterized by health advice, but no close relationship.

Table 4-4 Network descriptives: health advice networks and close relationship networks

	Voluntary association 1		**Voluntary association 2**		**Voluntary association 3**		**All[a]**	
	HAN	**CRN**	**HAN**	**CRN**	**HAN**	**CRN**	**HAN**	**CRN**
Density	0.040	0.076	0.035	0.058	0.049	0.075	0.041	0.070
Average degree	2.094	3.962	1.533	2.533	2.178	3.289	1.944	3.301
Reciprocity	0.306	0.333	0.464	0.421	0.224	0.378	0.330	0.375
Transitivity	0.260	0.377	0.286	0.427	0.279	0.443	0.274	0.414
Homophily								
Age	0.362	0.240	0.278	0.141	0.006	-0.069	0.223	0.112
Education	0.173	0.138	-0.005	0.105	0.055	0.139	0.080	0.128
Gender	-	-	0.065	-0.018	-	-	-	-
Health								
Physical health	-0.038	0.035	-0.095	-0.104	0.076	-0.048	-0.020	-0.034
Mental health	0.013	-0.062	-0.042	-0.019	-0.041	-0.020	-0.021	-0.035
Jaccard Index	0.354		0.397		0.268		0.335	

[a] Numbers are weighted by sizes of the voluntary associations, except for the Jaccard Index.
HAN = Health advice network, CRN = Close relationship network

Also, health advice were sparser than close relationships, as people—on average—perceived 1.94 members of the voluntary association as health advisor (SD = 3.06) and indicated 3.3 close relationships (SD = 4.75). Transitivity was higher in close relationship networks compared to HANs across all voluntary associations (see Table 4-4). This descriptive finding is also confirmed visually, as clear differences in the structures between HANs and close relationship networks can be found (see Figure 4-1). The networks of close ties seemed denser and clustered more than did the networks of health advice. These descriptive findings support H1, which expects transitive closure to be more pronounced in networks of close relationships as compared with HANs.

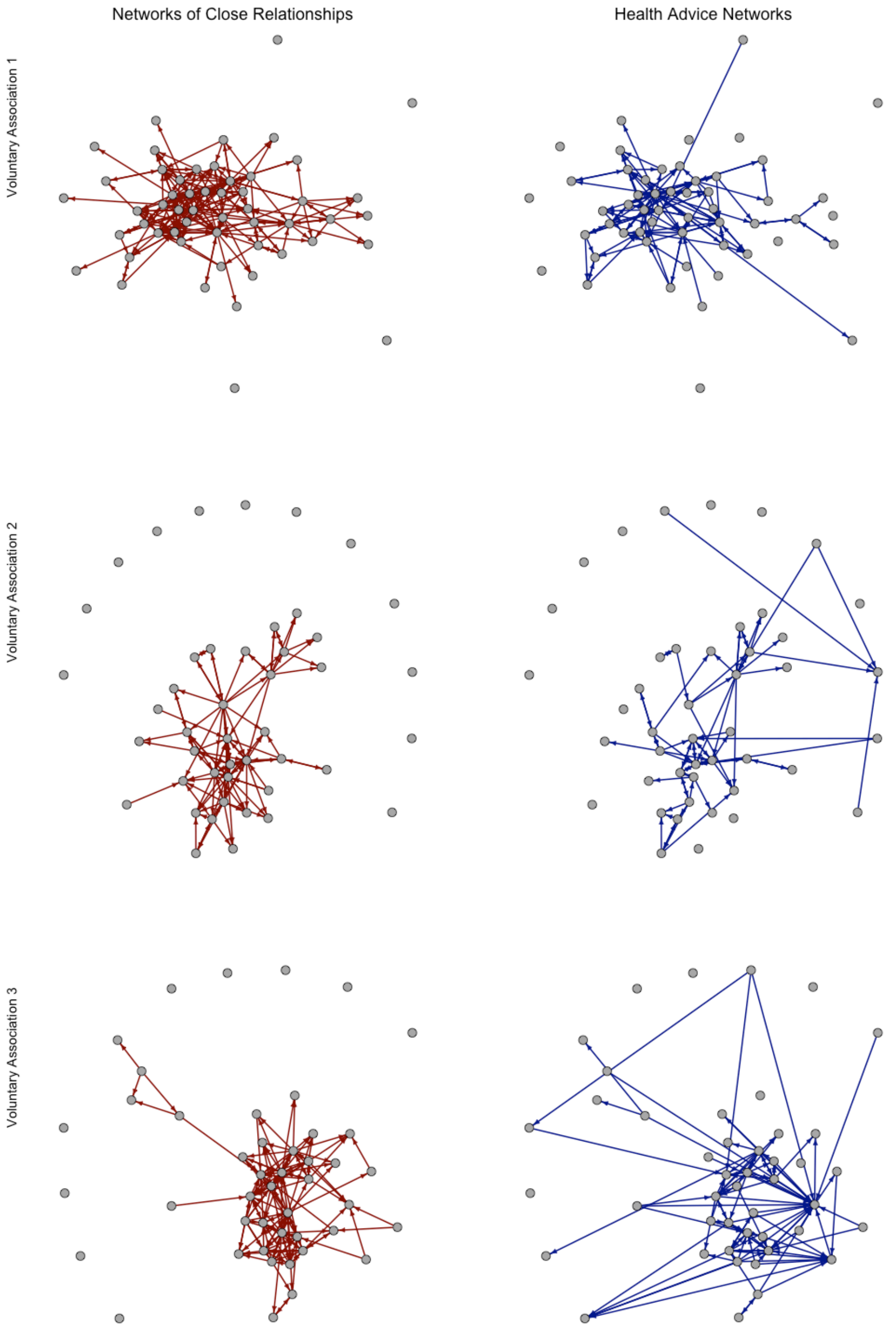


Figure 4-1 Visual comparison of HAN and network of close relationships

The descriptive patterns (see Table 4-4) show age homophily to be stronger in HANs than in networks of close relationships, albeit varying degrees between the voluntary associations. The overall education homophily is stronger in close relationships networks compared to HANs, with some variability between the associations. In the mixed-gender voluntary association, gender homophily is stronger in HANs than networks of close ties. Descriptive findings barely suggest experiential homophily to be apparent in both networks, as the homophily measures based on mental or physical health are all close to zero.

4.5.2 Hypothesis testing

Table 4-5 shows the results of the ERGMs, the average marginal effects, their corresponding delta standard errors, and the scaled average marginal effects (Duxbury, 2023). The theoretically relevant coefficients of the scaled AMEs are visually presented in Figure 4-2. Note that the confidence intervals refer to testing the predictions to be equal to 0, rather than referring to the significance level of the comparisons.

Table 4-5 Average marginal effects (AME) of exponential random graph models (ERGMs) for HAN and network of close ties

	Health advice network		**Network of close ties**	
Parameter	**AME**	**Scaled AME**	**AME**	**Scaled AME**
Mutual	0.009** (0.003)	22.243	0.008** (0.003)	10.959
GWESP (decay=0.5)	0.008*** (0.001)	18.115	0.024*** (0.001)	34.28
GWDSP (decay=0.5)	-0.001** (<0.001)	-2.329	-0.002*** (<0.001)	-3.24
Entrainment: close tie/ health advice	0.032*** (0.001)	76.529	0.045*** (0.002)	63.737
Entrainment: kin	0.023*** (0.004)	55.287	0.017*** (0.004)	24.068
Poor physical health: send	-0.003* (0.001)	-7.143	0.001 (0.001)	1.399
Poor physical health: receive	-0.001 (0.001)	-1.977	0.003* (0.001)	3.586
Same physical health	0.002† (0.001)	5.316	0.001 (0.001)	0.762
Poor mental health: send	-0.002 (0.002)	-5.282	<0.001 (0.002)	-0.091
Poor mental health: receive	-0.001 (0.002)	-3.203	<0.001 (0.001)	-0.358
Same mental health	<0.001 (0.002)	-0.978	0.002 (0.002)	3.452
Age 45-65: send	-0.001 (0.002)	-3.417	0.001 (0.002)	1.101
Age 65+: send	<0.001 (0.002)	0.046	<0.001 (0.002)	0.347
Age 45-65: receive	0.005* (0.002)	11.913	-0.003* (0.002)	-4.596
Age 65+: receive	0.007** (0.002)	17.327	-0.005** (0.002)	-7.669
Same age group	0.003* (0.001)	7.134	0.001 (0.001)	2.021
Education middle: send	-0.002 (0.002)	-4.589	-0.002 (0.002)	-2.414
Education high: send	-0.003† (0.002)	-6.545	-0.001 (0.001)	-1.24
Education middle: receive	0.001 (0.002)	2.277	<0.001 (0.002)	0.524
Education high: receive	0.002 (0.002)	5.685	-0.003† (0.002)	-3.737
Same education	0.001 (0.001)	2.987	0.002 (0.001)	2.208
Female: send	<0.001 (0.003)	-0.598	0.002 (0.002)	2.61
Female: receive	0.005* (0.003)	13.232	-0.002 (0.002)	-3.126

	Health advice network		Network of close ties	
Parameter	**AME**	**Scaled AME**	**AME**	**Scaled AME**
Same gender	0.01*** (0.002)	23.507	0.006* (0.002)	8.001
Employment health sector: receive	0.007*** (0.001)	16.615	-0.002 (0.002)	-3.052
N ties	6,716		6,716	
Nested in nodes	143		143	

Note. —Delta standard errors (Duxbury, 2019) are reported in parentheses. Scaled AME are AME divided by the weighted network density and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AME by 100 to provide a measure capturing the percentage change of the baseline probability.
*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*

Transitivity

In keeping with our theoretical expectations, the results indicated that both network types were marked by transitive closure. As expected and descriptively suggested, transitive closure was more pronounced in networks of close relationships as compared with HANs (H1). This indicates that potential information sharing reaches beyond immediate, local interactions in HANs.

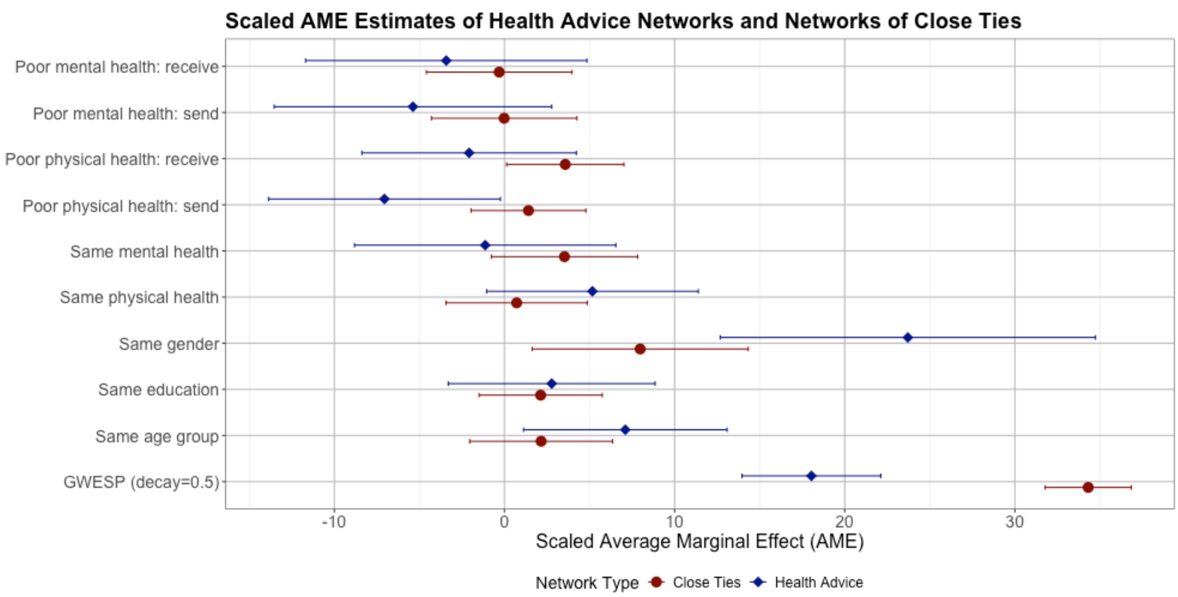


Figure 4-2 Scaled AME of the health advice network and network of close ties; Note: only theoretically relevant coefficients of M1 are displayed here; confidence intervals refer to testing the predictions to be equal to 0 and do not refer to the significance

Homophily

We expected that both networks would be characterized, to a similar extent, by homophily with respect to gender, age, and education (H2). Our results indicated that HANs exhibited gender and age homophily, but not educational homophily, whereas networks of close ties did not seem to be segregated along any social category. Networks of close ties initially appeared to be segregated with respect to gender; however, when examining the only mixed-gender club separately, no such effect was evident (see Table A4-6). This initial finding (see Table 4-5) was an artefact driven by the two other male-only networks.

More specifically, having the same gender increased the probability of forming a health advice tie by 26% (see Table A4-6), whereas being in the same age group increased the probability of forming a health advice tie by 7% (see Table 4-5). The gender and age homophily effects were constant, albeit varying model specifications (see Appendix, Table A4-4, Table A4-5). No educational homophily was evident in HANs.

Interestingly, age was predictive of receiving nominations in both network types. Whereas older people were more likely to be perceived as health advisor, they were less likely to be nominated as a close tie. Being 45–65 years old or older than 65 increased the probability of being perceived as health advisor by 12% or 17%, respectively, and it decreased the probability of being nominated as a close tie by 5% or 8%, respectively (see Table 4-5). Furthermore, women did not perceive significantly more network members as health advisors than men did, but they had a 33% higher probability of being nominated as health advisor, compared to men (see Table A4-6).

Network structure and health

When focusing on the conditions that make perceptions of health-related advice more likely, we expected individuals with poor health to have fewer network partners in close relationships, but more in health advice, and that this effect would be more pronounced among those with poor physical health than those with poor mental health (H3a). Contrary to our expectations, neither individuals with poor physical nor those with poor mental health were more or less likely to be perceived as health advisor, compared to healthy individuals. However, those with poor physical health had a 4% increased probability of being nominated as a close tie. Furthermore, we expected that individuals with poor health would nominate fewer close relationships but more health advisors, although the degree of this effect would vary according to health condition (H3b). There was no association with close ties, and we found people with poor mental health to be not more or less likely to perceive others as health advisors than those in good mental health. Contrary to our expectations, less physically healthy respondents perceived significantly fewer health advice partners. Poor physical health decreased the probability of nominating health advisors by 7% (see Table 4-5). Additionally, we found suggestive evidence for experiential homophily among those in poor physical health (H3c). Sharing the same physical health status increases the probability of forming a health advice tie by 5% (see Table 4-5). However, this evidence does not necessarily hold across model specifications and should thus, be interpreted as suggestive rather than definite evidence (see Table A4-4).

4.5.3 Goodness of fit and alternative model specifications

We evaluated GOF for all models by simulating networks based on estimated ERGMs and comparing their degree, edgewise-shared partner, and geodesic distance statistics with the observed statistics in the corresponding network (Hunter et al., 2008). Figure A4-1 shows the model fit for the HANs and Figure A4-2 for the network of close relationships, respectively. In summary, results indicated that the GOF for the degree distribution, edgewise-shared partners, and geodesic distances was sufficient.

For the estimation process, we also estimated a variety of specifications under different settings. The effects were largely stable across models with different model specifications (see Appendix, Table A4-4, Table A4-5). However, models that did not account for network endogenous effects overestimated homophily effects in close tie networks. Once we accounted for higher structural factors, the effects become insignificant. This discrepancy highlights that network-endogenous effects in sociometric data—such as mutual ties and triadic closure—play a significant role in explaining the observed patterns of homophily among close tie networks.

4.6 Discussion

This study aimed to describe the self-organizing principles of HANs through a comparison with close relationship networks. Previous research has highlighted the importance of HANs to health outcomes (Perry & Pescosolido, 2010, 2015; Schafer, 2013) and emphasized their similarities with close relationship networks. The structural anatomy of HANs, however, has received little theoretical and empirical consideration until now.

Our study demonstrates that perceptions of health advice constitute a distinct relational process that exhibits different structural patterns than networks of close relationship. Similar to previous studies (Small, 2013), we found that a substantial share (16%) of all ties is exclusively characterized by health advice, without the presence of a close relationship. This supports the notion that advice relationships are function specific and goal oriented (Perry & Pescosolido, 2010; Small, 2013), which is to say that people would also seek advice from others with whom they have no strong personal connection. Additionally, this finding extends Small's (2009) argument that also non-institutional settings, such as voluntary associations, can serve as unexpected conduits for valuable resources. In this regard, voluntary associations bear similarities to urban communes (Martin et al., 2001), which provide structured yet informal social environments where relationships evolve organically and serve multiple functions beyond their explicit purpose. Individuals do not always actively seek health-related advice, yet they perceive the possibility to obtain health-related advice also in casual or situational interactions within these associations. This suggests that voluntary associations play a crucial role in expanding access to diverse health information, beyond the boundaries of close personal networks. Moreover, we found that homophily in sociodemographic characteristics and individual health is associated with variations in the tendency to perceive others as health advisors. People's perceptions in obtaining health advice are thus shaped by their personal attributes, as well as by the social structure inherent to dyadic ties and local communities.

4.6.1 Theoretical implications

Based on the transitive closure common to various networks (Coleman, 1968; Ellwardt et al., 2012; Kilduff & Krackhardt, 1994; McFarland et al., 2014; Moody, 2001; Vörös et al., 2021; Wimmer & Lewis, 2010), we expected transitive closure in HANs, albeit to a lesser extent than in networks of close relationships, due to the broader scope of interactions (Small, 2017). In keeping with our expectations, we find that perceived health advice extends beyond close social circles. Hence, advice networks may form around needs and availability, rather than preexisting strong ties (Small, 2017; Small et al., 2015). In contrast to clustered close relationship networks—reinforcing existing knowledge through tightly knit connections (Burt, 1992; Granovetter, 1973)—lower transitive closure in HANs connects a broader range of people and thereby facilitates the flow of novel and diverse advice. This is particularly beneficial where access to up-to-date, accurate, and specialized information and advice can meaningfully impact health outcomes.

Contrary to theoretical expectations (McPherson et al., 2001) and previous descriptive analyses, which suggest no segregation along social categories in people experiencing an acute health crisis (Perry & Pescosolido, 2010), we found homophily with respect to gender and age in HANs. These mostly salient characteristics may serve as a proxy for shared experiences and increase comfort in seeking health advice, as previous research has indicated (Edwards et al., 2021). In addition, in our study, women were more likely to be perceived as health advisors. This is in keeping with previous research that identified women as more willing and effective discussion partners and sources of social support than men (Beutel & Marini, 1995; Fischer, 1982; Perry & Pescosolido, 2010; Wellman & Frank, 2001).

Our results indicating no homophily in networks of close relationships contrast with previous research on gender homophily in school settings (McMillan, 2022; Shrum et al., 1988; Stehlé et al., 2013) and the workplace (Mollenhorst et al., 2008). However, the dynamics of social network segregation may vary by context. The voluntary nature of the associations in our sample comes with less formalized, self-selected social environments, with greater individual agency in forming social connections (Rawlings et al., 2023), and—also based on the older age—members may be more open to mingling across gender boundaries. Similar to findings on ethnic segregation as an unintended byproduct of opinion homophily in schools (Stark & Flache, 2012), in this context, too, close relationships may be driven by shared interests rather than demographic similarities. Voluntary associations may promote a more inclusive environment in which members connect through joint activities, rather than segregating along the lines of gender, age, and education.

Further, we were interested in the conditions that make health advice perceptions more likely – particularly when involving weak ties. Based on the Network Episode Model (Pescosolido, 1992), we expected individuals with poor health to receive fewer nominations and nominate fewer network partners as close relationships, but perceive, and be perceived more as health advisors. Our results support the notion that social integration into different networks varies by health condition. Surprisingly, we found individuals in poor health to be less likely to nominate health advisors, and this effect was more pronounced among those with poor physical health than those with poor mental health. This suggests that obtaining health advice when in poor health is not as common contexts of voluntary associations, perhaps because of the fear of stigmatization that visible illnesses carry (Link & Phelan, 2001). Moreover, individuals with specific health problems may not perceive others as knowledgeable about their condition or may have already experienced unhelpful advice. In other words, shared activity does not automatically imply willingness—or social openness—to obtain advice about sensitive matters, even perceiving advisors.

Further, the findings imply that stigma operates differently for physical versus mental health. Individuals with poor physical health seem to be more likely to be nominated as a close tie as compared with healthy individuals, whereas there is no difference in likelihood of being nominated as a close tie between those with poor mental health and those with good mental health. This contrasts with research on adolescents, which found that health factors, particularly those that are both stigmatized and visible, influence friendship formation (Ali et al., 2011; Crosnoe et al., 2008). This discrepancy in findings suggests that unlike adolescents, older adults may not view poor health as a relevant determinant of close relationships. Older individuals may be less concerned about the implications of poor health for their reputation, perhaps because physical limitations are more prevalent and socially normalized within this population. Again, voluntary associations may serve as important venues for social participation, even for those with poor health, providing a sense of inclusion and community, despite physical health challenges.

Contrary to previous research focusing on adolescents (Crosnoe et al., 2008; Hogue & Steinberg, 1995; Schaefer et al., 2011), retirement communities (Schafer, 2016), and egocentric

HANs (Perry & Pescosolido, 2010), we did not find experiential homophily in the HANs. This could be a byproduct of the lower tendency of individuals in poor health to perceive health advisors. Another explanation relates to how HANs are measured—as reflecting perceived rather than received informational support. When considering perceived sensitive exchanges, individuals may not differentiate between others based on shared health status. Also recall that participation in our study and membership in these associations required a minimal level of mobility, meaning that severely impaired people were excluded. This sample selectivity may have led to a more homogeneous group in terms of health and fewer shared critical experiences.

4.6.2 Limitations and future research

A limitation that our investigation shares with other network studies is the fact that it is bound to a particular setting (Ellwardt et al., 2012; Schafer, 2016; Vörös et al., 2021; Yap & Harrigan, 2015), thus limiting the generalizability of our results. Case studies, by design, offer rich contextual insights but often do so at the expense of broad applicability. In our case, we examine members of voluntary associations, a group that is likely to be more socially integrated than the general population. Furthermore, carnival clubs may attract individuals who identify closely with local cultural and linguistic traditions, potentially reinforcing a distinctive social composition. Notably, only three percent of the study population was born outside present-day Germany, suggesting a marked underrepresentation of migrants relative to national demographics (Zensus 2022, 2024). While ethnicity is often a network segregating factor (Glitz, 2014; Hu et al., 2022; Kroneberg & Wittek, 2023; Wittek et al., 2020), it appears to be a negligible factor within these carnival clubs. Although our focus was on complete networks, we lack information about other perceived advisors outside these networks, including spouses, children, or friends. Previous research has shown that when examined egocentrically, HANs often consist of core supporters (Perry & Pescosolido, 2010), suggesting that close ties are key. However, we believe in the added benefit of researching local communities beyond the personal network, because in our data, both types of ties coincided in only in 34% of cases.

Another limitation lies in the quantitative study design, which provided no data on why some people are more likely to be perceived as health advisors than others. Integrating qualitative evidence in future research may contribute to a more nuanced understanding of perceptions about, and ultimately, whom to turn to to receive informational support among older and middle-aged adults.

A third limitation is the relatively small sample size—only three voluntary associations with 45–56 members each—which affects statistical power. However, it is important to emphasize that the ERGM method relies on ties as the primary data unit. Additionally, in the early phase of social network analysis, studies with similar sample sizes successfully tested hypotheses (Breiger, 1974; Burt, 1973; Freeman, 1978; White et al., 1976), reinforcing the validity of our approach. Furthermore, because smaller samples make it more challenging to achieve statistical significance, any significant findings are likely to be robust, reflecting a conservative bias rather than an overestimation of effects.

A fourth limitation concerns other important mechanisms in social networks—specifically, reciprocity and popularity—that we did not explore in depth in this study (Rivera et al., 2010). While we did include reciprocity in our models and considered popularity as part of our iterative modeling strategy (see Table 4-2), these mechanisms were not central to our analysis. Descriptively, we observed lower levels of reciprocity in HAN compared to close-tie networks, although results from more advanced models (e.g., ERGMs) were less conclusive. Ultimately, our focus was on mechanisms—such as transitivity and homophily—that showed consistency across descriptive statistics and multivariate modeling. Future research should more systematically examine how further network mechansism, such as reciprocity and popularity, shape HANs.

A fifth limitation concerns the cross-sectional nature of our analyses. The present study identified structural features of HANs and compared them with the structural anatomy of close relationships. Future research may take our study as a starting point and investigate the relational dynamics between networks and health status. For example, longitudinal models would allow to disentangle whether people influence each other in their health behaviors and outcomes or whether they select each other as advisors based on their health status. We know from previous research that changes in social networks shape individual health, and vice versa (Haas et al., 2010; K. P. Smith & Christakis, 2008). Understanding these temporal dynamics could help to identify members at risk of social exclusion or unhealthy behaviors, as well as to design interventions to support healthy aging and social integration in later life.

Importantly, carnival clubs exemplify a compelling yet understudied form of voluntary, community-based participation. Although this research focuses on one specific setting, the findings likely extend to many types of voluntary associations. With tens of millions involved in Germany and the U.S. alone (AmeriCorps, 2024; Priemer et al., 2019), voluntary engagement affects a substantial portion of the population across the world. This widespread involvement highlights the importance of voluntary contexts for studying social networks, health, and aging—particularly as older adults often engage in formal volunteering to sustain social ties and reduce loneliness (Donnelly & Hinterlong, 2010; Jongenelis et al., 2022). Given their meaningful, long-term, and self-selected nature, such associations may serve as valuable sites for public health initiatives.

Taken together, we conclude that voluntary associations may exhibit unanticipated gains (Small, 2009), as they provide inclusive spaces where individuals can engage socially with both close and distant confidents without fear of being marginalized based on their health. Putnam (2001) has emphasized the role of civic engagement in fostering social trust and community bonds. Voluntary associations like those in our study may help transcend traditional demographic divides, and ultimately contribute to public health and social cohesion.

4.7 References

Abbott, K. M., Bettger, J. P., Hanlon, A., & Hirschman, K. B. (2012). Factors associated with health discussion network size and composition among elderly recipients of long-term services and supports. *Health Communication*, *27*(8), 784–793. https://doi.org/10.1080/10410236.2011.640975

Ali, M. M., Amialchuk, A., & Rizzo, J. A. (2011). The influence of body weight on social network ties among adolescents. *Economics & Human Biology*, *10*(1), 20–34. https://doi.org/10.1016/j.ehb.2011.10.001

AmeriCorps. (2024). *More than 75.7 million people volunteered in America, AmeriCorps Reports*. AmeriCorps. https://americorps.gov/newsroom/press-release/more-757-million-people-volunteered-america-americorps-reports

Aral, S. (2016). The future of weak ties. *American Journal of Sociology*, *121*(6), 1931–1939. https://doi.org/10.1086/686293

Bearman, P. S., Moody, J., & Stovel, K. (2004). Chains of affection: The structure of adolescent romantic and sexual networks. *American Journal of Sociology*, *110*(1), 44–91. https://doi.org/10.1086/386272

Beck, A. T. (1967). *Depression.* Harper and Row.

Beck, A. T. (1979). *Cognitive therapy and the emotional disorders*. Penguin Publishing Group.

Berger, C., & Dijkstra, J. K. (2013). Competition, envy, or snobbism? How popularity and friendships shape antipathy networks of adolescents. *Journal of Research on Adolescence*, *23*(3), 586–595. https://doi.org/10.1111/jora.12048

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social Science & Medicine*, *51*(6), 843–857. https://doi.org/10.1016/S0277-9536(00)00065-4

Beutel, A. M., & Marini, M. M. (1995). Gender and values. *American Sociological Review*, *60*(3), 436. https://doi.org/10.2307/2096423

Breiger, R. L. (1974). The duality of persons and groups. *Social Forces*, *53*(2), 181. https://doi.org/10.2307/2576011

Bruch, E., & Newman, M. (2019). Structure of online dating markets in U.S. cities. *Sociological Science*, *6*, 219–234. https://doi.org/10.15195/v6.a9

Bunger, A. C., Doogan, N., Hanson, R. F., & Birken, S. A. (2018). Advice-seeking during implementation: A network study of clinicians participating in a learning collaborative. *Implementation Science*, *13*(1), 101. https://doi.org/10.1186/s13012-018-0797-7

Burt, R. S. (1973). The differential impact of social integration on participation in the diffusion of innovations. *Social Science Research*, *2*(2), 125–144. https://doi.org/10.1016/0049-089X(73)90015-X

Burt, R. S. (1992). *Structural holes: The social structure of competition*. Harvard University Press.

Cacioppo, J. T., & Cacioppo, S. (2014). Social relationships and health: The toxic effects of perceived social isolation. *Social and Personality Psychology Compass*, *8*(2), 58–72. https://doi.org/10.1111/spc3.12087

Centola, D., & Van De Rijt, A. (2015). Choosing your network: Social preferences in an online health community. *Social Science & Medicine*, *125*, 19–31. https://doi.org/10.1016/j.socscimed.2014.05.019

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, *357*(4), 370–379. https://doi.org/10.1056/NEJMsa066082

Coleman, J. S. (1968). Equality in educational opportunity. *Equity & Excellence in Education*, *6*(5), 19–28. https://doi.org/10.1080/0020486680060504

Crawford, J. R., & Henry, J. D. (2004). The Positive and Negative Affect Schedule (PANAS): Construct validity, measurement properties and normative data in a large non-clinical sample. *British Journal of Clinical Psychology*, *43*(3), 245–265. https://doi.org/10.1348/0144665031752934

Crosnoe, R., Frank, K., & Mueller, A. S. (2008). Gender, body size and social relations in American high schools. *Social Forces*, *86*(3), 1189–1216. https://doi.org/10.1353/sof.0.0004

Donnelly, E. A., & Hinterlong, J. E. (2010). Changes in social participation and volunteer activity among recently widowed older adults. *The Gerontologist*, *50*(2), 158–169. https://doi.org/10.1093/geront/gnp103

Dunn, A. G., Surian, D., Leask, J., Dey, A., Mandl, K. D., & Coiera, E. (2017). Mapping information exposure on social media to explain differences in HPV vaccine coverage in the United States. *Vaccine*, *35*(23), 3033–3040. https://doi.org/10.1016/j.vaccine.2017.04.060

Duxbury, S. W. (2023). The problem of scaling in exponential random graph models. *Sociological Methods & Research*, *52*(2), 764–802. https://doi.org/10.1177/0049124120986178

Duxbury, S. W., & Wertsching, J. (2023). Scaling bias in pooled exponential random graph models. *Social Networks*, *74*, 19–30. https://doi.org/10.1016/j.socnet.2023.02.003

Edwards, A. L., Shaw, P. A., Halton, C. C., Bailey, S. C., Wolf, M. S., Andrews, E. N., & Cartwright, T. (2021). "It just makes me feel a little less alone": A qualitative exploration of the podcast Menopause: Unmuted on women's perceptions of menopause. *Menopause*, *28*(12), 1374–1384. https://doi.org/10.1097/GME.0000000000001855

Ellwardt, L., Steglich, C., & Wittek, R. (2012). The co-evolution of gossip and friendship in workplace social networks. *Social Networks*, *34*(4), 623–633. https://doi.org/10.1016/j.socnet.2012.07.002

Engstler, H., Stuth, S., Lozano Alcántara, A., Luitjens, M., Klaus, D., Schwichtenberg-Hilmert, B., Behaghel, C. F., Kortmann, L., Martin, J., Drewitz, M., & Körber, M. (2022). *German Ageing Survey—Deutscher Alterssurvey: Documentation of instruments and* *variables – Instrumenten- und Variablendokumentation*. German Centre of Gerontology – Deutsches Zentrum für Altersfragen.

Federal Institute for Vocational Education and Training. (2024). *Comparative Analysis of Social Mobility in Industrial Nations (CASMIN)*. https://metadaten.bibb.de/en/classification/detail/16

Feld, S. L. (1981). The focused organization of social ties. *American Journal of Sociology*, *86*(5), 1015–1035. https://doi.org/10.1086/227352

Fischer, C. S. (1982). *To dwell among friends: Personal networks in town and city*. University of Chicago Press.

Freeman, L. C. (1978). Segregation in social networks. *Sociological Methods & Research*, *6*(4), 411–429. https://doi.org/10.1177/004912417800600401

Galenkamp, H., & Deeg, D. J. H. (2016). Increasing social participation of older people: Are there different barriers for those in poor health? Introduction to the special section. *European Journal of Ageing*, *13*(2), 87–90. https://doi.org/10.1007/s10433-016-0379-y

Glitz, A. (2014). Ethnic segregation in Germany. *Labour Economics*, *29*, 28–40. https://doi.org/10.1016/j.labeco.2014.04.012

Gould, R. V. (2002). The origins of status hierarchies: A formal theory and empirical test. *American Journal of Sociology*, *107*(5), 1143–1178. https://doi.org/10.1086/341744

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380. https://doi.org/10.1086/225469

Greenfield, E. A., & Marks, N. F. (2004). Formal volunteering as a protective factor for older adults' psychological well-being. *The Journals of Gerontology Series B*, *59*(5), S258–S264. https://doi.org/10.1093/geronb/59.5.S258

Haas, S. A., Schaefer, D. R., & Kornienko, O. (2010). Health and the structure of adolescent social networks. *Journal of Health and Social Behavior*, *51*(4), 424–439. https://doi.org/10.1177/0022146510386791

Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., & Morris, M. (2008). statnet: Software tools for the representation, visualization, analysis and simulation of network data. *Journal of Statistical Software*, *24*(1), 1–11. https://doi.org/10.18637/jss.v024.i01

Heider, F. (1958). *The psychology of interpersonal relation*. John Wiley & Sons.

Hogue, A., & Steinberg, L. (1995). Homophily of internalized distress in adolescent peer groups. *Developmental Psychology, 31*(6), 897–906. https://doi.org/10.1037/0012-1649.31.6.897

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *PLoS Medicine*, *7*(7), e1000316. https://doi.org/10.1371/journal.pmed.1000316

Hu, L., Moayyed, H., & Frank, N. (2022). Racial/ethnic and class segregation at workplace and residence: A Los Angeles case study. *Journal of Urban Affairs*, *44*(7), 907–925. https://doi.org/10.1080/07352166.2020.1782224

Hunter, D. R. (2007). Curved exponential family models for social networks. *Social Networks*, *29*(2), 216–230. https://doi.org/10.1016/j.socnet.2006.08.005

Hunter, D. R., Handcock, M. S., Butts, C. T., Goodreau, S. M., & Morris, M. (2008). ergm: A package to fit, simulate and diagnose exponential-family models for networks. *Journal of Statistical Software*, *24*(3), 1–29. https://doi.org/10.18637/jss.v024.i03

Isakov, A., Fowler, J., Airoldi, E., & Christakis, N. (2019). The structure of negative social ties in rural village networks. *Sociological Science*, *6*, 197–218. https://doi.org/10.15195/v6.a8

Jongenelis, M. I., Jackson, B., Newton, R. U., & Pettigrew, S. (2022). Longitudinal associations between formal volunteering and well-being among retired older people: Follow-up results from a randomized controlled trial. *Aging & Mental Health*, *26*(2), 368–375. https://doi.org/10.1080/13607863.2021.1884845

Kawachi, I., & Berkman, L. F. (2001). Social ties and mental health. *Journal of Urban Health*, *78*(3), 458–467. https://doi.org/10.1093/jurban/78.3.458

Kilduff, M., & Krackhardt, D. (1994). Bringing the individual back in: A structural analysis of the internal market for reputation in organizations. *Academy of Management Journal*, *37*(1), 87–108. https://doi.org/10.2307/256771

Kim, M., & Fernandez, R. M. (2023). What makes weak ties strong? *Annual Review of Sociology*, *49*(1), 177–193. https://doi.org/10.1146/annurev-soc-030921-034152

Kreager, D. A., Young, J. T. N., Haynie, D. L., Schaefer, D. R., Bouchard, M., & Davidson, K. M. (2021). In the eye of the beholder: Meaning and structure of informal status in women's and men's prisons. *Criminology*, *59*(1), 42–72. https://doi.org/10.1111/1745-9125.12260

Kroneberg, C., & Wittek, M. (2023). The ethnic lens: Social networks and the salience of ethnicity in the school context. *Sociological Science*, *10*, 613–639. https://doi.org/10.15195/v10.a22

Kuiper, J. S., Zuidersma, M., Zuidema, S. U., Burgerhof, J. G. M., Stolk, R. P., Oude Voshaar, R. C., & Smidt, N. (2016). Social relationships and cognitive decline: A systematic review and meta-analysis of longitudinal cohort studies. *International Journal of Epidemiology*, 1169–1206. https://doi.org/10.1093/ije/dyw089

Kuiper, J., Zuidersma, M., Voshaar, R., Zuidema, S., van den Heuvel, E., Stolk, R., & Smidt, N. (2015). Social relationships and risk of dementia: A systematic review and meta-analysis of longitudinal cohort studies. *Ageing Research Reviews*, *22*, 39–57. https://doi.org/10.1016/j.arr.2015.04.006

Lenkewitz, S., & Wittek, M. (2022). Social networks and educational decisions: Who has access to social capital and for whom is it beneficial? *KZfSS Kölner Zeitschrift Für Soziologie Und Sozialpsychologie*, *74*(4), 437–472. https://doi.org/10.1007/s11577-022-00866-z

Link, B. G. (1987). Understanding labeling effects in the area of mental disorders: an assessment of the effects of expectations of rejection. *American Sociological Review*, *52*(1), 96–112. https://doi.org/10.2307/2095395

Link, B. G., Cullen, F. T., Struening, E., Shrout, P. E., & Dohrenwend, B. P. (1989). A Modified Labeling Theory Approach to Mental Disorders: An Empirical Assessment. *American Sociological Review*, *54*(3), 400–423. https://doi.org/10.2307/2095613

Link, B. G., & Phelan, J. C. (2001). Conceptualizing stigma. *Annual Review of Sociology*, *27*(1), 363–385. https://doi.org/10.1146/annurev.soc.27.1.363

Lusher, D., Koskinen, J., & Robins, G. (Eds.). (2013). *Exponential random graph models for social networks: Theory, methods, and applications*. Cambridge University Press.

Marsden, P. V. (1987). Core discussion networks of Americans. *American Sociological Review*, *52*(1), 122–131. https://doi.org/10.2307/2095397

Martin, J. L. (2009). *Social structures*. Princeton University Press.

Martin, J. L., Yeung, K.-T., & Zablocki, B. D. (2001). The urban communes data set. *Connections, 24*(2), 54–58.

McFarland, D. A., Jurafsky, D., & Rawlings, C. (2013). Making the connection: Social bonding in courtship situations. *American Journal of Sociology*, *118*(6), 1596–1649. https://doi.org/10.1086/670240

McFarland, D. A., Moody, J., Diehl, D., Smith, J. A., & Thomas, R. J. (2014). Network ecology and adolescent social structure. *American Sociological Review*, *79*(6), 1088–1121. https://doi.org/10.1177/0003122414554001

McMillan, C. (2022). Strong and weak tie homophily in adolescent friendship networks: An analysis of same-race and same-gender ties. *Network Science*, *10*(3), 283–300. https://doi.org/10.1017/nws.2022.24

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Mollenhorst, G., Völker, B., & Flap, H. (2008). Social contexts and personal relationships: The effect of meeting opportunities on similarity for relationships of different strength. *Social Networks*, *30*(1), 60–68. https://doi.org/10.1016/j.socnet.2007.07.003

Moody, J. (2001). Race, school integration, and friendship segregation in America. *American Journal of Sociology*, *107*(3), 679–716. https://doi.org/10.1086/338954

Newman, M. E. J. (2001). The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences*, *98*(2), 404–409. https://doi.org/10.1073/pnas.98.2.404

Perkins, J. M., Subramanian, S. V., & Christakis, N. A. (2015). Social networks and health: A systematic review of sociocentric network studies in low- and middle-income countries. *Social Science & Medicine*, *125*, 60–78. https://doi.org/10.1016/j.socscimed.2014.08.019

Perry, B. L., & Pescosolido, B. A. (2010). Functional specificity in discussion networks: The influence of general and problem-specific networks on health outcomes. *Social Networks*, *32*(4), 345–357. https://doi.org/10.1016/j.socnet.2010.06.005

Perry, B. L., & Pescosolido, B. A. (2015). Social network activation: The role of health discussion partners in recovery from mental illness. *Social Science & Medicine*, *125*, 116–128. https://doi.org/10.1016/j.socscimed.2013.12.033

Pescosolido, B. A. (1992). Beyond rational choice: The social dynamics of how people seek help. *American Journal of Sociology*, *97*(4), 1096–1138. https://doi.org/10.1086/229863

Priemer, J., Bischoff, A., Hohendanner, C., Krebstakies, R., Rump, B., & Schmitt, W. (2019). Organisierte Zivilgesellschaft. In H. Krimmer (Ed.), *Datenreport Zivilgesellschaft* (1st ed, pp. 7–54). Springer Fachmedien Wiesbaden.

Putnam, R. D. (2001). *Bowling alone: The collapse and revival of American community* (1. Touchstone ed). Simon & Schuster [u.a.].

Rawlings, C. M., Smith, J. A., Moody, J., & McFarland, D. A. (2023). *Network analysis: Integrating social network theory, method, and application with R* (1st ed). Cambridge University Press.

Reiner, A., & Steinhoff, P. (2024). The association of social networks and depression in community-dwelling older adults: A systematic review. *Systematic Reviews*, *13*(1), 161. https://doi.org/10.1186/s13643-024-02581-6

Rivera, M. T., Soderstrom, S. B., & Uzzi, B. (2010). Dynamics of dyads in social networks: Assortative, relational, and proximity mechanisms. *Annual Review of Sociology*, *36*(1), 91–115. https://doi.org/10.1146/annurev.soc.34.040507.134743

Robert Koch-Institut. (2018). *The subjective health of adults in Germany*. https://doi.org/10.17886/RKI-GBE-2018-073

Robins, G., & Pattison, P. (2006). *Multiple networks in organizations*. MelNet, University of Melbourne.

Salathé, M., & Bonhoeffer, S. (2008). The effect of opinion clustering on disease outbreaks. *Journal of The Royal Society Interface*, *5*(29), 1505–1508. https://doi.org/10.1098/rsif.2008.0271

Schaefer, D. R., Kornienko, O., & Fox, A. M. (2011). Misery does not love company: Network selection mechanisms and depression homophily. *American Sociological Review*, *76*(5), 764–785. https://doi.org/10.1177/0003122411420813

Schafer, M. H. (2013). Discussion networks, physician visits, and non-conventional medicine: Probing the relational correlates of health care utilization. *Social Science & Medicine*, *87*, 176–184. https://doi.org/10.1016/j.socscimed.2013.03.031

Schafer, M. H. (2016). Health as status? Network relations and social structure in an American retirement community. *Ageing and Society*, *36*(1), 79–105. https://doi.org/10.1017/S0144686X14000993

Shrum, W., Cheek, N. H., & Hunter, S. MacD. (1988). Friendship in school: Gender and racial homophily. *Sociology of Education*, *61*(4), 227–239. https://doi.org/10.2307/2112441

Small, M. L. (2009). *Unanticipated gains: Origins of network inequality in everyday life*. Oxford University Press.

Small, M. L. (2013). Weak ties and the core discussion network: Why people regularly discuss important matters with unimportant alters. *Social Networks*, *35*(3), 470–483. https://doi.org/10.1016/j.socnet.2013.05.004

Small, M. L. (2017). *Someone to talk to*. Oxford University Press.

Small, M. L., Brant, K., & Fekete, M. (2024). The avoidance of strong ties. *American Sociological Review*, *89*(4), 615–649. https://doi.org/10.1177/00031224241263602

Small, M. L., Deeds Pamphile, V., & McMahan, P. (2015). How stable is the core discussion network? *Social Networks*, *40*, 90–102. https://doi.org/10.1016/j.socnet.2014.09.001

Smith, K. P., & Christakis, N. A. (2008). Social networks and health. *Annual Review of Sociology*, *34*(1), 405–429. https://doi.org/10.1146/annurev.soc.34.040507.134601

Smith, S., McFarland, D. A., Van Tubergen, F., & Maas, I. (2016). Ethnic composition and friendship segregation: Differential effects for adolescent natives and immigrants. *American Journal of Sociology*, *121*(4), 1223–1272. https://doi.org/10.1086/684032

Stark, T. H., & Flache, A. (2012). The double edge of common interest: Ethnic segregation as an unintended byproduct of opinion homophily. *Sociology of Education*, *85*(2), 179–199. https://doi.org/10.1177/0038040711427314

Stehlé, J., Charbonnier, F., Picard, T., Cattuto, C., & Barrat, A. (2013). Gender homophily from spatial behavior in a primary school: A sociometric study. *Social Networks*, *35*(4), 604–613. https://doi.org/10.1016/j.socnet.2013.08.003

Steinhoff, P., Ellwardt, L., & Wermeyer, M. (2024). Well-being in middle-aged and older adults who volunteer: A qualitative network analysis. *Aging & Mental Health*, *0*(0), 1–9. https://doi.org/10.1080/13607863.2024.2393250

Suitor, J., & Keeton, S. (1997). Once a friend, always a friend? Effects of homophily on women's support networks across a decade. *Social Networks*, *19*(1), 51–62. https://doi.org/10.1016/S0378-8733(96)00290-0

Surian, D., Nguyen, D. Q., Kennedy, G., Johnson, M., Coiera, E., & Dunn, A. G. (2016). Characterizing twitter discussions about HPV vaccines using topic modeling and community detection. *Journal of Medical Internet Research*, *18*(8), e232. https://doi.org/10.2196/jmir.6045

Thoits, P. A. (1986). Social support as coping assistance. *Journal of Consulting and Clinical Psychology*, *54*(4), 416–423. https://doi.org/10.1037/0022-006X.54.4.416

Thoits, P. A. (2011). Mechanisms linking social ties and support to physical and mental health. *Journal of Health and Social Behavior*, *52*(2), 145–161. https://doi.org/10.1177/0022146510395592

Uchino, B. N. (2009). understanding the links between social support and physical health: A life-span perspective with emphasis on the separability of perceived and received support. *Perspectives on Psychological Science*, *4*(3), 236–255. https://doi.org/10.1111/j.1745-6924.2009.01122.x

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3), 1–67. https://doi.org/10.18637/jss.v045.i03

Vega Yon, G. G., Slaughter, A., & De La Haye, K. (2021). Exponential random graph models for little networks. *Social Networks*, *64*, 225–238. https://doi.org/10.1016/j.socnet.2020.07.005

Vörös, A., Boda, Z., Elmer, T., Hoffman, M., Mepham, K., Raabe, I. J., & Stadtfeld, C. (2021). The Swiss StudentLife Study: Investigating the emergence of an undergraduate community through dynamic, multidimensional social network data. *Social Networks*, *65*, 71–84. https://doi.org/10.1016/j.socnet.2020.11.006

Waite, L. J., Laumann, E. O., Levinson, W. S., Lindau, S. T., & O'Muircheartaigh, C. A. (2007). *National Social Life, Health, and Aging Project (NSHAP): Round 1, 2005-2006: Version 10* [Dataset]. ICPSR - Interuniversity Consortium for Political and Social Research. https://doi.org/10.3886/ICPSR20541.V10

Webster, N. J., Ajrouch, K. J., & Antonucci, T. C. (2021). Volunteering and health: The role of social network change. *Social Science & Medicine*, *285*, 114274. https://doi.org/10.1016/j.socscimed.2021.114274

Wellman, B., & Frank, K. A. (2001). Network capital in a multilevel world: Getting support from personal communities. In N. Lin, K. Cook, & R. S. Burt, *Social Capital* (1st ed., pp. 233–273). Routledge. https://doi.org/10.4324/9781315129457-10

White, H. C., Boorman, S. A., & Breiger, R. L. (1976). Social structure from multiple networks. I. Blockmodels of roles and positions. *American Journal of Sociology*, *81*(4), 730–780. https://doi.org/10.1086/226141

Wills, T. A., & Shinar, O. (2000). Measuring perceived and received social support. In S. Cohen, L. G. Underwood, & B. H. Gottlieb (Eds.), *Social support measurement and intervention* (pp. 86–135). Oxford University Press. https://doi.org/10.1093/med:psych/9780195126709.003.0004

Wimmer, A., & Lewis, K. (2010). Beyond and below racial homophily: ERG Models of a friendship network documented on Facebook. *American Journal of Sociology*, *116*(2), 583–642. https://doi.org/10.1086/653658

Wittek, M., Bartenhagen, C., & Berthold, F. (2023). The development of stratification and segregation in a new scientific field: A study of collaboration among scientists in neuroblastoma research between 1975 and 2016. *Social Networks*, *72*, 80–107. https://doi.org/10.1016/j.socnet.2022.05.001

Wittek, M., Kroneberg, C., & Lämmermann, K. (2020). Who is fighting with whom? How ethnic origin shapes friendship, dislike, and physical violence relations in German secondary schools. *Social Networks*, *60*, 34–47. https://doi.org/10.1016/j.socnet.2019.04.004

Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: A meta-analysis. *Psychological Bulletin*, *139*(1), 53–80. https://doi.org/10.1037/a0028601

Yap, J., & Harrigan, N. (2015). Why does everybody hate me? Balance, status, and homophily: The triumvirate of signed tie formation. *Social Networks*, *40*, 103–122. https://doi.org/10.1016/j.socnet.2014.08.002

Young, L. E., Mayaud, J., Suen, S.-C., Tambe, M., & Rice, E. (2020). Modeling the dynamism of HIV information diffusion in multiplex networks of homeless youth. *Social Networks*, *63*, 112–121. https://doi.org/10.1016/j.socnet.2020.06.001

Zensus 2022. (2024). *2022 Census: 19% of population immigrated to Germany*. https://www.zensus2022.de/EN/News/2022_census_19_percent_of_population_immigrated_to_germany.html?utm_source=chatgpt.com

During the preparation of this work the author(s) used Cambridge Proofreading, ChatGPT and DeepL in order to refine the manuscript's language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

4.8 Appendix

Goodness of fit

Figure A4-1 Goodness of fit: Health advice network

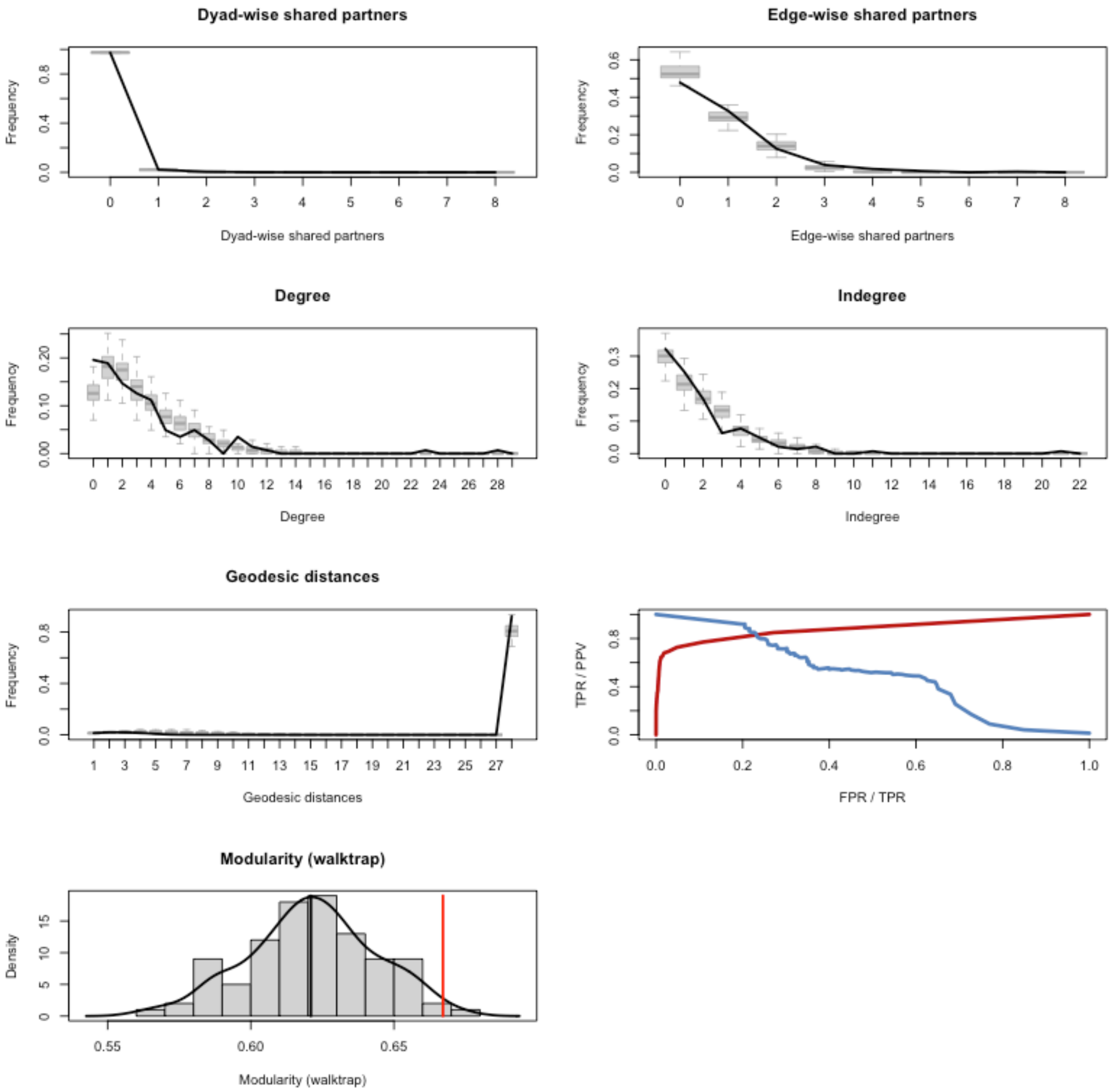
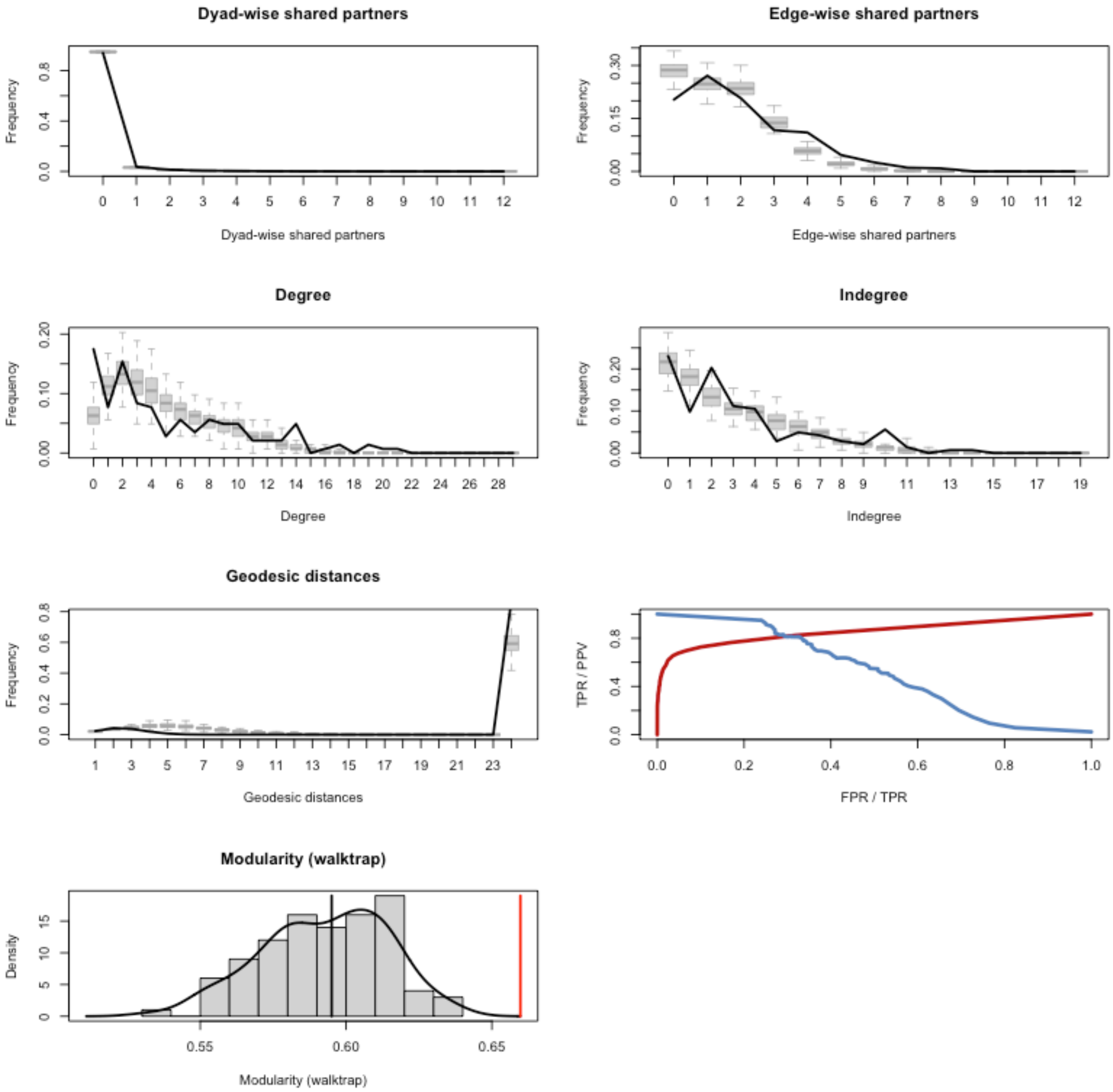


Figure A4-2 Goodness of fit: Network of close relationships



Sensitivity analyses

A first set of sensitivity analyses used other operationalizations of health variables and the network of close relationships but the same modelling approach as the main analyses. The results suggest the results to be largely robust (see Table A4-1, Table A4-2, Table A4-3). The second set of sensitivity analyses tests for different model specifications, as explained in the section concerning model specifications (see Table A4-4 for health advice network, and Table A4-5 for close tie network). The results of the mixed-gender voluntary association can be found in Table A4-6.

Table A4-1 Sensitivity analysis: Operationalization of physical health as self-rated health

	Health advice network		Network of close ties	
Parameter	**AME**	**Scaled AME**	**AME**	**Scaled AME**
Mutual	0.009** (0.003)	21.721	0.008** (0.003)	10.977
GWESP (decay=0.5)	0.007*** (0.001)	17.963	0.024*** (0.001)	34.303
GWDSP (decay=0.5)	-0.001** (<0.001)	-2.385	-0.002*** (<0.001)	-3.251
Entrainment: close tie/ health advice	0.032*** (0.001)	76.496	0.044*** (0.002)	62.954
Entrainment: kin	0.023*** (0.004)	55.639	0.018*** (0.004)	25.326
Poor physical health: send	-0.001 (0.002)	-1.546	-0.002 (0.002)	-2.248
Poor physical health: receive	0.002 (0.002)	4.037	-0.003† (0.002)	-4.639
Same physical health	0.002 (0.002)	5.281	-0.004† (0.002)	-5.639
Poor mental health: send	-0.003 (0.002)	-6.615	<0.001 (0.002)	0.088
Poor mental health: receive	-0.002 (0.002)	-3.925	<0.001 (0.002)	0.641
Same mental health	<0.001 (0.002)	-0.13	0.002 (0.002)	3.491
Age 45-65: send	-0.001 (0.002)	-3.488	0.001 (0.002)	0.806
Age 65+: send	<0.001 (0.002)	0.52	<0.001 (0.002)	0.269
Age 45-65: receive	0.005* (0.002)	11.31	-0.003† (0.002)	-4.222
Age 65+: receive	0.007** (0.002)	16.822	-0.005** (0.002)	-6.948
Same age group	0.003* (0.001)	7.176	0.002 (0.002)	2.425
Education middle: send	-0.001 (0.002)	-3.259	-0.002 (0.002)	-2.483
Education high: send	-0.002 (0.002)	-4.25	-0.001 (0.001)	-1.409
Education middle: receive	0.001 (0.002)	2.598	<0.001 (0.002)	0.433
Education high: receive	0.003 (0.002)	6.357	-0.003† (0.002)	-4.339
Same education	0.001 (0.001)	2.618	0.001 (0.001)	1.936
Female: send	<0.001 (0.003)	-0.587	0.002 (0.002)	3.006
Female: receive	0.006* (0.003)	13.46	-0.002 (0.002)	-2.978
Same gender	0.01*** (0.002)	24.348	0.006* (0.002)	8.061
Employment health sector: receive	0.007*** (0.001)	16.515	-0.002 (0.002)	-2.852

Note. —Delta standard errors (Duxbury, 2019) are reported in parentheses. Scaled AME are AME divided by the weighted network density and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AME by 100 to provide a measure capturing the percentage change of the baseline probability.
*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*

Table A4-2 Sensitivity analysis: Operationalization of mental health as loneliness

	Health advice network		Network of close ties	
Parameter	**AME**	**Scaled AME**	**AME**	**Scaled AME**
Mutual	0.009*** (0.003)	22.856	0.008** (0.003)	11.186
GWESP (decay=0.5)	0.008*** (0.001)	18.833	0.024*** (0.001)	34.075
GWDSP (decay=0.5)	-0.001** (<0.001)	-2.118	-0.002*** (<0.001)	-3.297
Entrainment: close tie/ health advice	0.032*** (0.002)	77.475	0.045*** (0.002)	64.2
Entrainment: kin	0.023*** (0.004)	54.983	0.017*** (0.004)	24.978
Poor physical health: send	-0.003* (0.001)	-8.375	0.001 (0.001)	1.219
Poor physical health: receive	-0.001 (0.001)	-2.039	0.002† (0.001)	3.359
Same physical health	0.002† (0.001)	5.381	0.001 (0.001)	0.791
Poor mental health: send	-0.001 (0.002)	-3.466	-0.001 (0.002)	-1.827
Poor mental health: receive	-0.001 (0.002)	-1.461	-0.001 (0.002)	-1.058
Same mental health	-0.004* (0.002)	-8.704	0.003† (0.002)	4.273
Age 45-65: send	-0.001 (0.002)	-2.499	0.001 (0.002)	1.691
Age 65+: send	<0.001 (0.002)	0.971	<0.001 (0.002)	0.493
Age 45-65: receive	0.005** (0.002)	13.25	-0.003* (0.002)	-4.341
Age 65+: receive	0.007** (0.002)	17.698	-0.005** (0.002)	-7.813
Same age group	0.003* (0.001)	6.516	0.002 (0.002)	2.169
Education middle: send	-0.002 (0.002)	-3.7	-0.001 (0.002)	-1.79
Education high: send	-0.002 (0.002)	-5.491	-0.001 (0.001)	-1.426
Education middle: receive	0.001 (0.002)	3.053	0.001 (0.002)	0.744
Education high: receive	0.003† (0.002)	7.022	-0.003† (0.002)	-4.29
Same education	0.001 (0.001)	2.852	0.002 (0.001)	2.255
Female: send	-0.001 (0.003)	-3.609	0.002 (0.002)	2.371
Female: receive	0.005† (0.003)	11.66	-0.002 (0.002)	-3.29
Same gender	0.01*** (0.002)	23.586	0.006* (0.002)	8.004
Employment health sector: receive	0.007*** (0.001)	15.846	-0.002 (0.002)	-2.781

Note. —Delta standard errors (Duxbury, 2019) are reported in parentheses. Scaled AME are AME divided by the weighted network density and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AME by 100 to provide a measure capturing the percentage change of the baseline probability.
*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*

Table A4-3 Sensitivity analysis: Operationalization of close tie network as being in contact at least once a month and respondents indicated the other person to give them great joy or great happiness

	Health advice network		Network of close ties	
Parameter	**AME**	**Scaled AME**	**AME**	**Scaled AME**
Mutual	0.011*** (0.003)	25.366	0.006* (0.003)	10.938
GWESP (decay=0.5)	0.01*** (0.001)	23.893	0.02*** (0.001)	36.376
GWDSP (decay=0.5)	-0.001*** (<0.001)	-2.854	-0.002*** (<0.001)	-2.977
Entrainment: close tie/ health advice	0.032*** (0.002)	76.961	0.038*** (0.002)	68.934
Entrainment: kin	0.025*** (0.003)	60.911	0.014*** (0.004)	25.941
Poor physical health: send	-0.002† (0.001)	-5.773	-0.001 (0.001)	-2.047
Poor physical health: receive	-0.001 (0.001)	-2.583	0.003* (0.001)	5.282
Same physical health	0.003* (0.001)	7.819	<0.001 (0.001)	-0.467
Poor mental health: send	-0.004* (0.002)	-8.826	0.002 (0.001)	3.747
Poor mental health: receive	-0.002 (0.002)	-4.68	<0.001 (0.001)	0.79
Same mental health	<0.001 (0.002)	0.958	0.002 (0.001)	2.961
Age 45-65: send	<0.001 (0.002)	-0.969	0.002 (0.002)	3.848
Age 65+: send	-0.002 (0.002)	-5.73	0.007*** (0.002)	13.159
Age 45-65: receive	0.004† (0.002)	9.294	-0.002 (0.002)	-3.55
Age 65+: receive	0.007** (0.002)	17.456	-0.007*** (0.002)	-13.575
Same age group	0.002† (0.001)	5.589	0.002 (0.001)	3.784
Education middle: send	-0.003† (0.002)	-8.05	0.001 (0.002)	1.701
Education high: send	-0.003 (0.002)	-6.203	<0.001 (0.001)	0.213
Education middle: receive	<0.001 (0.002)	1.193	-0.001 (0.002)	-1.811
Education high: receive	0.002 (0.002)	5.036	-0.003† (0.002)	-5.432
Same education	0.003* (0.001)	6.397	<0.001 (0.001)	-0.431
Female: send	-0.004 (0.003)	-9.354	0.007** (0.002)	12.144
Female: receive	0.005† (0.003)	12.251	-0.002 (0.002)	-3.277
Same gender	0.011*** (0.003)	25.366	0.007*** (0.002)	11.95
Employment health sector: receive	0.007*** (0.001)	16.3	-0.001 (0.001)	-2.058

Note. —Delta standard errors (Duxbury, 2019) are reported in parentheses. Scaled AME are AME divided by the weighted network density and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AME by 100 to provide a measure capturing the percentage change of the baseline probability.
*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*

Table A4-4 Health advice network: AME estimation results of other model specifications

Parameter	M2	M3	M4	M5	M6	M7	M8
Mutual	0.01*** (0.003)	0.008** (0.003)	0.008** (0.003)	0.008** (0.003)		0.021*** (0.003)	0.009** (0.003)
GWESP (decay=0.5)	0.007*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)		0.022*** (0.001)	0.008*** (0.001)
GWDSP (decay=0.5)	-0.001*** (<0.001)	-0.001*** (<0.001)	-0.001*** (<0.001)	-0.001*** (<0.001)		-0.002*** (<0.001)	-0.001*** (<0.001)
GWIDEG (decay=0.5)	-0.006* (0.002)						
Entrainment: close tie	0.031*** (0.001)	0.033*** (0.001)	0.033*** (0.001)	0.032*** (0.001)			0.032*** (0.001)
Entrainment: kin	0.023*** (0.004)	0.02*** (0.004)	0.021*** (0.004)	0.023*** (0.004)			0.023*** (0.004)
Poor physical health: send	-0.003* (0.001)		-0.003* (0.001)		-0.004* (0.002)		-0.003* (0.001)
Poor physical health: receive	-0.001 (0.001)		<0.001 (0.001)		0.001 (0.002)		-0.001 (0.001)
Same physical health	0.002 (0.001)		0.002† (0.001)		0.002 (0.002)		0.002 (0.001)
Poor mental health: send	-0.002 (0.002)		-0.002 (0.002)		-0.005* (0.002)		<0.001 (0.002)
Poor mental health: receive	-0.001 (0.002)		-0.001 (0.002)		-0.003 (0.002)		0.002 (0.002)
Same mental health	-0.001 (0.002)		0.001 (0.002)		0.005** (0.002)		0.001 (0.002)
Age 45-65: send	-0.001 (0.002)			-0.001 (0.002)	0.003 (0.003)		<0.001 (0.002)
Age 65+: send	0.001 (0.002)			<0.001 (0.002)	0.007** (0.003)		0.002 (0.002)
Age 45-65: receive	0.004* (0.002)			0.005** (0.002)	0.01*** (0.003)		0.005** (0.002)
Age 65+: receive	0.006** (0.002)			0.008*** (0.002)	0.014*** (0.003)		0.008*** (0.002)
Same age group	0.003* (0.001)			0.003* (0.001)	0.004* (0.002)		0.003* (0.001)
Education middle: send	-0.002 (0.002)			-0.001 (0.002)	-0.005* (0.002)		-0.001 (0.002)
Education high: send	-0.003† (0.002)			-0.001 (0.002)	-0.006** (0.002)		-0.002 (0.002)
Education middle: receive	0.001 (0.002)			0.001 (0.002)	-0.001 (0.003)		<0.001 (0.002)
Education high: receive	0.002 (0.002)			0.005** (0.002)	0.002 (0.002)		0.002 (0.002)
Same education	0.001 (0.001)			0.001 (0.001)	0.007*** (0.002)		0.001 (0.001)
Female: send	<0.001 (0.003)			-0.001 (0.002)	0.008* (0.003)		-0.001 (0.003)
Female: receive	0.005* (0.002)			0.007** (0.002)	0.013*** (0.003)		0.005* (0.003)
Same gender	0.009*** (0.002)			0.01*** (0.002)	0.019*** (0.003)		0.01*** (0.002)
Employment health sector: receive	0.006*** (0.001)						0.006*** (0.002)
Employed: receive							<0.001 (0.002)
Employed: send							<0.001 (0.002)

Note. —Delta standard errors (Duxbury, 2019) are reported in parentheses.
*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*

Table A4-5 Close tie network: AME estimation results of other model specifications

Parameter	M2	M3	M4	M5	M6	M8
Mutual	0.007** (0.003)	0.008** (0.003)	0.008** (0.003)	0.008** (0.003)		0.009** (0.003)
GWESP (decay=0.5)	0.024*** (0.001)	0.025*** (0.001)	0.025*** (0.001)	0.024*** (0.001)		0.024*** (0.001)
GWDSP (decay=0.5)	-0.002*** (<0.001)	-0.002*** (<0.001)	-0.002*** (<0.001)	-0.002*** (<0.001)		-0.002*** (<0.001)
GWIDEG (decay=0.5)	0.002 (0.003)					
Entrainment: health advice	0.045*** (0.002)	0.043*** (0.002)	0.044*** (0.002)	0.044*** (0.002)		0.044*** (0.002)
Entrainment: kin	0.017*** (0.004)	0.016*** (0.004)	0.015*** (0.004)	0.018*** (0.004)		0.017*** (0.004)
Poor physical health: send	0.001 (0.001)		0.001 (0.001)		<0.001 (0.002)	0.001 (0.001)
Poor physical health: receive	0.003* (0.001)		0.002† (0.001)		0.003 (0.002)	<0.001 (0.001)
Same physical health	<0.001 (0.001)		<0.001 (0.002)		0.001 (0.002)	0.001 (0.001)
Poor mental health: send	<0.001 (0.002)		-0.001 (0.001)		-0.006* (0.003)	0.002 (0.002)
Poor mental health: receive	<0.001 (0.002)		<0.001 (0.001)		-0.005† (0.003)	-0.002 (0.002)
Same mental health	0.002 (0.002)		0.002 (0.001)		0.009*** (0.003)	0.002 (0.002)
Age 45-65: send	0.001 (0.002)			0.001 (0.002)	0.009** (0.003)	0.002 (0.002)
Age 65+: send	<0.001 (0.002)			0.001 (0.002)	0.013*** (0.003)	0.004 (0.002)
Age 45-65: receive	-0.003* (0.002)			-0.003† (0.002)	0.005 (0.003)	-0.005*** (0.001)
Age 65+: receive	-0.005** (0.002)			-0.005** (0.002)	0.006† (0.003)	-0.007*** (0.002)
Same age group	0.001 (0.001)			0.002 (0.002)	0.004† (0.002)	0.001 (0.001)
Education middle: send	-0.002 (0.002)			-0.001 (0.002)	-0.011*** (0.003)	-0.002 (0.002)
Education high: send	-0.001 (0.001)			-0.001 (0.001)	-0.013*** (0.003)	-0.001 (0.001)
Education middle: receive	<0.001 (0.002)			<0.001 (0.002)	-0.004 (0.003)	<0.001 (0.002)
Education high: receive	-0.003† (0.002)			-0.004* (0.002)	-0.01*** (0.003)	-0.003 (0.002)
Same education	0.001 (0.001)			0.001 (0.001)	0.011*** (0.002)	0.001 (0.001)
Female: send	0.002 (0.002)			0.002 (0.002)	0.013** (0.004)	0.002 (0.002)
Female: receive	-0.002 (0.002)			-0.003 (0.002)	0.007† (0.004)	-0.002 (0.002)
Same gender	0.006* (0.002)			0.006** (0.002)	0.028*** (0.004)	0.005* (0.002)
Employment health sector: receive	-0.002 (0.002)					-0.003† (0.002)
Employed: receive						<0.001 (0.002)
Employed: send						0.003† (0.002)

Note. —Delta standard errors (Duxbury, 2019) are reported in parentheses.
*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*

Table A4-6 Mixed-gender voluntary association: AME estimation results

	Health advice network		Network of close ties	
Parameter	**AME**	**Scaled AME**	**AME**	**Scaled AME**
Mutual	0.031*** (0.009)	88.139	0.012 (0.011)	21.024
GWESP (decay=0.5)	0.006* (0.003)	18.22	0.042*** (0.004)	73.168
GWDSP (decay=0.5)	<0.001 (0.002)	0.077	-0.004** (0.001)	-6.098
Entrainment: close tie/ health advice	0.067*** (0.007)	192.109	0.106*** (0.011)	183.237
Entrainment: kin	0.039*** (0.01)	112.912	0.022† (0.012)	38.775
Poor physical health: send	0.01 (0.007)	28.661	0.008 (0.005)	14.491
Poor physical health: receive	0.009 (0.007)	25.91	-0.009 (0.006)	-16.428
Same physical health	-0.005 (0.006)	-13.065	0.002 (0.007)	3.937
Poor mental health: send	-0.001 (0.007)	-4.199	<0.001 (0.006)	-0.277
Poor mental health: receive	0.006 (0.006)	16.608	0.005 (0.006)	9.175
Same mental health	-0.003 (0.005)	-8.941	0.005 (0.006)	8.394
Age 45-65: send	-0.008 (0.008)	-24.112	0.015* (0.007)	26.054
Age 65+: send	0.005 (0.011)	15.258	-0.016 (0.013)	-28.293
Age 45-65: receive	0.015* (0.007)	43.623	-0.009 (0.008)	-15.018
Age 65+: receive	-0.016 (0.013)	-47.293	0.007 (0.009)	12.592
Same age group	0.009 (0.006)	24.399	0.004 (0.008)	6.515
Education middle: send	0.03** (0.011)	84.979	-0.013† (0.008)	-23.114
Education high: send	0.031** (0.01)	89.023	-0.019* (0.008)	-33.667
Education middle: receive	-0.014 (0.01)	-39.104	0.008 (0.009)	14.257
Education high: receive	0.015 (0.009)	41.821	-0.011 (0.007)	-18.53
Same education	-0.005 (0.006)	-13.18	0.003 (0.007)	5.706
Female: send	-0.008 (0.008)	-21.707	-0.006 (0.006)	-11.088
Female: receive	0.014† (0.007)	39.603	-0.017* (0.007)	-29.658
Same gender	0.011† (0.006)	30.799	0.002 (0.007)	3.597
Employment health sector: receive	0.017** (0.007)	49.724	0.003 (0.006)	5.084

Note. —Delta standard errors (Duxbury, 2019) are reported in parentheses. Scaled AMEs are AMEs divided by the weighted network density and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AMEs by 100 to provide a measure capturing the percentage change of the baseline probability.
*† $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$*

CHAPTER 5. MOVING BEYOND CONSTRAINED SETTINGS: HEALTH AND NETWORK DYNAMICS AMONG MIDDLE-AGED AND OLDER ADULTS IN VOLUNTARY CLUBS

Amelie Reiner & James Moody

Abstract
Social networks influence health outcomes, yet declining health can also reshape social ties. While prior research has focused on constrained settings, the impact of health on social networks in fully voluntary contexts remains underexplored. This study examines the reciprocal relationship between health and social networks in voluntary settings, assessing whether previously observed patterns persist. We analyzed three-wave longitudinal whole network data from two voluntary clubs (N = 102, mean age = 54 years) in North-Rhine Westphalia, Germany, using Stochastic Actor-Oriented Models to distinguish between selection and influence effects across self-rated, mental, and physical health measures. Our analyses suggest diverging patterns observed in more constrained settings. We found no evidence of peer influence on health across any measures. While self-rated health showed some evidence of selection effects, avoidance was limited to individuals with poor physical health. Notably, we found no evidence of withdrawal; instead, individuals with poorer health were more likely to nominate others in the network, suggesting they actively sought social connections as a compensatory strategy. These findings challenge existing assumptions about health-based network dynamics, emphasizing the need to reconsider how social networks function in voluntary contexts. Future research should explore how the degree of setting constraints shape health-related network dynamics.

Keywords: peer networks; health; network dynamics; SAOM; voluntary clubs

5.1 Background

Health is deeply social—shaped recurvisly by the structure and dynamics of our social connections. Voluntary associations—spaces where people choose to connect—offer a unique lens through which to examine how social networks shape health outcomes. Our networks not only channel communicable diseases, but are also crucial determinants of non-communicable health outcomes, such as cognitive decline (Kuiper et al., 2016), dementia (Kuiper et al., 2015), depression (Reiner & Steinhoff, 2024), and premature mortality (Holt-Lunstad et al., 2010).

Conversely, health declines can lead to social network contraction, with individuals in poor health often withdrawing from social ties, forming smaller, more localized networks, and occupying less central social positions than their healthier peers (Copeland et al., 2023; Haas et al., 2010).

Historically, much of the empirical work examining network dynamics and health has been conducted in constrained settings such as schools, workplaces, and other institutional contexts (Chancellor et al., 2017; Copeland et al., 2023; Haas et al., 2010). In these environments, social ties are often formed under implicit assumptions of compulsion and sorting—students are assigned to classes, employees to teams, and retirement residents to floors—so that entry, exit, and interaction rhythms are externally governed. In these settings, individuals are confined to a limited pool and tend to form homophilous ties with others who share similar characteristics (McPherson et al., 2001). Research has provided evidence for health-based homophily in schools (Crosnoe et al., 2008; Schaefer et al., 2011; Van Zalk et al., 2010a), workplaces (Chancellor et al., 2017), retirement residents (Schafer, 2016) and low-income senior housing (Flatt et al., 2012). Particularly in older adulthood, health often becomes a salient factor in shaping social networks, as individuals and their environments face increasing health challenges (Wrzus et al., 2013). Such mechanisms of homophilous sorting and network formation are shaped by the inherent constraints of these environments. However, these scope conditions—critical to understanding how social networks and health interact—remain underspecified in the literature.

This study asks whether the results identified in these sorts of settings hold generally in the fully voluntary contexts we study here, which have rarely been studied. While research on social networks in voluntary settings is scarce, studies on religious affiliations provides some guidance (Nam et al., 2019, 2023); though these tend to be semi-constrained by factors such as denomination and region. Fully voluntary contexts differ fundamentally from institutional contexts. They operate under continuous self-selection, as members choose whether to join and stay based on individual costs, benefits, and personal needs (Rawlings et al., 2023). Older adults in particular may actively use clubs as an agency strategy to maintain a social network and alleviate loneliness (Donnelly & Hinterlong, 2010; Jongenelis et al., 2022; Steinhoff et al., 2024). Because the very act of membership is voluntary, the feedback loop between health and social networks may play out differently than in institutional settings—both in the direction and magnitude of peer influence, and in how individuals may cope with declining health through selective compensation. This study aims to investigate these dynamics, addressing the research question: How does health shape social networks in fully voluntary settings, and vice versa?

To address this research question, we use whole network data from two clubs in North-Rhine Westphalia, Germany, and apply Stochastic Actor-Oriented Models (SAOM). This approach allows us to examine the dynamic nature of networks in relation to health while properly accounting for these higher-order structural factors. Specifically, we distinguish between selection (how health predicts tie formation) and influence (how network members affect subsequent health), as well as self-rated, mental and physical health as network processes may differ by health condition. The findings reveal a divergence from patterns observed in more constrained settings. We found no evidence of peer influence on health across all health measures. Furthermore, results suggest some sorting of social relations along the lines of self-rated health. Additionally, we find evidence for avoidance only among those in poor physical health. We observe reversed effects—instead of withdrawing, individuals in poorer health are sometimes more central within the social network, possibly leveraging these connections as a form of social compensation. This challenges existing assumptions and highlights the need to reconsider the underlying mechanisms linking health and social networks in fully voluntary contexts.

5.2 Theory

Close relationship networks consistently show patterns of segregation along various social categories, including gender, age, and educational background (McPherson et al., 2001). According to Wimmer and Lewis (2010), such segregation arises from a combination of factors: the availability of potential connections (opportunity structures), dynamics within the network itself, and individuals' tendencies to favor relationships with those who share similar social characteristics—a phenomenon known as homophily. Homophily has been found to occur among those with similar occupational statuses, gender, race and ethnic group, and beliefs and values (McPherson et al., 2001). Homophilous ties are more likely to be activated for support because similarity facilitates communication, increases predictability, promotes trust and reciprocity, and reduces conflict (McPherson et al., 2001; Suitor & Keeton, 1997). Health was also found to be an important determinant along which social networks are structured. Research has provided evidence for health-based homophily in schools (Crosnoe et al., 2008; Schaefer et al., 2011), workplaces (Chancellor et al., 2017), retirement residents (Schafer, 2016) and low-income senior housing (Flatt et al., 2012).

There are two general mechanisms that help to explain why health-based homophily is commonly observed within networks: selection and influence (McPherson et al., 2001). Selection refers to the tendency of individuals to form social ties based on personal preferences, shared characteristics, or contextual factors. In contrast, influence highlights how individuals affect each other's behaviors, attitudes, and health outcomes through ongoing social interactions. These mechanisms—selection and influence—are not mutually exclusive; together, they shape the structure and dynamics of social networks and their impact on health. While the relative importance of each mechanism may vary across contexts, much of the existing research has focused on constrained environments, such as schools or workplaces, where opportunities for tie formation are often limited by structural or institutional factors. Less is known about how these processes operate in more voluntary and self-directed environments, where individuals exercise greater agency in choosing their social connections.

5.2.1 Network selection and health

Selection processes have been particularly emphasized in the study of health-based homophily (Crosnoe et al., 2008). Scholars have observed that individuals with similar health statuses often form close ties, especially in contexts where health challenges are salient. Depressed adolescents are often avoided by peers, leaving them with few friendship options beyond others experiencing similar mental health challenges (Hogue & Steinberg, 1995; Schaefer et al., 2011). Comparable patterns have been observed among adolescents with obesity (Crosnoe et al., 2008). Among older adults, health-based homophily also emerges, as retirement residents were found to interact more frequently with peers who share similar health statuses (Schafer, 2016). Particularly in older adults, health status may become a more salient factor in determination of who is friends with whom, as individuals and their environments face increasing health challenges (Wrzus et al., 2013).

Evidence for health-based homophily has mostly been tested in constrained settings, like schools (Crosnoe et al., 2008; Schaefer et al., 2011), workplaces (Chancellor et al., 2017), retirement residents (Schafer, 2016) and low-income senior housing (Flatt et al., 2012). A key assumption underlying these settings is that individuals form social ties within a fixed pool of potential connections. This fixed pool often exhibits pre-existing demographic or socio-economic similarities due to systemic factors such as institutional policies or societal segregation (McPherson et al., 2001). Consequently, individuals are more likely to encounter others who share similar characteristics.

Additionally, external factors—such as institutional hierarchies in workplaces or assigned classrooms in schools—further segment individuals into specific subgroups, narrowing their choices for potential connections (McPherson et al., 2001; Moody, 2001). Even in voluntary settings, these constraints persist, as the options available are inherently limited. This constrained structure increases the likelihood of homophilous ties forming. Building on this theoretical foundation, we extend these expectations to health-based homophily. We posit that even in less constrained or fully voluntary settings, the general patterns of homophilous selection should hold. Based on this reasoning, we propose the following hypothesis:

Hypothesis 1 (Selection): Health similarity predicts the presence of close ties.

In general, networks reflect competing preferences to associate with individuals that are perceived as highly desirable (e.g., Martin, 2009). Individuals tend to form social ties with those perceived as successful, attractive, or in good health—traits commonly associated with higher social status within a group (Centola & Van De Rijt, 2015). Conversely, poor health is a stigmatized condition (Link & Phelan, 2001). Particularly when it is both visible and stigmatized, poor health has been shown to shape adolescents' friendship formations (Ali et al., 2011; Crosnoe et al., 2008). Similarly, research indicates that older adults experiencing depression tend to have smaller social networks (for a review, see Reiner & Steinhoff, 2024). Several mechanisms may underlie the social avoidance of individuals in poor health.

First, individuals in poor health may be viewed as less appealing companions due to their limited ability to engage consistently in shared group activities (Galenkamp & Deeg, 2016). Second, the social stigma attached to certain health conditions may lead others to avoid association with them, potentially out of concern for their own social reputation (Crosnoe et al., 2008; Haas et al., 2010). As a result, individuals in poor health may receive fewer close tie nominations from others, indicating a process of avoidance.

Hypothesis 2 (Avoidance): People in poor health will be less likely to receive close tie nominations.

In particular, we expect that those with more visible health issues will be avoided more than those with less visible health issues, which suggests a stronger effect of physical health.

Conversely, individuals experiencing poor health may engage in behaviors like concealing their condition or withdrawing from social situations, which can inadvertently contribute to their social isolation (Link, 1987; Link et al., 1989). Anticipating stigma or negative social interactions, they may withdraw themselves from social relationships as a protective strategy (Link & Phelan, 2001). This is expected to hold particularly for stigmatized conditions, mostly associated with mental health. According to the *Cognitive Theory of Depression* (Beck, 1967, 1979), distorted thought patterns can cause individuals to overlook or dismiss positive social experiences. This bias may strain relationships and contribute to social withdrawal. Similarly, diminished positive reinforcement from social interactions can intensify the withdrawal and depressive symptoms in a downward cycle (Lewinsohn, 1974). As a result, we expect individuals in poor health to send fewer close tie nominations to others, particularly those with poor mental health, indicating a process of withdrawal:

Hypothesis 3 (Withdrawal): People in poor health will be less likely to nominate others as close ties.

5.2.2 Network influence and health

The other mechanism through which health-based homophily arises is network influence. Social Contagion Theory (Christakis & Fowler, 2013) posits that individuals are influenced by the contacts surrounding them, who are themselves influenced by their surrounding contacts. This social contagion has been shown for multiple non-communicable health outcomes, including obesity, loneliness, depression, and happiness in the general population (Cacioppo et al., 2009; Christakis & Fowler, 2007; Fowler & Christakis, 2008; Rosenquist et al., 2011). While peer influence effects of physical health has mainly been attributed to the adoption of health behaviors (Christakis & Fowler, 2007), emotional contagion has been theorized to be the main driver of peer effects in mental health (Block & Burnett Heyes, 2022; Chancellor et al., 2017; Hatfield et al., 1993).

Peer influence effects in physical health have mainly been attributed to the adoption of health behaviors (Christakis & Fowler, 2007). These effects are thus expected to happen over a longer time period. Christakis and Fowler (2007) found obesity to spread through networks over the time period of 32 years. A peer influence effect of health behaviors, such as smoking (Mercken et al., 2012; Schaefer et al., 2013), eating (De La Haye et al., 2013; Hutchinson & Rapee, 2007) or exercising (De La Haye et al., 2011) has been empirically widely confirmed in school settings. Beyond adolescence, only two studies have examined peer influence on physical activity using social media linkages (Aral & Nicolaides, 2017; Franken et al., 2023). However, these studies are limited by highly selective samples consisting of health-conscious, motivated individuals who share their performance primarily to encourage and compete with one another, potentially exaggerating peer influence effects.

The main mechanism of peer effects in mental health has been emotional contagion (Hatfield et al., 1993). Positive and negative emotional states can be transferred directly from one individual to another by emotional contagion, gradually spreading through social networks (Block & Burnett Heyes, 2022; Hill et al., 2010). Emotional contagion is likely to have both unconscious and conscious elements. The unconscious element could relate to automatic mimicry (Hatfield et al., 1993) and unconsciously aligning with negative or positive thought patterns present in their social surroundings, which could be conveyed in shared conversations (Lakey & Tanner, 2013). The conscious component could be due to direct communication, as in co-rumination (Van Zalk et al., 2010b). The peer influence of emotional moods has been described to occur over a short timescale (Hill et al., 2010), while clinically relevant depressive states can also spread between contact over longer timescales (Joiner & Katz, 1999; Kensbock et al., 2022; Ueno, 2005).

Generally, health is expected to spread through the network. This phenomenon reflects health-based homophily as a result of social influence, net of selection. Therefore, we hypothesize:

Hypothesis 4 (Influence): Changes in adults' health are predicted by the average health of their close ties.

5.2.3 Study context

Much of the existing research on the relationship between social networks and health dynamics has focused on constrained settings such as schools, workplaces, and institutional environments. In these contexts, social networks are often shaped by imposed boundaries and limited pools of interaction, which can obscure the voluntary processes underlying network formation and health dynamics. However, social life also occurs in fully voluntary settings, where individuals have greater agency in choosing their social ties. This distinction is particularly relevant for older adults, who often face shrinking social networks due to retirement, health decline, and other life course transitions (Wrzus et al., 2013).

To counteract social isolation, older adults frequently turn to formal social participation, especially volunteering, as a key strategy to maintain and expand their networks and alleviate loneliness (Donnelly & Hinterlong, 2010; Jongenelis et al., 2022). Volunteering—defined as non-mandatory, unpaid work for an organization or community (Donnelly & Hinterlong, 2010)—has been widely recognized for its contributions to healthy aging. It is associated with numerous positive health outcomes, including improved self-rated health, greater life satisfaction, reduced mortality, lower levels of depressive symptoms, and decreased functional dependence (Greenfield & Marks, 2004; Webster et al., 2021).

This study focuses on carnival clubs in a region in Germany that organize annual cultural festivities around the Carnival season. Carnival is a lively and traditional festival filled with parades, music, costumes, and parties, celebrating the lead-up to Lent in the Christian calendar. Deeply rooted in the region's history and culture, it emphasizes the local dialect, customs, and a strong sense of community. Carnival clubs extend their activities beyond the carnival period, engaging members in year-round social interactions and meetings, such as organizing a summer festival, at least monthly informal gatherings and charity events. In qualitative interviews of members of carnival clubs published elsewhere (Steinhoff et al., 2024), the primary reason for joining carnival clubs was not carnival itself but rather the sense of community it provided. The two following quotes highlight the importance of carnival clubs as an active strategy to engage with others (Steinhoff et al., 2024, p. 5):

> *"Because I basically had these two centres of life, it was simply difficult to build a normal, let's say, social organisation around myself, i.e. a circle of friends, etc. [...] And basically that was one of the main arguments at the time, to look at it, to do it and say, yes, I have a circle of friends that is organised in a secondary way, so to speak." (69 years, retired, male)*

> *"I don't have that much interest in carnival. I have a great interest in the club. And that I walk through the streets and know people. [...] It's also nice to have an extended circle of acquaintances. And socialising is something I enjoy." (58 years, working, male)*

In this regard, carnival clubs facilitate the formation of a social network with minimal effort, as maintaining contacts is not contingent on continuous engagement. Additionally, members in retirement used these carnival clubs as a proactive approach to attain a sense of purpose and to compensate for the role and status loss associated with retirement. Engagement in these clubs enhanced the perception of being useful and necessary, which are crucial contributors to well-being (Steinhoff et al., 2024).

This makes them an ideal case for studying the interplay between social networks and health in voluntary settings, particularly for middle-aged and older adults. First, these associations provide a voluntary leisure setting in which informal socializing takes place in a heterogeneous group, outside the contexts of family, neighborhood, and work organizations (cf. Granovetter, 1973). Second, they often include a disproportionate share of adults in the second half of life. Third, because membership is formally defined, they offer a clearly demarcated network boundary, a crucial requirement for employing social network analysis to distinguish social selection and influence effects. Moreover, these associations persisted through social distancing measures during the Covid-19 pandemic and are accessible to everyone without members having to fulfill requirements.[5] Unlike other voluntary settings such as sports clubs or retirement homes, these clubs are less selective regarding members' health. Membership is open to all, with no health requirements for participation. Additionally, health profiles within the clubs align closely with the general German population (Robert Koch-Institut, 2018), suggesting they do not disproportionately attract healthier individuals. This inclusivity provides a

[5] In some of these clubs, women cannot be members. Here, club 1 comprise only men, whereas club 2 is mixed-gender.

unique opportunity to examine health-network interactions without a large bias of initial health-based selection.

The two carnival clubs studied differ in key ways that underscore the variability in voluntary social settings and offer insight into how these differences may shape social networks and health outcomes. The first club, an all-male organization, is characterized by stability, with an average membership duration of 19 years at baseline. Its long-standing structure and traditions reflect a cohesive, enduring social environment. In contrast, the second club, which is mixed gender, presents a more dynamic context. With an average membership duration of six years, this club experienced significant turnover in its steering committee prior to data collection, leading to a shift in its mission and a subsequent change in membership composition. These contrasting contexts provide a valuable opportunity to explore how differences in organizational structures influence the dynamics of social networks and health.

5.3 Methods

5.3.1 Data

We used sociometric survey data collected from two clubs described above. The three-wave data was collected between November 2022/ January 2023 and November 2023/ February 2024, with a six-month time interval, with a total of 102 participants ($N_{club1} = 56$, $N_{club2} = 46$) and a response rate of 75%–89%. One of the two clubs consisted exclusively of men. Within the second club, 44% of the members were male. The baseline mean age is 54 years (total age range = 21–86 years), and 96% of the respondents were born in the territory of present-day Germany. 69% of the respondents were employed. The minority lived on their own (20%), while the majority lived with their (marital) partner, children, parents (or in-laws), and/or another nonrelated person.

Research staff initially leveraged professional contacts and further used snowball sampling to gain access to further clubs. To ensure that all individuals in the sample had a realistic opportunity to interact with one another, only active members were included. Following a briefing with each club's management, individuals who were permanently inactive, residing in institutions, living at a significant distance (including abroad), or unable to participate due to serious health conditions were excluded. This resulted in a target sample of 102 members, with individual club samples ranging from 46 to 56 members. Importantly, there was no overlap in membership between the two clubs, resulting in two fully distinct social networks.

Following initial contact and announcement by each club's manager, participants were invited to complete a web-based questionnaire. The use of a digital format was practical, as the participating organizations had largely transitioned to online communication during the Covid-

19 pandemic, and most respondents were comfortable using digital devices such as computers or smartphones. For those requiring additional support, we offered the option of in-home assistance, which applied to one participant. On average, participants spent 25.8 minutes completing the survey.

Achieving high response rates is essential for conducting social network analyses that rely on complete network data. To encourage participation, we implemented an incentive structure in which monetary donations were offered to each club, contingent on the level of participation. Specifically, clubs could receive up to 500€, with the exact amount scaled to their response rate (e.g., an 80% response rate yielded 400€). Additionally, we offered clubs the opportunity to include tailored questions at the end of the survey, allowing them to collect anonymous feedback on topics relevant to their interests.

Ethical approval for the study was granted by the ethics committee of the University of Cologne (reference: 220036LE) prior to data collection. Informed consent was obtained from all participants, and we adhered to strict data protection guidelines.

5.3.2 Measures

Network variable: close relationships

The network data collection used a roster design such that respondents could select individual members from a list of all members. To minimize respondent burden and the time required to fill in the survey, respondents were initially asked to identify individuals with whom they had ever had contact with. Only those selected in this initial step were included in the following rosters. *Close relationships* were operationalized as positive relationship quality. Respondents had to indicate all other club members to which the following applies: “There are people we know who give you great joy or great happiness. Which people within the *club name* are these for you?“ (Engstler et al., 2022, own translation). This results a directed network with sent and received nominations.

Individual variables

Poor physical health was assessed using a single item that asked respondents whether, in the past six months, they had experienced limitations in activities they typically engage in due to health issues. We categorized individuals as having poor physical health if they reported either mild or severe activity restrictions, with those reporting no limitations serving as the reference group.

Poor mental health was evaluated using the Negative Affect Subscale of the Positive and Negative Affect Schedule (Crawford & Henry, 2004). For each emotion, respondents had to indicate whether they never, rather rarely, sometimes, often or very often felt sad, depressed, disappointed and exhausted. We constructed a rounded mean index and built a categorical measure with values of one and two indicating good mental health, value of three indicating medium mental health and values of four and five indicating poor mental health.

Self-rated health was captured by respondents' self-assessment of their health. We collapsed very bad, bad and medium health into one poor health category, as the group of respondents with generally poor self-rated health is too sparse. This results in a categorical variable: very good self-rated health, good self-rated health and poor self-rated health.

Age was categorized into three groups: less than 45 years, 45–64 years, and 65 years and older. *Gender* was treated as a binary measure, with males serving as the reference category. *Education* was constructed based on the CASMIN classification (Federal Institute for Vocational Education and Training, 2024), resulting in three educational levels: low, middle, and high education. Further, we assessed the *employment* status of the individual by asking whether they are currently engaged in paid work of at least 19 hours per week.

5.3.3 Method

Stochastic Actor-Oriented Models

We use *Stochastic Actor-Oriented Models* (SAOMs), as implemented in RSiena (Ripley et al., 2024), for directed networks to account for higher-order structural factors within the network and to more precisely capture complex network dynamics over time. In SAOMs, changes in networks and individual attributes are viewed from an actor-oriented perspective. Time intervals between observations are divided into micro-steps, reflecting the assumption that both networks and attributes evolve continuously over time. During each micro-step, actors can modify their social ties or adjust personal attributes. These decisions depend on the current state of the network and the attributes of others in the network (Ripley et al., 2024; Snijders et al., 2010; Steglich et al., 2010).

While some network dynamics, such as close ties and their feedback effects on health, can be analyzed longitudinally using methods like cross-lagged panel analysis (e.g., Kenny, 2014), RSiena offers a key advantage. It allows for the modeling of multiple structural network parameters, essential for understanding social relationship dynamics. They are particularly suitable for modeling network evolution as they allow for the simultaneous examination of multiple relational processes, such as influence, selection, avoidance, and withdrawal, based on individual health characteristics. Additionally, SAOMs enable the integration of network dependencies—such as triadic closure and homophily effects—thereby providing a comprehensive framework to assess how both health status and network structure jointly contribute to tie formation and dissolution.

We specified our convergence algorithm as such, as that the first two phases are estimated by Maximum Likelihood and the third phase by Methods of Moments estimation. The first is used to yield more precise estimates compensating for the relatively small sample size. The latter was used to be able to assess goodness of fit.

To account for network size changes over time, we used the method of joiners and leavers proposed by Huisman and Snijders (2003). We applied multiple imputation techniques using chained equations to account for missing behavioral data (van Buuren & Groothuis-Oudshoorn, 2011).

Model specifications

To detect social network change and health dynamics, we need to distinguish between selection and influence mechanisms. SAOMs allow us to account for these confounding processes by explicitly modelling the co-evolution of having a close relationship and health. To do so, we specified two equations with different dependent variables guiding actors' decisions: actors' selection function modeling their close tie dynamics and actors' influence function modeling their health dynamics. Estimating both functions simultaneously, we end up with estimates of evaluations of healthy dynamics net of confounding via social influence.

To model *network dynamics*, we include the structural effects addressing the general relational mechanisms known to affect the emergence of positive ties among people: outdegree, reciprocity, triadic closure – captured by the geometrically weighted edgewise shared partners (GWESP) term, an interaction term between reciprocity and GWESP, indegree activity (sqrt), outdegree activity and balance. In addition, we include *similar educational level*. This effect accounts for homophilous tendencies with respect to education. Further, we included the *employment ego* effect to approximate the time available that can be spent in a club due to being employed. Finally, to specifically account for relational mechanisms tied to older adults' health, the phenomenon of main interest, we include the effects *health alter, health ego* and *similar/same health.* We model the health homophily parameter with the evaluation function, which captures the presence of ties regardless of whether they were newly created or maintained.

To model *health dynamics*, we include as basic controls the *linear shape* and *quadratic shape* effects, in line with previous research (Ripley et al., 2024). The latter is excluded for physical health due to its binary nature. Further, we include the *average similarity* effect to account for social influence of health. In addition, we include age, education and gender effects to avoid spurious peer influence effects.

5.4 Results

5.4.1 Descriptive analysis

Descriptive statistics are presented in Table 5-1. Across both clubs, self-rated health remained relatively stable over time, with the majority of participants consistently rating their health as good. Physical health showed a slight, gradual decline, reflected in decreasing percentages of participants without physical limitations in later waves. Most participants in both networks reported good mental health, although this number decreased over time, particularly in the second club. Regarding individual health changes over time (see Table 5-2), most participants' (50%–76%), health remained stable across self-rated, physical, and mental health dimensions. Nevertheless, a notable share experienced changes: improvements were reported by 4%–28% depending on the health dimension and time interval, while 13%–29% reported declines. These dynamics were more pronounced in mental health, particularly in the second club, where worsening mental health increased in the later period.

The two clubs differ within their demographic profile. While the first one consists only of men, the second one has a balanced gender mix. Also, the first club seems to be quite equal in terms of educational background and age group, while the second one is comprised of more middle and highly educated people as well as adults of the second age category (45 to 64 years).

A descriptive overview over network density and average degree can be found in Table 5-1. On average, members of clubs nominated 9 peers in club 1, with the average degree remaining largely stable over the waves. In club 2, the average degree has halved from 9.45 in the first wave to 4.8 in the third wave. This decline is likely linked to the club's dynamic context, particularly the substantial turnover in its steering committee prior to data collection, as detailed in the study context section.

Table 5-1 Descriptive overview of variables

	Club 1 (n = 56)						Club 2 (n = 46)					
	Wave 1		Wave 2		Wave 3		Wave 1		Wave 2		Wave 3	
Close tie network (time-variant)												
Density		0.16		0.16		0.17		0.21		0.12		0.11
Average degree		8.95		8.56		9.40		9.45		5.49		4.80
Health (time- variant)												
Self-rated health												
Very good	10	(18%)	9	(16%)	8	(14%)	4	(9%)	5	(11%)	4	(9%)
Good	28	(50%)	29	(52%)	27	(48%)	25	(54%)	22	(48%)	26	(57%)
Medium	17	(30%)	17	(30%)	20	(36%)	15	(33%)	14	(30%)	13	(28%)
Bad and very bad	1	(2%)	1	(2%)	1	(2%)	2	(4%)	5	(11%)	3	(7%)
Physical health												
Good	34	(61%)	32	(57%)	29	(52%)	27	(57%)	26	(57%)	25	(54%)
Limited	21	(38%)	24	(43%)	27	(48%)	19	(41%)	20	(43%)	21	(46%)
Mental health												
Good	41	(73%)	37	(66%)	39	(70%)	31	(67%)	28	(61%)	23	(50%)
Medium	13	(23%)	14	(25%)	11	(20%)	11	(22%)	10	(22%)	19	(41%)
Poor	2	(4%)	5	(9%)	6	(11%)	4	(17%)	8	(17%)	4	(9%)

	Club 1 (n = 56)				Club 2 (n = 46)			
	Wave 1		Wave 2	Wave 3	Wave 1	Wave 2		Wave 3
Socio-demographics (time-invariant)								
Age group								
< 45 years	18	(32%)				15	(33%)	
45 – 64 years	21	(38%)				24	(52%)	
65 + years	17	(30%)				7	(15%)	
Education								
Low	21	(38%)				5	(11%)	
Middle	26	(46%)				24	(52%)	
High	9	(16%)				17	(37%)	
Gender								
Male	56	(100%)				20	(43%)	
Female	0	(0%)				26	(57%)	

These discrepancies are reflected by the network dynamics (see Table 5-2). The first club's network remained stable, with similar percentages of ties maintained, formed, and dissolved. In contrast, the second club had fewer ties maintained or dissolved, while a similar number of new ties formed in period 2 compared to period 1. The Jaccard index, ranging from 0.48 to 0.51 in the first club and 0.41 to 0.47 in the second, indicates greater network change in the latter.

Table 5-2 Changes over time: network composition and health

	Club 1 (n = 56)				Club 2 (n = 46)			
	T1 to T2		T2 to T3		T1 to T2		T2 to T3	
Composition changes								
Number of adults leaving the network		3		1		1		0
Number of adults joining the network		6		0		6		0
Close tie changes								
Ties maintained		201		221		107		87
Ties dissolved		87		116		91		74
Ties formed		104		123		30		53
No tie – no tie		1,264		1,529		722		1,106
Jaccard Index		0.51		0.48		0.47		0.41
Health changes								
Self-rated health								
Improved health	13	(23%)	7	(13%)	11	(24%)	13	(28%)
Worsened health	10	(18%)	16	(29%)	12	(26%)	9	(20%)
Maintained health	33	(59%)	33	(59%)	23	(50%)	24	(52%)
Physical health								
Improved health	5	(9%)	6	(11%)	2	(4%)	9	(20%)
Worsened health	11	(20%)	8	(14%)	9	(20%)	6	(13%)
Maintained health	40	(71%)	42	(75%)	35	(76%)	31	(67%)
Mental health								
Improved health	6	(11%)	8	(14%)	9	(20%)	8	(17%)
Worsened health	10	(18%)	8	(14%)	12	(26%)	13	(28%)
Maintained health	40	(71%)	40	(71%)	25	(54%)	25	(54%)

Visual examination of the network reveals no clear clustering related to health (see Figure 5-1). Also, when looking at Moran's I, we do not find evidence for clustering or dispersion for the health measures across both clubs, as all values are close to zero (see Table 5-3). These results hardly indicate that there is evidence of health-related homophily.

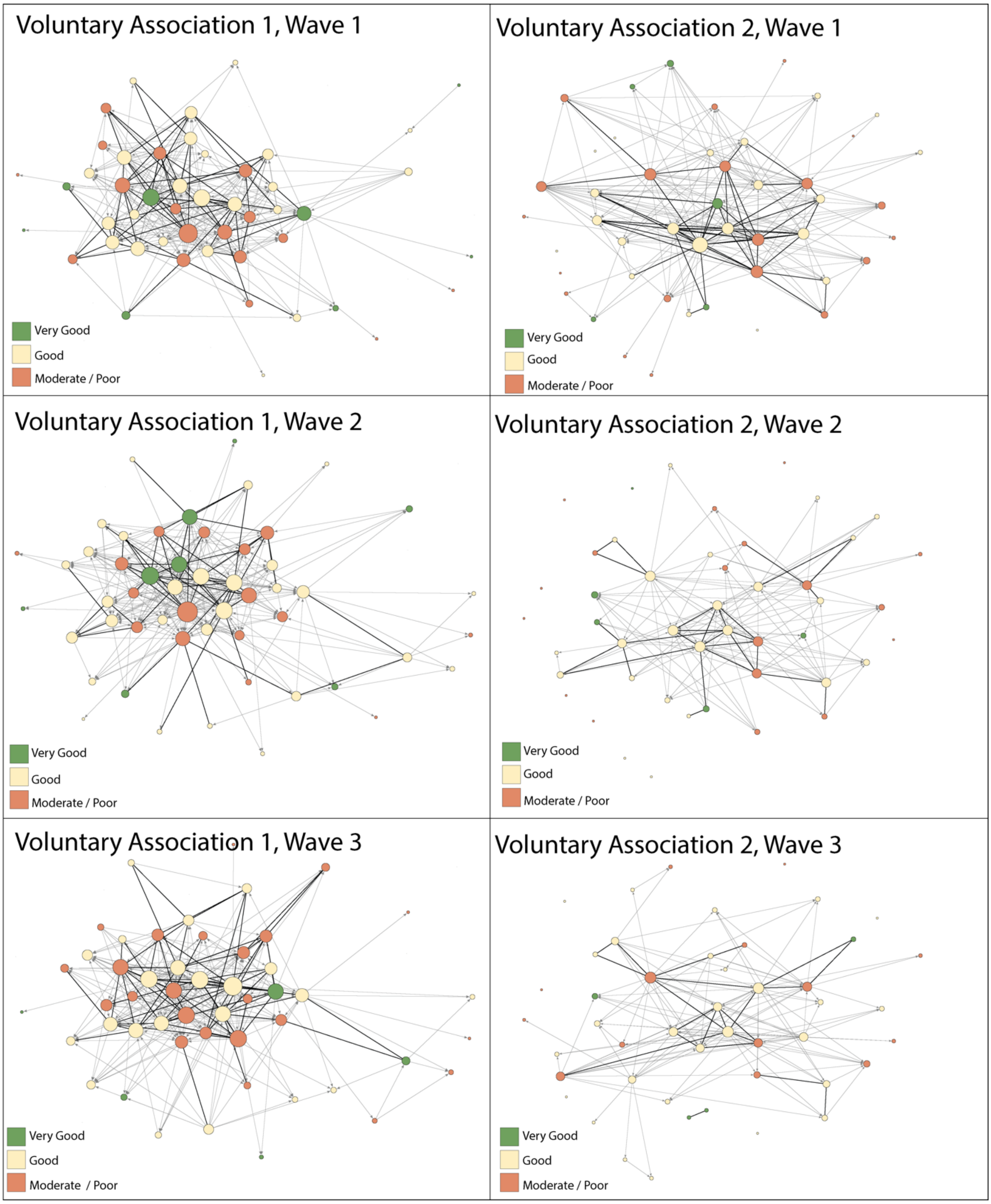


Figure 5-1 Visualization of networks of close ties over time, node colors indicating self-rated health, size by degree. Layout held constant across waves within clubs to facilitate comparison.

Table 5-3 Moran's I: Autocorrelation

	Club 1 (n = 56)			Club 2 (n = 46)		
	Wave 1	**Wave 2**	**Wave 3**	**Wave 1**	**Wave 2**	**Wave 3**
Self-rated health	-0.011	-0.114	-0.058	0.023	0.086	-0.066
Physical health	0.072	0.036	-0.022	0.068	-0.078	0.071
Mental health	0.029	0.062	0.014	-0.010	-0.034	-0.015

Figure 5-2 presents the degree distribution by health status across both clubs. Indegree and outdegree distributions are largely similar across self-rated health categories. However, individuals with poor mental health tend to have slightly lower degree values than those with medium or good mental health, while the spread of values is wider for those with good mental health, particularly in the indegree distribution. Additionally, while outdegree distribution remains consistent across physical health statuses, individuals with poor physical health exhibit slightly higher indegree values.

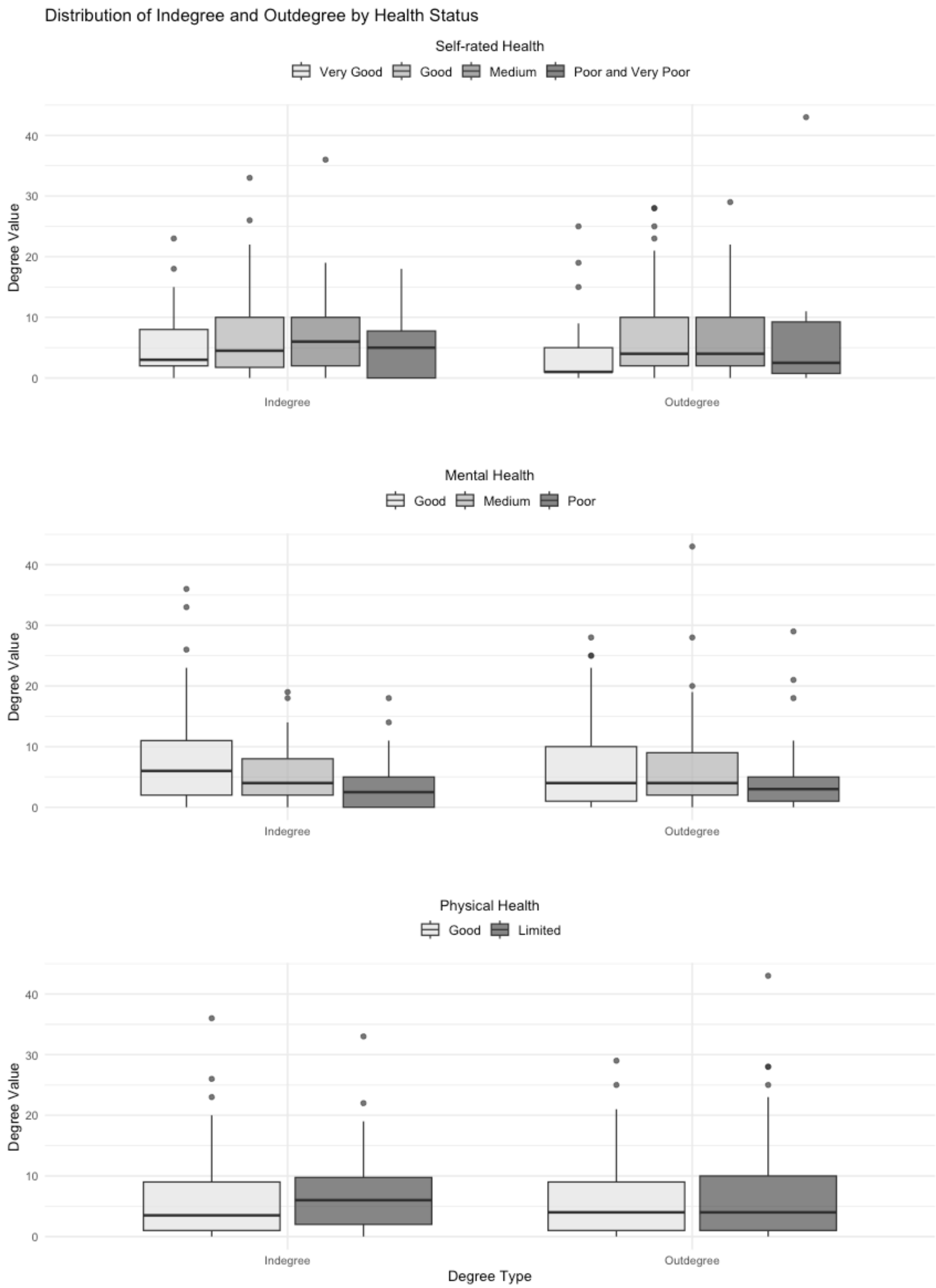


Figure 5-2 Degree distribution by health; pooled data across waves

5.4.2 Stochastic Actor-Oriented Models

We performed SAOM to examine health and network dynamics in voluntary clubs across the three waves (see Table 5-4). Convergence ratios across all models were good (<0.2; Ripley et al., 2024).

The negative degree density parameter across all models (b = -2.1 to -2.5, SE = 0.4 to 0.6) is reflective of the low density of close tie networks in both clubs. The positive and significant GWESP parameter (b = 1.4 to 2.3, SE = 0.2 to 0.6) confirms that the captured structures show strong tendencies for triadic closure. Similarly, we find evidence for reciprocity within close tie networks (b = 2.3 to 3.6, SE = 0.4 to 0.9), highlighting a preference for mutual ties.

The interaction between reciprocity and GWESP is significant and negative across all models (b = -0.9 to -1.7, SE = 0.3 to 0.6). Figure 5-3 illustrates the probability of forming a new tie as a function of triadic closure, differentiating between cases where the existing tie in the triad is reciprocal or non-reciprocal. In both clubs, the results suggest reciprocal ties to significantly influence triadic closure, meaning that mutual connections make it more likely that a new tie forms. This suggests that reciprocity and transitivity complement each other, which is consistent with earlier work suggesting that peer groups form initially reciprocal ties and then closing triads amongst common friends (Hallinan, 1974, 1978). Network balance is observed in the first club (b = 0.03 to 0.04, SE = 0.01 to 0.03), indicating an additional layer of structural cohesion.

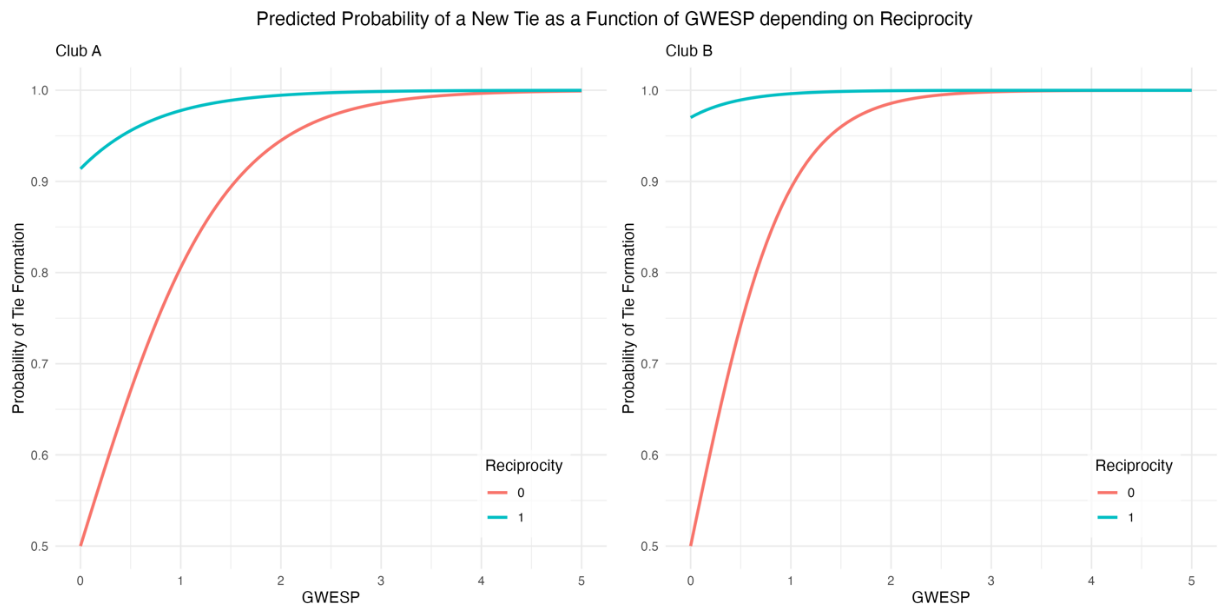


Figure 5-3 Predicted probability of tie formation as a function of GWESP, for reciprocal and non-reciprocal dyads, exemplary for the self-rated health SAOM

Regarding individual activity, the square root of the indegree activity term is significantly negative in both clubs (b = -0.4 to -0.5, SE = 0.2), meaning that popular individuals (those with many incoming ties) are less likely to nominate new close ties, reinforcing stability in social positions. This effect is stronger for highly popular individuals. However, the outdegree activity effect is significant and positive only in the first club (b = 0.05, SE = 0.01), indicating that socially active individuals in the first club continue expanding their close ties, while this pattern is absent in the second club.

Regarding dyadic structures, educational homophily is predominantly evident in the first club (b = 0.5 to 0.6, SE = 0.1 to 0.3). Additionally, in the second club, employment status predicts nomination behavior, with employed individuals being less likely to nominate others as close ties compared to those not working (b = -1.0 to -1.1, SE = 0.3 to 0.4).

Network selection and health

Regarding the selection hypothesis, we find significant evidence for self-rated health homophily, meaning that individuals with similar self-reported health are more likely to form ties (b = 1.3, SE = 0.7). The significant selection effect does hold across different model specifications but is only apparent in the second club. Notably, self-rated health similarity appears to be particularly influential in forming new friendships (see Table A5-1), likely driving the observed health homophily effect.

Regarding the avoidance hypothesis, we find that in the first club, individuals in poor physical health receive significantly fewer nominations (b = -0.3, SE = 0.2). This effect remains stable in size and significance across different model specifications. However, we find no evidence of avoidance based on poor health in the second club or across other health measures.

Interestingly, in the first club, individuals with poorer self-rated (b = 0.3, SE = 0.1) and mental health (b = 0.8, SE = 0.3) are more likely to nominate others as close ties (see Table 5-4). This contradicts expectations that poorer health would lead to social withdrawal. Notably, this effect remains stable across different model specifications.

Network influence and health

We do not find significant evidence for health influence effects in either club. Peers do not appear to influence individuals' health over time.

Regarding socio-demographic characteristics, we find no strong effects on health. Gender is not predictive across models, and the effect of education is suggestive but inconsistent across specifications. However, age significantly influences health (b = 0.8, SE = 0.3) but only in the second club.

Table 5-4 SAOM results

Hypoth-eses	Parameter	Self-rated health Club 1	Self-rated health Club 2	Mental health Club 1	Mental health Club 2	Physical health Club 1	Physical health Club 2
	Network Dynamics						
	Amount of network change in period 1	10.722***	10.456***	10.299***	10.407***	11.093***	10.587***
		(1.439)	(1.493)	(1.296)	(1.733)	(1.34)	(1.838)
	Amount of network change in period 2	12.09***	8.482***	11.675***	7.888***	12.367***	8.217***
		(1.616)	(1.298)	(1.305)	(1.148)	(1.504)	(1.159)
	Outdegree (density)	-2.1***	-2.245***	-2.269***	-2.193***	-2.236***	-2.47***
		(0.424)	(0.49)	(0.455)	(0.577)	(0.405)	(0.551)
	Reciprocity	2.361***	3.521***	2.473***	3.598***	2.322***	3.561***
		(0.46)	(0.87)	(0.474)	(0.852)	(0.413)	(0.874)
	Balance	0.041**	0.038	0.04**	0.034	0.042**	0.034
		(0.014)	(0.028)	(0.013)	(0.03)	(0.014)	(0.029)
	GWESP	1.402***	2.15***	1.455***	2.261***	1.382***	2.236***
		(0.249)	(0.61)	(0.249)	(0.567)	(0.226)	(0.602)
	Reciprocity x GWESP	-0.936**	-1.659**	-1.004**	-1.663**	-0.907**	-1.656**
		(0.31)	(0.548)	(0.336)	(0.573)	(0.281)	(0.539)
	Indegree Activity (Sqrt)	-0.505*	-0.442†	-0.427*	-0.501†	-0.456*	-0.501*
		(0.21)	(0.226)	(0.204)	(0.259)	(0.185)	(0.214)
	Outdegree Activity	0.046***	0.01	0.046***	0.004	0.046***	0.01
		(0.011)	(0.03)	(0.011)	(0.028)	(0.011)	(0.028)
H1	Similarity on health[a]	0.953	1.348†	0.507	-0.463	0.127	0.353
		(0.592)	(0.716)	(0.47)	(0.96)	(0.219)	(0.323)
H2	Health alter	-0.058	0.02	0.001	0.077	-0.335*	-0.065
		(0.109)	(0.144)	(0.131)	(0.299)	(0.151)	(0.225)
H3	Health ego	0.286†	-0.28	0.799**	-0.582	0.093	-0.329
		(0.146)	(0.217)	(0.266)	(0.418)	(0.152)	(0.304)
	Employment ego	0.073	-1.116**	-0.001	-1.111**	0.085	-0.979**
		(0.113)	(0.346)	(0.127)	(0.385)	(0.104)	(0.313)
	Similarity on education	0.528***	0.434†	0.514***	0.569*	0.508***	0.371
		(0.132)	(0.253)	(0.137)	(0.259)	(0.127)	(0.226)
	Health Dynamics						
	Amount of behavioral change in period 1 on health	1.388*** (0.414)	1.897** (0.696)	1.811* (0.736)	4.413 (3.366)	1.119* (0.476)	0.885* (0.429)
	Amount of behavioral change in period 2 on health	1.573** (0.515)	1.401** (0.481)	1.679** (0.519)	2.412* (0.942)	0.823** (0.301)	1.373* (0.592)

Hypoth-eses		**Self-rated health**		**Mental health**		**Physical health**	
	Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
	Health linear shape	-0.071	-1.105†	0.192	-2.354†	1.457	1.65
		(0.36)	(0.616)	(0.982)	(1.415)	(1.295)	(1.452)
	Health quadratic shape	-0.504	-0.542	0.905	-0.862		
		(0.56)	(0.44)	(0.652)	(1.582)		
H4	Health average similarity	1.911	-0.757	6.584	-4.092	2.282	1.145
		(4.594)	(3.635)	(5.374)	(5.921)	(3.051)	(2.403)
	Health x Age	0.171	0.754*	-0.321	0.634	-0.392	0.316
		(0.215)	(0.34)	(0.409)	(0.51)	(0.582)	(0.67)
	Health x Education	0.01	0.164	0.275	0.404	-0.787	-1.211†
		(0.241)	(0.259)	(0.425)	(0.423)	(0.586)	(0.716)
	Health x Gender		0.475		1.593		-0.428
			(0.354)		(1.131)		(0.817)
	Convergence Ratios	**0.141**	**0.150**	**0.137**	**0.188**	**0.108**	**0.165**

*† $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

Additional analyses

We conducted additional analyses to assess the stability of the observed effects. Specifically, we examined age homophily, but the results indicate that it is not significant (see Table A5-2). This suggests that individuals are no more likely to form close ties with others of the same age, implying that age does not play a significant role in the segregation of these clubs.

Similarly, we found no significant evidence of gender homophily in the second club (see Table A5-3). Further, we accounted for the kinship or marriage ties within the clubs. While these ties were predictive of tie nominations in the second club, they were not significant in the first (see Table A5-4). This discrepancy may be due to marriage within the club being a stronger predictor of network dynamics than kinship ties, whereby marriage ties are only prevalent in the second club.

Additionally, we tested whether steering committee membership influenced close tie nominations or increased mutual nominations among committee members. Both effects were insignificant (see Table A5-5), suggesting that leadership roles do not strongly influence network dynamics.

Further, we tested whether general perceived support (see Table A5-6) or higher frequency of participation in the club (see Table A5-7) influenced the likelihood of nominating others as close ties. However, neither perceived support nor participation frequency was predictive of nomination behavior in close-tie networks.

Finally, we investigated whether peer influence effects were particularly pronounced for central individuals in the network (see Table A5-8). This effect was not significant, confirming that an individual's health is not influenced by the health of those who nominate them as close ties. Additionally, central individuals in the club are no more susceptible to health influence effects than those in more peripheral network positions.

Goodness of fit

To assess the Goodness of fit (GOF), the networks simulated by the SAOM were compared to the observed data using three auxiliary network statistics: outdegree, indegree, and triad census distribution (see Lospinoso & Snijders, 2019). Additionally, the model was evaluated for its ability to capture the distribution of self-rated, mental, and physical health values over time. Model convergence was largely confirmed, with t-ratios for deviations from target statistics below 0.1 and an overall maximum convergence ratio below 0.2. Overall, the current model specification demonstrated good GOF. In the Appendix, Figure A5-1 visualizes the GOF for the first club, Figure A5-2 does the same respectively for the second club.

5.5 Discussion

This study aimed to investigate network and health dynamics in fully voluntary settings. Previous research has mainly examined these dynamics in constrained settings, such as schools, workplaces, and other institutional contexts (Chancellor et al., 2017; Crosnoe et al., 2008; Flatt et al., 2012; Schaefer et al., 2011; Schafer, 2016; Van Zalk et al., 2010a). These are often formed under implicit assumptions of compulsion and sorting, where individuals are confined to a limited pool and tend to form homophilous ties with others who share similar characteristics (McPherson et al., 2001). However, it remained unclear whether these dynamics also hold in fully voluntary settings, in which members often self-select into groups (Rawlings et al., 2023). Voluntary clubs are a prime example of such settings. Particularly, the long-term nature of club memberships, often lasting several years or even decades, makes these networks particularly meaningful for participants, offering a unique lens into how social ties and health interact outside imposed institutional structures. Using whole network data on two clubs and employing SAOM allow us to examine the dynamic nature of networks in relation to health, distinguishing between selection and influence effects.

Our study diverges from patterns observed in more commonly studied settings. Our tie formation models are consistent with prior work suggesting the importance of social closure and homophily, however, just not in terms of health. Contrary to other studies (Van Zalk et al., 2010a), we do not find evidence for peer influence on health across all health measures. Furthermore, results suggest some sorting of social relations along the lines of self-rated health. Additionally, we find evidence for avoidance only among those in poor physical health. We observe reversed effects—individuals in poorer health are sometimes more active in forming close ties, possibly leveraging these connections as a form of social compensation. This challenges existing assumptions and highlights the need to reconsider the underlying mechanisms linking health and social networks in fully voluntary contexts.

5.5.1 Theoretical implications

We initially anticipated finding evidence of health-based homophily, a phenomenon that may be driven by mechanisms of selection or influence (McPherson et al., 2001). Specifically, we expected to observe a health selection effect, wherein individuals with similar health statuses were more likely to form close social ties. We observed a degree of sorting in social relationships based on self-rated health in one of the two clubs. Within this club, a similar health status is most probable attributable to the formation of new ties, rather than the maintenance of already existing ties. Since we only found this evidence in one club and not across all health measures, our overall findings only suggestively support the general expectation of health-based homophily as established by previous research (e.g., Crosnoe et al., 2008; Schafer, 2016). In particular, the effect of health-based selection homophily appears to be weaker in fully voluntary social settings compared to more constrained environments.

Notably, in line with theoretical expectations and earlier studies, we found evidence that individuals with poor physical health are avoided by peers. However, we only find this evidence in one club and only regarding physical health. However, this is in line with previous research which found that particularly stigmatized and visible medical conditions influence friendship choices (Ali et al., 2011; Crosnoe et al., 2008).

Furthermore, we did not observe patterns of social withdrawal among individuals with poor health. On the contrary, our findings revealed that individuals with poorer self-rated health and particularly mental health were more likely to actively nominate others as close ties. This suggests that rather than withdrawing, these individuals may leverage social connections as a form of social compensation or support.

The absence of withdrawal in voluntary settings is an encouraging finding. It indicates that such environments allow individuals to participate without fear of being marginalized due to their health status. In fact, the active engagement of individuals in poorer health may reflect their recognition of the value of social ties in mitigating the challenges associated with their condition. Social networks have been shown to buffer stress and contribute to resilience, particularly for individuals dealing with health-related difficulties (Cohen, 2004; Thoits, 2011). These findings underscore the importance of fostering inclusive social spaces where people, regardless of health status, can build and maintain meaningful relationships. They also highlight the potential of voluntary settings to serve as vital sources of social support and resilience, particularly for those facing health-related challenges.

Contrary to our assumptions, we did not find evidence for health influence. Previous research has found evidence for the social contagion of health over longer time periods. Physical health, such as obesity, was found to spread through the network over 32 years (Christakis & Fowler, 2007), and mental health over five to 20 years (Cacioppo et al., 2009; Fowler & Christakis, 2008; Hill et al., 2010; Kensbock et al., 2022; Rosenquist et al., 2011). We might not have detected significant influence effects because contagion effects do not happen over such short period of 1.5 years. Also, social contacts in voluntary associations may of course also not be as important and thus, influential for health as family or close friends.

Theoretical postulations and previous research on health homophily have primarily been tested in constrained settings. Our study, however, reveals a significant divergence from these patterns. We propose that the theoretical framework of health homophily in social networks is most applicable in constrained settings where contact intensity is high. This suggests that the implicit scope conditions for health homophily are shaped by the nature of the setting and the frequency of interactions within it. To refine these scope conditions and deepen theoretical understanding, future research should systematically examine a variety of settings characterized by different levels of contact intensity and boundary constraints.

Examples of such settings are outlined in Table 5-5, which categorizes them by contact intensity and setting boundedness. Future studies should test these categories to evaluate the consistency of health homophily dynamics and explore potential deviations. Critical tests could include examining in which contexts and under which scope conditions health homophily emerges. By delineating distinctions, we can refine our understanding of the mechanisms driving health and social network formation across a broader spectrum of populations and settings.

Table 5-5 Exemplary settings according to setting constraints and contact intensity

	Low contact intensity	**High contact intensity**
Fully constrained	Neighborhoods in urban areas	Schools Retirement homes
Semi-constrained	Religious affiliations	Workplaces
Fully voluntary	Voluntary associations/ clubs Political activism	Team sports Musical ensembles

5.5.2 Limitations and future research

A limitation that our investigation shares with other whole network studies is the fact that we lack information about close ties outside the observed networks, including spouses, children, or friends. Previous research has shown that particularly these relationships have a profound impact on individual health, both directly—through social support—and indirectly, by their health as well as influencing behaviors and perceptions related to health (Berkman et al., 2000; Holt-Lunstad et al., 2010; Uchino, 2006).

Another limitation is the sample size of our study. A larger sample size and data from additional clubs could enhance statistical power, enabling researchers to distinguish between effects that are genuinely absent and those that are merely undetectable due to limited data. However, even with extensive sensitivity analyses, effects remained stable in size and significance, suggesting that these effects may genuinely be robust.

A third limitation is the short time frame of the study. While many health contagion effects have been documented over longer periods, such as decades (Cacioppo et al., 2009; Christakis & Fowler, 2007; Fowler & Christakis, 2008; Hill et al., 2010; Kensbock et al., 2022; Rosenquist et al., 2011), our study examined health effects over only 1.5 years. Future research should explore similar settings over extended time frames to better capture potential health influence effects that may take longer to manifest.

The findings of this study underscore the importance of considering the setting's boundedness and its influence on social network dynamics. While our study provides valuable insights into health and social networks in voluntary settings, further research is needed to examine how different levels of contact intensity and environmental constraints impact health selection and influence effects. Future studies should explore various settings to better understand the nuanced ways in which social ties influence health outcomes. Additionally, these insights have important implications for promoting inclusive environments where individuals can build meaningful social networks without fear of marginalization. Voluntary clubs and other self-selecting settings may provide valuable spaces for individuals to engage socially and emotionally, thereby enhancing resilience and mitigating the impact of health challenges. As such, fostering these spaces can play an important role in improving public health and promoting social cohesion, particularly in aging populations.

5.6 References

Ali, M. M., Amialchuk, A., & Rizzo, J. A. (2011). The influence of body weight on social network ties among adolescents. *Economics & Human Biology*, *10*(1), 20–34. https://doi.org/10.1016/j.ehb.2011.10.001

Aral, S., & Nicolaides, C. (2017). Exercise contagion in a global social network. *Nature Communications*, *8*(1), 14753. https://doi.org/10.1038/ncomms14753

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social Science & Medicine*, *51*(6), 843–857. https://doi.org/10.1016/S0277-9536(00)00065-4

Block, P., & Burnett Heyes, S. (2022). Sharing the load: Contagion and tolerance of mood in social networks. *Emotion*, *22*(6), 1193–1207. https://doi.org/10.1037/emo0000952

Cacioppo, J. T., Fowler, J. H., & Christakis, N. A. (2009). Alone in the crowd: The structure and spread of loneliness in a large social network. *Journal of Personality and Social Psychology*, *97*(6), 977–991. https://doi.org/10.1037/a0016076

Centola, D., & Van De Rijt, A. (2015). Choosing your network: Social preferences in an online health community. *Social Science & Medicine*, *125*, 19–31. https://doi.org/10.1016/j.socscimed.2014.05.019

Chancellor, J., Layous, K., Margolis, S., & Lyubomirsky, S. (2017). Clustering by well-being in workplace social networks: Homophily and social contagion. *Emotion*, *17*(8), 1166–1180. https://doi.org/10.1037/emo0000311

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, *357*(4), 370–379. https://doi.org/10.1056/NEJMsa066082

Christakis, N. A., & Fowler, J. H. (2013). Social contagion theory: Examining dynamic social networks and human behavior. *Statistics in Medicine*, *32*(4), 556–577. https://doi.org/10.1002/sim.5408

Cohen, S. (2004). Social relationships and health. *American Psychologist*, *59*(8), 676–684. https://doi.org/10.1037/0003-066X.59.8.676

Copeland, M., Kamis, C., & West, J. S. (2023). To make and keep friends: The role of health status in adolescent network tie formation and persistence. *Social Networks*, *74*, 216–223. https://doi.org/10.1016/j.socnet.2023.04.005

Crawford, J. R., & Henry, J. D. (2004). The Positive and Negative Affect Schedule (PANAS): Construct validity, measurement properties and normative data in a large non-clinical sample. *British Journal of Clinical Psychology*, *43*(3), 245–265. https://doi.org/10.1348/0144665031752934

Crosnoe, R., Frank, K., & Mueller, A. S. (2008). Gender, body size and social relations in American high schools. *Social Forces*, *86*(3), 1189–1216. https://doi.org/10.1353/sof.0.0004

De La Haye, K., Robins, G., Mohr, P., & Wilson, C. (2011). How physical activity shapes, and is shaped by, adolescent friendships. *Social Science & Medicine*, *73*(5), 719–728. https://doi.org/10.1016/j.socscimed.2011.06.023

De La Haye, K., Robins, G., Mohr, P., & Wilson, C. (2013). Adolescents' intake of junk food: Processes and mechanisms driving consumption similarities among friends. *Journal of Research on Adolescence*, *23*(3), 524–536. https://doi.org/10.1111/jora.12045

Donnelly, E. A., & Hinterlong, J. E. (2010). Changes in social participation and volunteer activity among recently widowed older adults. *The Gerontologist*, *50*(2), 158–169. https://doi.org/10.1093/geront/gnp103

Engstler, H., Stuth, S., Lozano Alcántara, A., Luitjens, M., Klaus, D., Schwichtenberg-Hilmert, B., Behaghel, C. F., Kortmann, L., Martin, J., Drewitz, M., & Körber, M. (2022). *German Ageing Survey—Deutscher Alterssurvey: Documentation of instruments and variables – Instrumenten- und Variablendokumentation.* German Centre of Gerontology – Deutsches Zentrum für Altersfragen.

Federal Institute for Vocational Education and Training. (2024). *Comparative Analysis of Social Mobility in Industrial Nations (CASMIN)*. https://metadaten.bibb.de/en/classification/detail/16

Flatt, J. D., Agimi, Y., & Albert, S. M. (2012). Homophily and health behavior in social networks of older adults. *Family & Community Health*, *35*(4), 312–321. https://doi.org/10.1097/FCH.0b013e3182666650

Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ*, *337*(a2338). https://doi.org/10.1136/bmj.a2338

Franken, R., Bekhuis, H., & Tolsma, J. (2023). Kudos make you run! How runners influence each other on the online social network Strava. *Social Networks*, *72*, 151–164. https://doi.org/10.1016/j.socnet.2022.10.001

Galenkamp, H., & Deeg, D. J. H. (2016). Increasing social participation of older people: Are there different barriers for those in poor health? Introduction to the special section. *European Journal of Ageing*, *13*(2), 87–90. https://doi.org/10.1007/s10433-016-0379-y

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380. https://doi.org/10.1086/225469

Greenfield, E. A., & Marks, N. F. (2004). Formal volunteering as a protective factor for older adults' psychological well-being. *The Journals of Gerontology: Series B, 59*(5), S258–S264. https://doi.org/10.1093/geronb/59.5.S258

Haas, S. A., Schaefer, D. R., & Kornienko, O. (2010). Health and the structure of adolescent social networks. *Journal of Health and Social Behavior*, *51*(4), 424–439. https://doi.org/10.1177/0022146510386791

Hallinan, M. T. (1974). A structural model of sentiment relations. *American Journal of Sociology*, *80*(2), 364–378. https://doi.org/10.1086/225804

Hallinan, M. T. (1978). The process of friendship formation. *Social Networks*, *1*(2), 193–210. https://doi.org/10.1016/0378-8733(78)90019-9

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1993). Emotional contagion. *Current Directions in Psychological Science*, *2*(3), 96–100. https://doi.org/10.1111/1467-8721.ep10770953

Hill, A. L., Rand, D. G., Nowak, M. A., & Christakis, N. A. (2010). Emotions as infectious diseases in a large social network: The SISa model. *Proceedings of the Royal Society B*, *277*(1701), 3827–3835. https://doi.org/10.1098/rspb.2010.1217

Hogue, A., & Steinberg, L. (1995). Homophily of internalized distress in adolescent peer groups. *Developmental Psychology, 31*(6), 897–906. https://doi.org/10.1037/0012-1649.31.6.897

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *PLoS Medicine*, *7*(7), e1000316. https://doi.org/10.1371/journal.pmed.1000316

Huisman, M., & Snijders, T. A. B. (2003). Statistical analysis of longitudinal network data with changing composition. *Sociological Methods & Research, 32*(2), 253–287. https://doi.org/10.1177/0049124103256096

Hutchinson, D. M., & Rapee, R. M. (2007). Do friends share similar body image and eating problems? The role of social networks and peer influences in early adolescence. *Behaviour Research and Therapy*, *45*(7), 1557–1577. https://doi.org/10.1016/j.brat.2006.11.007

Joiner, T. E., & Katz, J. (1999). Contagion of depressive symptoms and mood: Meta-analytic review and explanations from cognitive, behavioral, and interpersonal viewpoints. *Clinical Psychology*, *6*(2), 149–164. https://doi.org/10.1093/clipsy.6.2.149

Jongenelis, M. I., Jackson, B., Newton, R. U., & Pettigrew, S. (2022). Longitudinal associations between formal volunteering and well-being among retired older people: Follow-up results from a randomized controlled trial. *Aging & Mental Health*, *26*(2), 368–375. https://doi.org/10.1080/13607863.2021.1884845

Kenny, D. A. (2014). Cross-Lagged Panel Design. In R. S. Kenett, N. T. Longford, W. W. Piegorsch, & F. Ruggeri (Eds.), *Wiley StatsRef: Statistics Reference Online* (1st ed.). Wiley. https://doi.org/10.1002/9781118445112.stat06464

Kensbock, J. M., Alkærsig, L., & Lomberg, C. (2022). The epidemic of mental disorders in business—how depression, anxiety, and stress spread across organizations through employee mobility*. *Administrative Science Quarterly*, *67*(1), 1–48. https://doi.org/10.1177/00018392211014819

Kuiper, J. S., Zuidersma, M., Zuidema, S. U., Burgerhof, J. G. M., Stolk, R. P., Oude Voshaar, R. C., & Smidt, N. (2016). Social relationships and cognitive decline: A systematic review and meta-analysis of longitudinal cohort studies. *International Journal of Epidemiology*, *45*(4), 1169–1206. https://doi.org/10.1093/ije/dyw089

Kuiper, J., Zuidersma, M., Voshaar, R., Zuidema, S., van den Heuvel, E., Stolk, R., & Smidt, N. (2015). Social relationships and risk of dementia: A systematic review and meta-analysis of longitudinal cohort studies. *Ageing Research Reviews*, *22*, 39–57. https://doi.org/10.1016/j.arr.2015.04.006

Lakey, B., & Tanner, S. M. (2013). Social influences in negative thinking and affect. *Cognitive Therapy and Research*, *37*(1), 160–172. https://doi.org/10.1007/s10608-012-9444-9

Link, B. G. (1987). Understanding labeling effects in the area of mental disorders: an assessment of the effects of expectations of rejection. *American Sociological Review*, *52*(1), 96–112. https://doi.org/10.2307/2095395

Link, B. G., Cullen, F. T., Struening, E., Shrout, P. E., & Dohrenwend, B. P. (1989). A modified labeling theory approach to mental disorders: An empirical assessment. *American Sociological Review*, *54*(3), 400–423. https://doi.org/10.2307/2095613

Link, B. G., & Phelan, J. C. (2001). Conceptualizing Stigma. *Annual Review of Sociology*, *27*(1), 363–385. https://doi.org/10.1146/annurev.soc.27.1.363

Lospinoso, J., & Snijders, T. A. (2019). Goodness of fit for stochastic actor-oriented models. *Methodological Innovations*, *12*(3), 2059799119884282. https://doi.org/10.1177/2059799119884282

Martin, J. L. (2009). *Social structures*. Princeton University Press.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Mercken, L., Steglich, C., Sinclair, P., Holliday, J., & Moore, L. (2012). A longitudinal social network analysis of peer influence, peer selection, and smoking behavior among adolescents in British schools. *Health Psychology*, *31*(4), 450–459. https://doi.org/10.1037/a0026876

Moody, J. (2001). Race, school integration, and friendship segregation in America. *American Journal of Sociology*, *107*(3), 679–716. https://doi.org/10.1086/338954

Nam, S., Jung, S., Vlahov, D., Latkin, C., Kershaw, T., & Whittemore, R. (2023). Body mass index and obesity-related behaviors in African American church-based networks: A social network analysis. *PLOS ONE*, *18*(3), e0281145. https://doi.org/10.1371/journal.pone.0281145

Nam, S., Jung, S., Whittemore, R., Latkin, C., Kershaw, T., Redeker, N. S., Jeon, S., & Vlahov, D. (2019). Social network structures in African American churches: Implications for health promotion programs. *Journal of Urban Health*, *96*(2), 300–310. https://doi.org/10.1007/s11524-018-00339-9

Rawlings, C. M., Smith, J. A., Moody, J., & McFarland, D. A. (2023). *Network analysis: Integrating social network theory, method, and application with R*. Cambridge University Press.

Reiner, A., & Steinhoff, P. (2024). The association of social networks and depression in community-dwelling older adults: A systematic review. *Systematic Reviews*, *13*(1), 161. https://doi.org/10.1186/s13643-024-02581-6

Ripley, R. M., Snijders, T. A. B., Boda, Z., Vörös, A., & Preciado, P. (2024). *Manual for RSiena*. http://www.stats.ox.ac.uk/~snijders/siena/RSiena_Manual.pdf

Robert Koch-Institut. (2018). *The subjective health of adults in Germany*. https://doi.org/10.17886/RKI-GBE-2018-073

Rosenquist, J. N., Fowler, J. H., & Christakis, N. A. (2011). Social network determinants of depression. *Molecular Psychiatry*, *16*(3), 273–281. https://doi.org/10.1038/mp.2010.13

Schaefer, D. R., adams, jimi, & Haas, S. A. (2013). Social networks and smoking: Exploring the effects of peer influence and smoker popularity through simulations. *Health Education & Behavior*, *40*(1_suppl), 24S-32S. https://doi.org/10.1177/1090198113493091

Schaefer, D. R., Kornienko, O., & Fox, A. M. (2011). Misery does not love company: Network selection mechanisms and depression homophily. *American Sociological Review*, *76*(5), 764–785. https://doi.org/10.1177/0003122411420813

Schafer, M. H. (2016). Health as status? Network relations and social structure in an American retirement community. *Ageing and Society*, *36*(1), 79–105. https://doi.org/10.1017/S0144686X14000993

Snijders, T. A. B., Van De Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks*, *32*(1), 44–60. https://doi.org/10.1016/j.socnet.2009.02.004

Steglich, C., Snijders, T. A. B., & Pearson, M. (2010). 8. Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology*, *40*(1), 329–393. https://doi.org/10.1111/j.1467-9531.2010.01225.x

Steinhoff, P., Ellwardt, L., & Wermeyer, M. (2024). Well-being in middle-aged and older adults who volunteer: A qualitative network analysis. *Aging & Mental Health*, *29*(2), 343–351. https://doi.org/10.1080/13607863.2024.2393250

Suitor, J., & Keeton, S. (1997). Once a friend, always a friend? Effects of homophily on women's support networks across a decade. *Social Networks*, *19*(1), 51–62. https://doi.org/10.1016/S0378-8733(96)00290-0

Thoits, P. A. (2011). Mechanisms linking social ties and support to physical and mental health. *Journal of Health and Social Behavior*, *52*(2), 145–161. https://doi.org/10.1177/0022146510395592

Uchino, B. N. (2006). Social Support and Health: A review of physiological processes potentially underlying links to disease outcomes. *Journal of Behavioral Medicine*, *29*(4), 377–387. https://doi.org/10.1007/s10865-006-9056-5

Ueno, K. (2005). The effects of friendship networks on adolescent depressive symptoms. *Social Science Research*, *34*(3), 484–510. https://doi.org/10.1016/j.ssresearch.2004.03.002

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3), 1-67. https://doi.org/10.18637/jss.v045.i03

Van Zalk, M. H. W., Kerr, M., Branje, S. J. T., Stattin, H., & Meeus, W. H. J. (2010). It takes three: Selection, influence, and de-selection processes of depression in adolescent friendship networks. *Developmental Psychology*, *46*(4), 927–938. https://doi.org/10.1037/a0019661

Webster, N. J., Ajrouch, K. J., & Antonucci, T. C. (2021). Volunteering and health: The role of social network change. *Social Science & Medicine*, *285*, 114274. https://doi.org/10.1016/j.socscimed.2021.114274

Wimmer, A., & Lewis, K. (2010). Beyond and below racial homophily: Erg models of a friendship network documented on Facebook. *American Journal of Sociology*, *116*(2), 583–642. https://doi.org/10.1086/653658

Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: A meta-analysis. *Psychological Bulletin*, *139*(1), 53–80. https://doi.org/10.1037/a0028601

Zalk, M. H. W. V., Kerr, M., Branje, S. J. T., Stattin, H., & Meeus, W. H. J. (2010). Peer contagion and adolescent depression: The role of failure anticipation. *Journal of Clinical Child & Adolescent Psychology*, *39*(6), 837–848. https://doi.org/10.1080/15374416.2010.517164

During the preparation of this work the author(s) used ChatGPT and DeepL in order to refine the manuscript's language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

5.7 Appendix

Goodness of Fit

Figure A5-1 GOF, Club 1

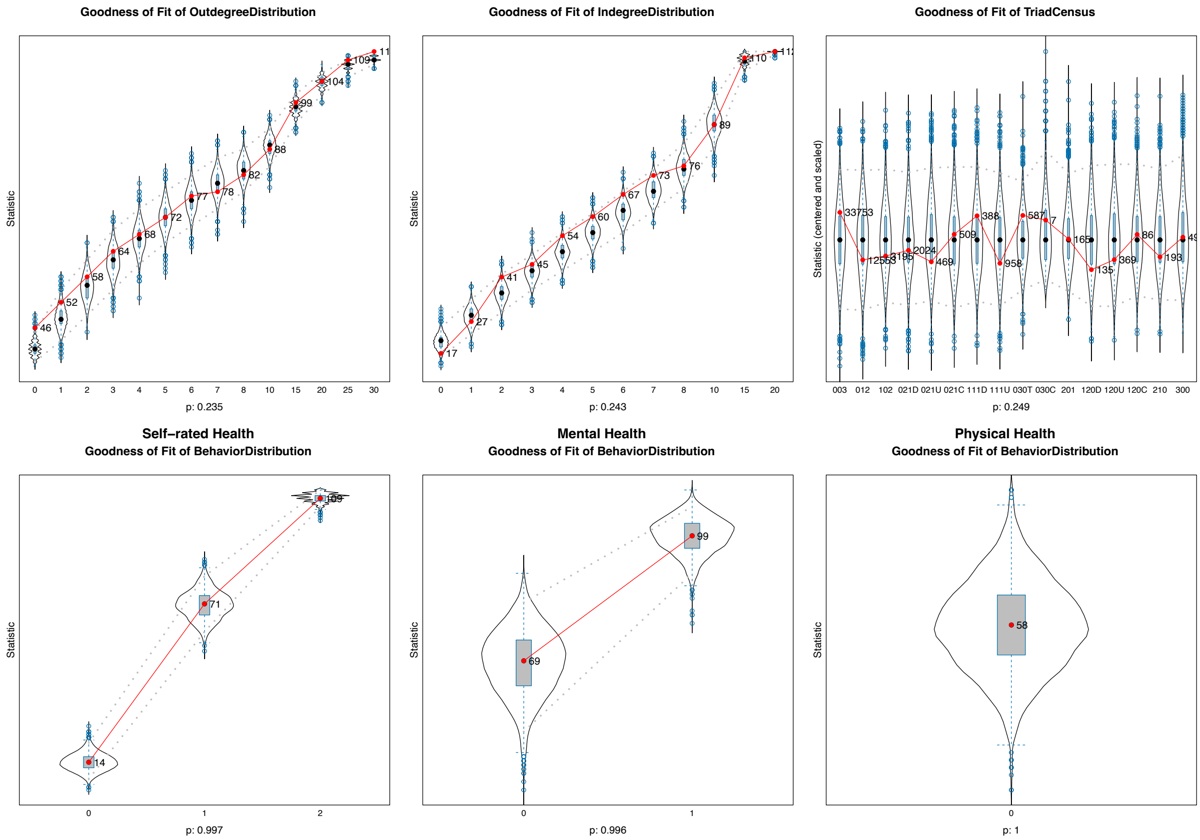
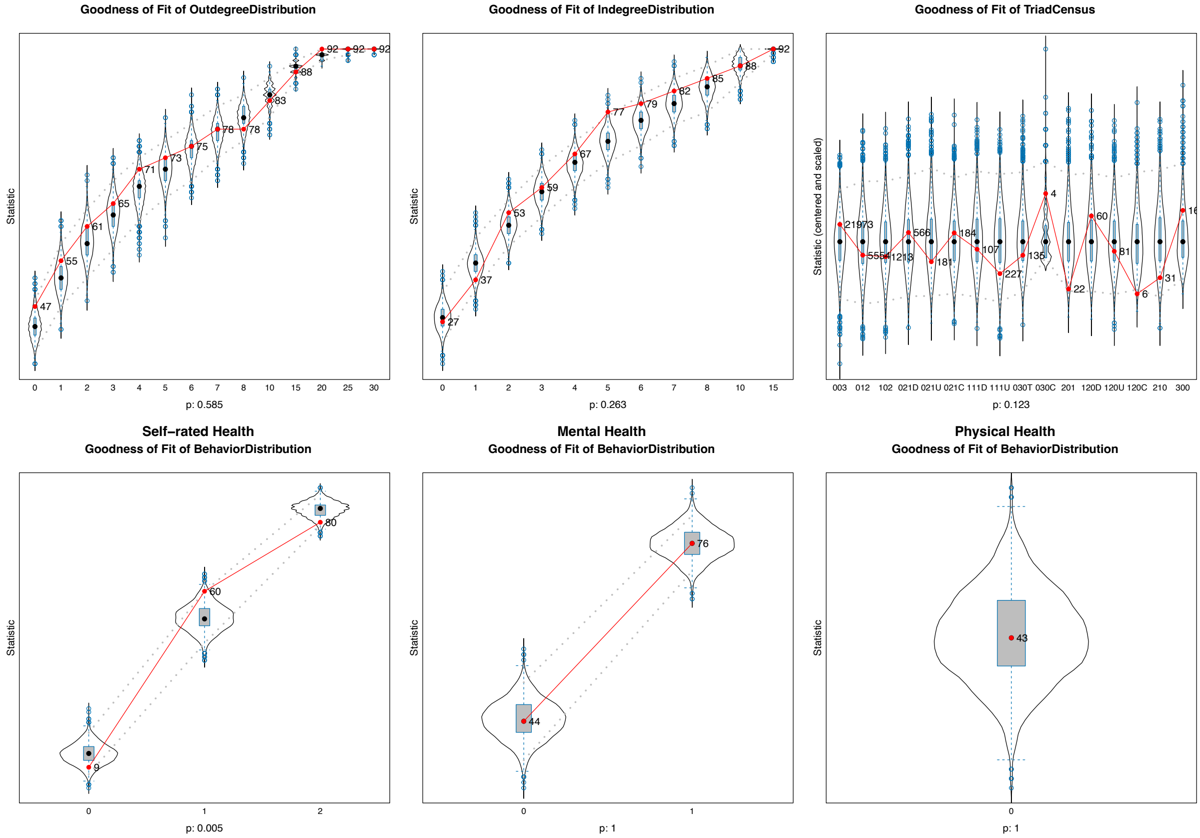


Figure A5-2 GOF, Club 2



Additional Analyses

Measures

Kinship ties indicated whether network members were related by blood or married. Kinship was coded as present when at least one individual indicated being related, hence it was coded as an undirected network.

To account for the organizational structure of the club, we investigated whether individuals currently hold or have previously held an official *position* within the club. We achieved this by asking respondents whether they are, or have ever been, members of the steering committee.

Additionally, we considered the level of general social *support*, as individuals with less support may be more inclined to utilize these clubs as a compensatory measure. We created a rounded additive index by combining responses from seven questions. Respondents indicated on a four-point scale—ranging from "fully true" to "not true at all"—whether there is someone who can offer advice when they are uncertain about a decision; someone who provides love and affection when they are feeling down; someone who would look after their apartment while they are away; someone to listen when they are worried; someone who would help with important tasks when they are unwell; someone who can offer guidance on handling a problem; and someone who would lend them money during financial difficulties. The resulting index scores range from one to four.

Furthermore, to evaluate whether the time spent in the club influences the reciprocal relationship between network involvement and health, we asked respondents to indicate how frequently they attend meetings, events, or sessions over the past six months. They could choose from options such as "less often," "several times in half a year," "several times a month," or "several times a week." Higher scores reflected greater frequency of participation.

Model Specifications

In this study, we followed an iterative model specification process. Due to the limited sample size, the model proved to be somewhat sensitive. To address this, we tested multiple model configurations that included different parameters. The model ultimately selected for analysis demonstrated the best fit and convergence ratios across the health measures and clubs studied.

Specifically, we tested for age homophily by including the *simX* term for an age homophily term for the age variable (see Table A5-2).

Additionally, to model the different processes of tie formation and tie maintenance, we specifically model tie formation and maintenance by including the health homophily parameter once with the *creation* function as well as the *endowment* function (see Table A5-1). While the creation function specifically models the creation of previously non existing ties, the endowment function models the maintenance of existing ties, with a positive effect indicating tie maintenance, and a negative effect indicating tie dissolution (Ripley et al., 2024).

Further, we checked for gender homophily in the network dynamics part for the second club (see Table A5-3).

Also, we accounted for the existence of kinship or marriage within the clubs (see Table A5-4). We additionally checked whether being or having been member in the steering committee within the club make people more likely to nominate others as close ties and whether there is homophilous sorting (see Table A5-5). We included the position variable as time constant.

Furthermore, we tested whether general perceived support also outside the club (see Table A5-6) or the time spent in the clubs (see Table A5-7) changes the results.

Also, we checked for whether peer influence effect is more pronounced among central people in the network by including the *avInSim* term instead of the *avSim* term (see Table A5-8).

Table A5-1 SAOM results, tie formation and maintenance

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Network Dynamics						
Amount of network change in period 1	10.89*** (1.299)	10.982*** (1.985)	10.359*** (1.346)	10.415*** (1.667)	11.341*** (1.217)	10.853*** (1.756)
Amount of network change in period 2	12.22*** (1.293)	9.023*** (1.616)	11.677*** (1.382)	7.88*** (1.332)	12.731*** (1.548)	8.507*** (1.266)
Outdegree (density)	-2.134*** (0.424)	-2.506*** (0.606)	-2.274*** (0.446)	-2.161*** (0.587)	-2.291*** (0.382)	-2.439*** (0.543)
Reciprocity	2.35*** (0.488)	3.617*** (1.085)	2.459*** (0.505)	3.625*** (0.914)	2.273*** (0.472)	3.479*** (0.811)
Balance	0.041** (0.014)	0.033 (0.029)	0.041** (0.014)	0.034 (0.03)	0.042** (0.014)	0.032 (0.027)
GWESP	1.396*** (0.257)	2.266** (0.711)	1.445*** (0.272)	2.258*** (0.584)	1.373*** (0.24)	2.203*** (0.587)
Indegree Activity (Sqrt)	-0.492* (0.2)	-0.468* (0.234)	-0.423* (0.209)	-0.512* (0.238)	-0.447* (0.182)	-0.483* (0.207)
Outdegree Activity	0.046*** (0.011)	0.004 (0.03)	0.047*** (0.011)	0.005 (0.031)	0.046*** (0.011)	0.01 (0.027)
Similarity on education	0.52*** (0.127)	0.412 (0.254)	0.513*** (0.14)	0.556† (0.285)	0.506*** (0.129)	0.345 (0.239)
Health alter	-0.083 (0.119)	0.148 (0.278)	0.031 (0.157)	0.173 (0.285)	-0.309* (0.156)	-0.139 (0.207)
Health ego	0.283† (0.146)	-0.372 (0.317)	0.805** (0.299)	-0.531 (0.479)	0.066 (0.149)	-0.345 (0.297)
Similarity on health: maintenance[a]	-0.188 (1.123)	-2.242 (1.609)	0.857 (1.208)	-0.228 (1.91)	0.68 (0.479)	0.897 (0.664)
Similarity on health: creation[a]	1.897 (1.156)	6.113† (3.247)	0.281 (0.606)	0.059 (1.627)	-0.234 (0.374)	-0.183 (0.645)
Employment ego	0.079 (0.109)	-1.097** (0.392)	0.003 (0.13)	-1.117* (0.437)	0.088 (0.104)	-0.953** (0.331)
Reciprocity x GWESP	-0.944** (0.336)	-1.723** (0.653)	-0.991** (0.341)	-1.673** (0.587)	-0.869** (0.319)	-1.624** (0.537)
Health Dynamics						
Amount of behavioral change in period 1 on health	1.399*** (0.42)	1.9* (0.759)	1.808** (0.657)	4.059 (2.497)	1.125** (0.429)	0.886* (0.42)

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Amount of behavioral change in period 2 on health	1.573** (0.531)	1.408** (0.507)	1.679* (0.667)	2.248** (0.861)	0.81** (0.286)	1.348* (0.592)
Health linear shape	-0.09 (0.532)	-1.089† (0.597)	-0.177 (1.027)	-2.342 (2.081)	2.209 (1.58)	1.596 (1.564)
Health quadratic shape	-0.544 (0.522)	-0.517 (0.349)	0.928 (0.639)	-0.788 (2.453)		
Health average similarity	1.603 (4.074)	-0.52 (3.279)	6.338 (5.215)	-3.888 (9.598)	2.277 (2.742)	1.155 (2.2)
Health x Age	0.175 (0.223)	0.744* (0.332)	-0.321 (0.388)	0.64 (0.774)	-0.383 (0.613)	0.372 (0.695)
Health x Education	0.013 (0.234)	0.158 (0.26)	0.284 (0.421)	0.403 (0.517)	-0.787 (0.56)	-1.188 (0.742)
Health x Gender		0.474 (0.351)		1.609 (1.712)		-0.419 (0.919)

*† $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

Table A5-2 SAOM results, age homophily

	Self-rated health		**Mental health**		**Physical health**	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Network Dynamics						
Amount of network change in period 1	10.726*** (1.277)	10.395*** (1.572)	10.278*** (1.176)	10.46*** (1.582)	11.058*** (1.274)	10.552*** (1.822)
Amount of network change in period 2	12.053*** (1.623)	8.405*** (1.248)	11.602*** (1.31)	7.852*** (1.143)	12.365*** (1.264)	8.191*** (1.227)
Outdegree (density)	-2.079*** (0.389)	-2.302*** (0.561)	-2.257*** (0.487)	-2.185*** (0.544)	-2.218*** (0.377)	-2.49*** (0.559)
Reciprocity	2.366*** (0.497)	3.53*** (0.964)	2.49*** (0.477)	3.573*** (1.023)	2.315*** (0.406)	3.508** (1.078)
Balance	0.039** (0.013)	0.035 (0.031)	0.039** (0.014)	0.032 (0.026)	0.04** (0.014)	0.032 (0.03)
GWESP	1.411*** (0.247)	2.201*** (0.621)	1.472*** (0.265)	2.262*** (0.588)	1.397*** (0.218)	2.236** (0.788)
Indegree Activity (Sqrt)	-0.513* (0.202)	-0.437† (0.233)	-0.436† (0.229)	-0.509* (0.236)	-0.464** (0.165)	-0.492† (0.262)
Outdegree Activity	0.045*** (0.01)	0.009 (0.029)	0.045*** (0.011)	0.005 (0.026)	0.044*** (0.01)	0.009 (0.033)
Similarity on age	0.124 (0.135)	-0.378 (0.257)	0.164 (0.141)	-0.208 (0.236)	0.136 (0.134)	-0.216 (0.244)
Similarity on education	0.518*** (0.128)	0.458† (0.245)	0.51*** (0.139)	0.568* (0.259)	0.511*** (0.127)	0.379 (0.246)
Health alter	-0.061 (0.107)	0.014 (0.154)	0.007 (0.127)	0.085 (0.318)	-0.341* (0.143)	-0.069 (0.23)
Health ego	0.28† (0.147)	-0.279 (0.216)	0.81** (0.288)	-0.564 (0.42)	0.083 (0.15)	-0.309 (0.285)
Similarity on health[a]	0.954 (0.596)	1.568* (0.793)	0.506 (0.408)	-0.42 (1.108)	0.119 (0.212)	0.405 (0.351)
Employment ego	0.072 (0.107)	-1.102*** (0.325)	0.002 (0.134)	-1.094** (0.36)	0.091 (0.103)	-0.961** (0.32)
Reciprocity x GWESP	-0.948** (0.321)	-1.66* (0.649)	-1.028** (0.337)	-1.626* (0.664)	-0.913** (0.284)	-1.63* (0.639)
Health Dynamics						
Amount of behavioral change in period 1 on health	1.394** (0.432)	1.889** (0.651)	1.826* (0.737)	4.208 (3.86)	1.118* (0.461)	0.921* (0.469)

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Amount of behavioral change in period 2 on health	1.586*** (0.479)	1.412** (0.486)	1.707** (0.641)	2.31** (0.88)	0.818** (0.286)	1.363* (0.53)
Health linear shape	-0.086 (0.532)	-1.106† (0.619)	-0.131 (1.088)	-2.319 (1.717)	2.194 (1.756)	1.562 (1.42)
Health quadratic shape	-0.508 (0.563)	-0.52 (0.421)	0.912 (0.578)	-0.796 (1.777)		
Health average similarity	1.849 (4.464)	-0.538 (3.613)	6.399 (5.208)	-3.759 (6.511)	2.081 (3.262)	1.149 (2.273)
Health x Age	0.173 (0.22)	0.749* (0.337)	-0.301 (0.39)	0.621 (0.676)	-0.385 (0.614)	0.353 (0.657)
Health x Education	0.012 (0.24)	0.17 (0.271)	0.261 (0.419)	0.401 (0.455)	-0.788 (0.561)	-1.173† (0.679)
Health x Gender		0.477 (0.364)		1.579 (1.422)		-0.408 (0.824)

*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

Table A5-3 SAOM results, gender homophily in club 2

Parameter	Self-rated health	Mental health	Physical health
Network Dynamics			
Amount of network change in period 1	10.56*** (1.704)	10.492*** (1.811)	10.555*** (1.432)
Amount of network change in period 2	8.541*** (1.696)	7.902*** (1.238)	8.18*** (1.264)
Outdegree (density)	-2.367*** (0.513)	-2.301*** (0.594)	-2.633*** (0.589)
Reciprocity	3.498** (1.143)	3.602*** (1.094)	3.636*** (1.032)
Balance	0.042 (0.032)	0.036 (0.03)	0.035 (0.029)
GWESP	2.118** (0.81)	2.249** (0.761)	2.282*** (0.668)
Indegree Activity (Sqrt)	-0.422 (0.285)	-0.49* (0.243)	-0.492* (0.248)
Outdegree Activity	0.013 (0.031)	0.006 (0.036)	0.01 (0.027)
Similarity on education	0.381 (0.275)	0.509† (0.265)	0.327 (0.234)
Same gender	0.141 (0.125)	0.159 (0.152)	0.143 (0.125)
Health alter	0.02 (0.134)	0.062 (0.284)	-0.067 (0.228)
Health ego	-0.277 (0.218)	-0.579 (0.413)	-0.331 (0.315)
Similarity on health[a]	1.351† (0.724)	-0.479 (1.048)	0.379 (0.3)
Employment ego	-1.094** (0.394)	-1.11* (0.435)	-0.986*** (0.28)
Reciprocity x GWESP	-1.66* (0.652)	-1.669* (0.677)	-1.712** (0.612)
Health Dynamics			
Amount of behavioral change in period 1 on health	1.885** (0.636)	4.313 (3.456)	0.891* (0.413)
Amount of behavioral change in period 2 on health	1.406** (0.514)	2.395** (0.919)	1.36* (0.554)
Health linear shape	-1.116† (0.61)	-2.359 (2.021)	1.577 (1.395)
Health quadratic shape	-0.539 (0.442)	-0.829 (2.744)	
Health average similarity	-0.723 (3.596)	-3.917 (9.755)	1.116 (2.217)
Health x Age	0.755* (0.346)	0.636 (0.771)	0.329 (0.641)
Health x Education	0.171 (0.268)	0.391 (0.499)	-1.169† (0.677)
Health x Gender	0.476 (0.356)	1.644 (1.994)	-0.407 (0.804)

*† $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

Table A5-4 SAOM results, Club 1, model specification to test for kin effects

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Network Dynamics						
Amount of network change in period 1	10.807*** (1.312)	11.782*** (1.893)	10.349*** (1.208)	11.694*** (2.062)	11.054*** (1.265)	12.386*** (2.254)
Amount of network change in period 2	12.169*** (1.435)	10.068*** (1.77)	11.766*** (1.293)	9.32*** (1.609)	12.471*** (1.497)	10.154*** (1.745)
Outdegree (density)	-2.087*** (0.405)	-2.327*** (0.479)	-2.283*** (0.482)	-2.181*** (0.419)	-2.23*** (0.452)	-2.582*** (0.433)
Reciprocity	2.345*** (0.479)	2.451*** (0.707)	2.481*** (0.468)	2.522*** (0.731)	2.345*** (0.467)	2.41*** (0.555)
Balance	0.041** (0.014)	0.034 (0.032)	0.041** (0.014)	0.026 (0.032)	0.042** (0.013)	0.027 (0.029)
GWESP	1.401*** (0.256)	1.753*** (0.455)	1.461*** (0.247)	1.896*** (0.487)	1.397*** (0.228)	1.797*** (0.392)
Indegree Activity (Sqrt)	-0.513* (0.2)	-0.222 (0.203)	-0.432* (0.204)	-0.339 (0.218)	-0.475* (0.205)	-0.295† (0.176)
Outdegree Activity	0.046*** (0.011)	0.015 (0.028)	0.047*** (0.011)	0.009 (0.026)	0.046*** (0.01)	0.015 (0.025)
Kin	0.622 (0.408)	2.432*** (0.426)	0.655 (0.407)	2.61*** (0.5)	0.623 (0.387)	2.51*** (0.463)
Similarity on education	0.515*** (0.128)	0.524* (0.234)	0.516*** (0.136)	0.66** (0.243)	0.506*** (0.126)	0.522* (0.251)
Health alter	-0.063 (0.111)	0.065 (0.135)	0.005 (0.133)	0.034 (0.322)	-0.33* (0.136)	0.019 (0.204)
Health ego	0.28* (0.127)	-0.235 (0.195)	0.783** (0.273)	-0.502 (0.373)	0.084 (0.154)	-0.036 (0.267)
Similarity on health[a]	0.944 (0.593)	1.518† (0.849)	0.469 (0.422)	-0.666 (1.155)	0.132 (0.223)	0.517 (0.375)
Employment ego	0.092 (0.113)	-0.899** (0.309)	0.019 (0.139)	-0.905** (0.286)	0.107 (0.104)	-0.7*** (0.209)
Reciprocity x GWESP	-0.931** (0.329)	-1.246* (0.491)	-1.023** (0.331)	-1.187* (0.513)	-0.926** (0.295)	-1.188** (0.423)
Health Dynamics						
Amount of behavioral change in period 1 on health	1.378*** (0.406)	1.887* (0.763)	1.803** (0.67)	4.57 (3.219)	1.112** (0.411)	0.909* (0.451)

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Amount of behavioral change in period 2 on health	1.579** (0.52)	1.412** (0.503)	1.698** (0.555)	2.356** (0.907)	0.833** (0.315)	1.376* (0.57)
Health linear shape	-0.083 (0.349)	-1.098† (0.634)	0.143 (0.967)	-2.035* (0.839)	1.42 (1.199)	1.604 (1.478)
Health quadratic shape	-0.502 (0.563)	-0.514 (0.377)	0.911 (0.594)	-0.525 (0.964)		
Health average similarity	1.872 (4.413)	-0.492 (3.141)	6.329 (5.209)	-2.638 (3.725)	2.161 (2.644)	0.852 (1.658)
Health x Age	0.179 (0.22)	0.742* (0.342)	-0.331 (0.396)	0.575 (0.38)	-0.397 (0.607)	0.331 (0.631)
Health x Education	0.013 (0.237)	0.168 (0.268)	0.269 (0.43)	0.314 (0.292)	-0.781 (0.542)	-1.172† (0.662)
Health x Gender		0.474 (0.365)		1.319* (0.663)		-0.422 (0.798)

*† $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

Table A5-5 SAOM results, official position in the clubs' steering committee

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Network Dynamics						
Amount of network change in period 1	10.762*** (1.213)	10.59*** (1.95)	10.228*** (1.135)	10.536*** (1.735)	11.028*** (1.53)	10.698*** (1.746)
Amount of network change in period 2	12.12*** (1.4)	8.585*** (1.409)	11.676*** (1.355)	8.011*** (1.324)	12.385*** (1.475)	8.338*** (1.216)
Outdegree (density)	-2.176*** (0.412)	-2.285*** (0.531)	-2.357*** (0.424)	-2.248*** (0.507)	-2.299*** (0.464)	-2.492*** (0.544)
Reciprocity	2.381*** (0.449)	3.446*** (0.851)	2.511*** (0.511)	3.548*** (0.957)	2.337*** (0.45)	3.476*** (0.839)
Balance	0.038** (0.014)	0.04 (0.029)	0.037** (0.012)	0.036 (0.028)	0.039** (0.014)	0.034 (0.032)
GWESP	1.401*** (0.232)	2.074*** (0.57)	1.465*** (0.25)	2.161*** (0.606)	1.375*** (0.244)	2.167*** (0.635)
Indegree Activity (Sqrt)	-0.518** (0.188)	-0.418† (0.24)	-0.453* (0.193)	-0.488† (0.252)	-0.485* (0.212)	-0.481* (0.234)
Outdegree Activity	0.045*** (0.011)	0.012 (0.029)	0.046*** (0.01)	0.009 (0.03)	0.045*** (0.01)	0.011 (0.029)
Similarity on education	0.521*** (0.128)	0.43† (0.223)	0.52*** (0.139)	0.565* (0.265)	0.511*** (0.124)	0.386† (0.23)
Position alter	0.094 (0.098)	0.085 (0.138)	0.106 (0.094)	0.178 (0.152)	0.115 (0.096)	0.096 (0.13)
Same position	0.122 (0.095)	0.003 (0.13)	0.143 (0.105)	-0.001 (0.129)	0.137 (0.105)	0.006 (0.131)
Health alter	-0.091 (0.123)	0.019 (0.139)	0.002 (0.138)	0.149 (0.267)	-0.364* (0.163)	-0.04 (0.224)
Health ego	0.276† (0.143)	-0.276 (0.197)	0.79** (0.288)	-0.549 (0.396)	0.097 (0.149)	-0.298 (0.313)
Similarity on health[a]	0.952† (0.564)	1.255† (0.76)	0.513 (0.506)	-0.372 (0.959)	0.126 (0.227)	0.362 (0.306)
Employment ego	0.069 (0.111)	-1.077** (0.359)	0.009 (0.13)	-1.086* (0.423)	0.087 (0.104)	-0.955** (0.296)
Reciprocity x GWESP	-0.945** (0.304)	-1.632** (0.56)	-1.025** (0.35)	-1.653** (0.629)	-0.898** (0.289)	-1.622** (0.526)
Health Dynamics						

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Amount of behavioral change in period 1 on health	1.385*** (0.413)	1.899** (0.717)	1.843* (0.828)	4.1 (2.654)	1.111** (0.406)	0.901* (0.435)
Amount of behavioral change in period 2 on health	1.576*** (0.444)	1.408** (0.496)	1.686** (0.651)	2.315* (0.979)	0.82* (0.319)	1.38* (0.614)
Health linear shape	-0.07 (0.361)	-1.119† (0.626)	0.175 (0.908)	-2.339 (1.459)	1.527 (1.302)	1.604 (1.444)
Health quadratic shape	-0.539 (0.568)	-0.567 (0.464)	0.905 (0.619)	-0.82 (1.541)		
Health average similarity	1.639 (4.406)	-0.902 (3.639)	6.456 (5.348)	-3.811 (5.924)	2.385 (2.788)	1.109 (2.246)
Health x Age	0.176 (0.227)	0.765* (0.352)	-0.333 (0.39)	0.659 (0.479)	-0.436 (0.628)	0.327 (0.64)
Health x Education	0.005 (0.235)	0.168 (0.264)	0.274 (0.464)	0.402 (0.469)	-0.788 (0.584)	-1.18† (0.681)
Health x Gender		0.472 (0.359)		1.604 (1.175)		-0.428 (0.824)

*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

Table A5-6 SAOM results, model specification to test for support

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Network Dynamics						
Amount of network change in period 1	10.777*** (1.246)	10.449*** (1.721)	10.341*** (1.091)	10.301*** (1.85)	11.102*** (1.357)	10.432*** (1.66)
Amount of network change in period 2	12.171*** (1.456)	8.515*** (1.377)	11.693*** (1.38)	7.811*** (1.436)	12.453*** (1.799)	8.238*** (1.345)
Outdegree (density)	-1.9*** (0.48)	-2.488*** (0.678)	-2.134*** (0.564)	-1.807† (1.054)	-2.12*** (0.49)	-2.573*** (0.719)
Reciprocity	2.347*** (0.463)	3.47*** (1.004)	2.46*** (0.443)	3.63** (1.108)	2.318*** (0.578)	3.578*** (0.896)
Balance	0.041** (0.015)	0.038 (0.028)	0.04** (0.014)	0.032 (0.03)	0.041** (0.015)	0.032 (0.029)
GWESP	1.398*** (0.234)	2.121** (0.674)	1.453*** (0.253)	2.285** (0.823)	1.394*** (0.293)	2.265*** (0.617)
Indegree Activity (Sqrt)	-0.494** (0.186)	-0.435† (0.25)	-0.42* (0.202)	-0.507 (0.338)	-0.449† (0.248)	-0.508* (0.235)
Outdegree Activity	0.046*** (0.011)	0.009 (0.028)	0.046*** (0.011)	0.002 (0.033)	0.045*** (0.011)	0.007 (0.029)
Similarity on education	0.521*** (0.126)	0.448† (0.231)	0.515*** (0.138)	0.591* (0.3)	0.517*** (0.122)	0.378 (0.239)
Health alter	-0.06 (0.111)	0.02 (0.136)	-0.006 (0.125)	0.074 (0.434)	-0.327* (0.138)	-0.061 (0.227)
Health ego	0.28* (0.142)	-0.277 (0.209)	0.786** (0.25)	-0.675 (0.489)	0.068 (0.168)	-0.34 (0.317)
Similarity on health[a]	0.975† (0.576)	1.318† (0.717)	0.491 (0.472)	-0.416 (1.561)	0.127 (0.22)	0.356 (0.296)
Employment ego	0.049 (0.11)	-1.119*** (0.337)	-0.013 (0.134)	-1.176* (0.527)	0.075 (0.108)	-1.003** (0.339)
Support ego	-0.061 (0.083)	0.077 (0.144)	-0.042 (0.093)	-0.094 (0.218)	-0.04 (0.075)	0.036 (0.142)
Reciprocity x GWESP	-0.93** (0.323)	-1.622* (0.642)	-0.998** (0.31)	-1.667* (0.65)	-0.912* (0.363)	-1.663** (0.606)
Health Dynamics						
Amount of behavioral change in period 1 on health	1.385** (0.445)	1.881** (0.668)	1.841* (0.719)	4.114† (2.494)	1.112* (0.476)	0.908* (0.424)

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Amount of behavioral change in period 2 on health	1.577*** (0.469)	1.413** (0.458)	1.673* (0.678)	2.348* (1.011)	0.845** (0.313)	1.358* (0.624)
Health linear shape	-0.079 (0.345)	-1.095† (0.615)	0.181 (1.011)	-2.385 (2.202)	1.473 (1.324)	1.635 (1.395)
Health quadratic shape	-0.524 (0.559)	-0.53 (0.426)	0.946 (0.68)	-0.803 (2.45)		
Health average similarity	1.693 (4.369)	-0.673 (3.651)	6.725 (5.949)	-3.871 (9.785)	2.312 (3.172)	1.099 (2.071)
Health x Age	0.176 (0.217)	0.744* (0.337)	-0.328 (0.399)	0.649 (0.788)	-0.409 (0.638)	0.333 (0.641)
Health x Education	0.009 (0.234)	0.165 (0.262)	0.288 (0.465)	0.408 (0.554)	-0.801 (0.554)	-1.196† (0.682)
Health x Gender		0.469 (0.355)		1.611 (1.719)		-0.449 (0.816)

*† $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

Table A5-7 SAOM results, model specification for frequency spent in club

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Network Dynamics						
Amount of network change in period 1	10.694*** (1.217)	10.528*** (1.591)	10.158*** (1.15)	10.359*** (2.054)	11.032*** (1.31)	10.734*** (1.533)
Amount of network change in period 2	12.02*** (1.395)	8.509*** (1.283)	11.506*** (1.393)	7.917*** (1.522)	12.315*** (1.443)	8.324*** (1.154)
Outdegree (density)	-2.261*** (0.379)	-2.274*** (0.503)	-2.485*** (0.4)	-2.37*** (0.588)	-2.371*** (0.38)	-2.614*** (0.54)
Reciprocity	2.361*** (0.469)	3.481*** (0.946)	2.478*** (0.494)	3.645*** (1.024)	2.301*** (0.486)	3.513*** (0.854)
Balance	0.037* (0.015)	0.039 (0.029)	0.036** (0.013)	0.032 (0.03)	0.038** (0.015)	0.033 (0.031)
GWESP	1.421*** (0.261)	2.118*** (0.589)	1.498*** (0.255)	2.284*** (0.683)	1.405*** (0.266)	2.209*** (0.569)
Indegree Activity (Sqrt)	-0.552** (0.198)	-0.432 (0.285)	-0.488* (0.21)	-0.564 (0.377)	-0.492* (0.21)	-0.51† (0.27)
Outdegree Activity	0.044*** (0.011)	0.01 (0.03)	0.044*** (0.01)	-0.001 (0.037)	0.043*** (0.011)	0.009 (0.029)
Similarity on education	0.517*** (0.132)	0.431† (0.236)	0.515*** (0.141)	0.595* (0.284)	0.52*** (0.128)	0.368 (0.231)
Health alter	-0.077 (0.112)	0.029 (0.141)	-0.012 (0.125)	0.073 (0.294)	-0.362* (0.157)	-0.055 (0.217)
Health ego	0.309* (0.147)	-0.273 (0.211)	0.826** (0.293)	-0.652 (0.566)	0.061 (0.152)	-0.323 (0.327)
Similarity on health[a]	0.857 (0.591)	1.343† (0.739)	0.478 (0.459)	-0.44 (1.075)	0.115 (0.216)	0.369 (0.33)
Employment ego	0.107 (0.122)	-1.108** (0.35)	0.045 (0.137)	-1.205* (0.563)	0.114 (0.109)	-0.979** (0.316)
Frequency ego	0.132 (0.084)	0.017 (0.178)	0.157† (0.092)	0.168 (0.29)	0.103 (0.076)	0.09 (0.161)
Similarity on frequency	0.3 (0.192)	-0.099 (0.251)	0.376† (0.195)	-0.123 (0.276)	0.375* (0.186)	-0.126 (0.248)
Reciprocity x GWESP	-0.925** (0.326)	-1.633** (0.603)	-0.99** (0.345)	-1.671** (0.628)	-0.883** (0.332)	-1.638** (0.552)
Health Dynamics						

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Amount of behavioral change in period 1 on health	1.388*** (0.396)	1.898* (0.739)	1.821* (0.831)	4.336 (3.719)	1.118* (0.458)	0.902* (0.416)
Amount of behavioral change in period 2 on health	1.582** (0.486)	1.412** (0.487)	1.656** (0.587)	2.327* (1.029)	0.818** (0.283)	1.362* (0.572)
Health linear shape	-0.083 (0.346)	-1.099† (0.623)	0.219 (1.148)	-2.342 (1.648)	1.454 (1.256)	1.614 (1.527)
Health quadratic shape	-0.508 (0.566)	-0.525 (0.468)	0.948 (0.727)	-0.865 (1.732)		
Health average similarity	1.85 (4.404)	-0.601 (3.948)	6.84 (6.985)	-4.075 (7.101)	2.275 (3.002)	1.092 (2.145)
Health x Age	0.18 (0.222)	0.746* (0.338)	-0.35 (0.409)	0.631 (0.523)	-0.393 (0.6)	0.324 (0.671)
Health x Education	0.01 (0.228)	0.167 (0.258)	0.305 (0.487)	0.394 (0.519)	-0.784 (0.572)	-1.185 (0.724)
Health x Gender		0.471 (0.359)		1.607 (1.21)		-0.427 (0.844)

*† p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

Table A5-8 SAOM results, alternative model specification for health influence

	Self-rated health		Mental health		Physical health	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Network Dynamics						
Amount of network change in period 1	10.757*** (1.391)	10.49*** (1.781)	10.402*** (1.238)	10.516*** (1.498)	11.021*** (1.417)	10.579*** (1.698)
Amount of network change in period 2	12.057*** (1.517)	8.431*** (1.396)	11.845*** (1.379)	7.975*** (1.241)	12.304*** (1.488)	8.177*** (1.33)
Outdegree (density)	-2.089*** (0.462)	-2.236*** (0.49)	-2.261*** (0.506)	-2.168*** (0.519)	-2.212*** (0.44)	-2.464*** (0.493)
Reciprocity	2.365*** (0.422)	3.487*** (0.879)	2.445*** (0.471)	3.606*** (0.819)	2.36*** (0.468)	3.568*** (0.891)
Balance	0.04** (0.014)	0.038 (0.03)	0.042** (0.015)	0.036 (0.03)	0.042** (0.014)	0.033 (0.033)
GWESP	1.414*** (0.235)	2.134*** (0.6)	1.423*** (0.236)	2.237*** (0.585)	1.4*** (0.252)	2.246*** (0.663)
Indegree Activity (Sqrt)	-0.51* (0.215)	-0.437† (0.242)	-0.42† (0.218)	-0.502* (0.242)	-0.478* (0.191)	-0.504* (0.236)
Outdegree Activity	0.046*** (0.011)	0.01 (0.029)	0.047*** (0.011)	0.006 (0.031)	0.046*** (0.011)	0.009 (0.031)
Similarity on education	0.517*** (0.131)	0.437† (0.238)	0.514*** (0.133)	0.561* (0.262)	0.509*** (0.126)	0.366 (0.233)
Health alter	-0.054 (0.106)	0.018 (0.133)	0.031 (0.121)	0.079 (0.329)	-0.334* (0.162)	-0.072 (0.229)
Health ego	0.272* (0.127)	-0.28 (0.23)	0.71** (0.235)	-0.599 (0.48)	0.099 (0.15)	-0.322 (0.287)
Similarity on health[a]	0.933 (0.596)	1.339† (0.745)	0.452 (0.423)	-0.444 (1.095)	0.137 (0.226)	0.351 (0.327)
Employment ego	0.08 (0.118)	-1.107** (0.378)	-0.007 (0.13)	-1.133** (0.421)	0.086 (0.105)	-0.979** (0.324)
Reciprocity x GWESP	-0.939** (0.292)	-1.643** (0.527)	-0.99** (0.32)	-1.671** (0.553)	-0.924** (0.31)	-1.657** (0.558)
Health Dynamics						
Amount of behavioral change in period 1 on health	1.345** (0.419)	1.913** (0.706)	1.673* (0.654)	4.613† (2.526)	1.034** (0.395)	0.874* (0.371)
Amount of behavioral change in period 2 on health	1.535*** (0.457)	1.424** (0.457)	1.687* (0.722)	2.317** (0.875)	0.832** (0.297)	1.358* (0.554)

	Self-rated health		**Mental health**		**Physical health**	
Parameter	**Club 1**	**Club 2**	**Club 1**	**Club 2**	**Club 1**	**Club 2**
Health linear shape	-0.056 (0.36)	-1.083† (0.621)	-0.662 (0.502)	-1.896** (0.66)	1.178 (0.974)	1.547 (1.486)
Health quadratic shape	-1.012 (1.229)	-0.491 (0.398)	0.186 (0.813)	-0.118 (0.591)		
Health average in-similarity	-1.857 (8.103)	-0.285 (3.415)	-1.578 (4.32)	-0.886 (2.701)	2.084 (2.221)	1.913 (2.375)
Health x Age	0.226 (0.261)	0.739* (0.339)	-0.542 (0.397)	0.501† (0.283)	-0.386 (0.61)	0.218 (0.743)
Health x Education	-0.011 (0.246)	0.163 (0.262)	0.166 (0.244)	0.281 (0.269)	-0.782 (0.528)	-1.212 (0.747)
Health x Gender		0.467 (0.362)		1.178** (0.433)		-0.511 (0.91)

*† $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$*
Standard errors in parentheses.
All t-ratios are below 0.1.
[a] For the binary variable physical health, we used the sameX term instead of the simX term.

DECLARATION ON OATH

Eidesstattliche Erklärung

nach § 8 Abs. 3 der Promotionsordnung vom 17.02.2015

Hiermit versichere ich an Eides Statt, dass ich die vorgelegte Arbeit selbstständig und ohne die Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Aussagen, Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Bei der Auswahl und Auswertung folgenden Materials haben mir die nachstehend aufgeführten Personen in der jeweils beschriebenen Weise ~~entgeltlich~~/unentgeltlich geholfen: Paula Steinhoff, Elena De Gioannis, Mark Wittek, Lea Ellwardt, James Moody

Weitere Personen, neben den ggf. in der Einleitung der Arbeit aufgeführten Koautorinnen und Koautoren, waren an der inhaltlich-materiellen Erstellung der vorliegenden Arbeit nicht beteiligt. Insbesondere habe ich hierfür nicht die entgeltliche Hilfe von Vermittlungs- bzw. Beratungsdiensten in Anspruch genommen. Niemand hat von mir unmittelbar oder mittelbar geldwerte Leistungen für Arbeiten erhalten, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen.

Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt.

Ich versichere, dass ich nach bestem Wissen die reine Wahrheit gesagt und nichts verschwiegen habe.

Ich versichere, dass die eingereichte elektronische Fassung der eingereichten Druckfassung vollständig entspricht.

Die Strafbarkeit einer falschen eidesstattlichen Versicherung ist mir bekannt, namentlich die Strafandrohung gemäß § 156 StGB bis zu drei Jahren Freiheitsstrafe oder Geldstrafe bei vorsätzlicher Begehung der Tat bzw. gemäß § 161 Abs. 1 StGB bis zu einem Jahr Freiheitsstrafe oder Geldstrafe bei fahrlässiger Begehung.

Köln,

Ort, Datum Unterschrift