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From social networks to health: Durkheim after the turn of the millennium

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Introduction

Beginning with the immeasurable contributions of Émile Durkheim in the late 1800s (Durkheim, 1967), it is by now widely recognized by public health, biomedical, and social scientists that social relationships matter for health and mental health. While the study of social networks was initially borrowed from the field of anthropology to study how social relationships beyond kinship influenced trading patterns, mate selection, and local politics (Barnes, 1954; Bott, 1971), new interest in the social network patterning of health and mental health has developed at a steady pace over the last several decades. Figure 1 shows the total number of articles published in leading epidemiologic, public health, and medical journals during the past several decades that included the phrase “social network” or “social networks” in the title or abstract.

Notably, the figure demonstrates a sharp uptick around the turn of the millennium. Prior to this point, the idea of “social networks” in the public health and medical literature was most often used in reference to the closely related but distinct concept of “social support,” such as has been described in the stress “buffering” literature (Cassel, 1976; Cobb, 1976) and quite akin to Durkheim’s notion of social cohesion and population well-being. Right before this uptick, Berkman et al. (2000) published, in the pages of this journal, a review paper that served as a call-to-arms of sorts, prodding researchers scientists to push the boundaries of network thinking. In their now-classic essay, which at the time of this writing has been cited more than 1,500 times, Berkman et al. (2000) provided a conceptual model for thinking about the ways that social networks might influence health, mental health, and health behaviors. Specifically, as we discuss below, Berkman et al. (2000) called for a more systematic empirical approach to the study of social networks and health that not only captured the sprit of Durkheim but also leveraged rapidly developing methodological and computational advancements.

This Special Issue of *Social Science and Medicine* provides an occasion for reflection about how far we have come since the prescient essay by Berkman et al. (2000). At that time, Google was only two years old, the Winklevi had not yet had the idea for Facebook’s predecessor, and the iPhone was still seven years away from release. Much has changed

since then. But the spirit of the Berkman et al. (2000) essay and their charge seems to be one that researchers have taken quite seriously. Today, scholars across a multitude of disciplines ranging from field-driven anthropology to theoretical physics engage in a growing field known as "network science" whose applications to the study of health and mental health continue to proliferate, as evidenced in Figure 1. In the remainder of this introduction, we provide a brief look back at the contribution of Berkman et al. (2000), summarize the themes raised by papers included in this Special Issue and how they advance our knowledge of networks and health, and conclude with remarks about potential avenues for future research.

Moving Beyond Social Support

Much of the early empirical work, noted Berkman et al. (2000), used the term "social networks" in a fairly loose sense, often interchangeably with related concepts such as "social integration" and "social support." In other words, prior to 2000, health researchers rarely measured and analyzed networks in formal graph-theoretical terms. Rather, the idea that social relationships matter -- and that they constituted some "web" of social relationships (Simmel, 1955) -- remained largely amorphous, both theoretically and methodologically. The conceptual model Berkman and colleagues (2000) presented, however, neatly illustrated the distinctions between these three constructs (Figure 2): social integration as the *extent* of participation in a range of relationships (Seeman, 1996); social networks as the formal *structure* of these relationships; and social support as the functional *content* of these relationships (Weiss, 1974). Berkman et al. (2000) further elaborated the *mechanisms* through which social networks are thought to affect health, mental health, and health behavior: through social influence (Marsden & Friedkin, 1993), by serving as conduits for the provision of social support (Weiss, 1974) or the direct transmission of disease (Klovdahl, 1985; Laumann et al., 1989; Obbo, 1993), or by providing opportunities for meaningful social engagement.

Berkman et al. (2000) issued two charges for scholars: to better understand the determinants of social network formation, and to more fully elucidate the mechanisms through which social networks affect health. In the ensuing 15 years, new developments in graph theory, large-scale data collection efforts, and computational methods have facilitated a proliferation of research on social networks and health. Particularly important turning points in the field include the public release of social network data from the National Longitudinal Study of Adolescent Health (AddHealth) (Bearman, Moody, & Stovel, 2004) -- which has by now been featured in nearly 5,000 publications -- as well as the discovery of relational data in the Framingham Heart Study (Christakis & Fowler, 2007).

Contributions in this Volume: Social Networks, Health, and Mental Health

The purpose of this Special Issue was to highlight cutting-edge developments in the application of network science to the study of health and mental health outcomes. The interdisciplinary nature of the field corresponds nicely with the scope of *Social Science and Medicine*, which seeks to provide an international and interdisciplinary forum for the dissemination of social science research on health. We therefore sought submissions from a

wide variety of fields, including those from researchers belonging to fields other than our own (medicine and sociology, respectively).

Beginning with an open call for manuscripts in November 2012, we received more than 100 submissions from scholars in a range of disciplines including anthropology, communications, computational science, criminology, economics, medicine, public health, and sociology. Thirty-six of these were sent out for initial review. We contacted 210 scholars to serve as reviewers, 51% of which agreed. We could not have accomplished our work as guest editors without enormously helpful feedback from experts in these various disciplines. For the median manuscript we rendered an initial decision in 69 days. Twelve manuscripts were rejected after review, while 24 manuscripts were provided with a revision opportunity for further consideration. After a median of 2 revisions each, 18 manuscripts were accepted for publication. These 18 articles speak to several of the key pathways outlined by Berkman et al. (2000) while at the same time pushing the boundaries of existing scholarship in several key subfields.

From Macro to Mezzo: Social Network Formation

One of the key concepts embedded in Figure 2 is the call for a richer understanding of how social, cultural, and economic forces condition the extent, shape, and nature of social networks -- to understand, in other words, how macro-level forces shape mezzo-level networks. Several of the papers in the Special Issue take this question quite seriously.

Patulny, Siminski, and Mendolia (this issue) used a series of natural experiments occasioned by Australian conscription lotteries to understand how the symbolic interactions embedded in military service affect the formation of bonding and bridging social capital. Thus, their study is not directly related to tie formation but rather is focused on a related but distinct concept that has to do with the positive feelings and generalized social trust that exist through mutual associations *apart* from network structure (Moody & Paxton, 2009). The authors found that military service reduced bonding social capital (partially by worsening mental health status and by crowding out ties to non-veterans) -- while increasing bridging social capital. They interpret these findings as providing support for the central theory underlying their analysis -- that social network capital is formed through symbolic interaction. Such findings may be relevant to understanding the different health and mental health issues facing returning military personnel as they navigate their familial, personal, and professional networks.

Increasingly, information technology and the Internet are shaping a wide range of health behaviors and medical decisions. From self-diagnosing health problems on WebMD to counting calories on WeightWatchers.com or tracking steps with a Fitbit (R), individuals are increasingly engaging technology to monitor their health. Centola and van de Rijt (this issue) designed a randomized controlled study that explores the evolution of tie formation among 432 participants in an online fitness improvement program. They found that study participants were highly likely to select ties on the basis of homophilous preferences (i.e., along the lines of age or gender) rather than on the basis of aspirational preferences (e.g., fitness or exercise intensity). Such behavior likely contributed to limitations on study

participants' available social capital and restricted their opportunities for exploring new sources of health information.

Adolescence represents one of the most formative periods in human development; it also happens to be the time in one's life when social and peer influences are at their greatest. Several papers in the Special Issue draw on the AddHealth data. The study by Daw, Margolis, and Verdery (this issue) examined fundamental questions pertaining to the relationship between adolescent networks and health: how homophilous are adolescent health behaviors, and how do such behaviors vary by network type? The authors found that levels of homophily are high across several health behaviors -- including smoking, drinking, exercising, and TV viewing -- and, further, that network ties play a key role in the observed homophily in health behaviors. Importantly, homophily on health behaviors varies by race, class, gender, and health status, indicating that these factors may play a role in explaining both network and health differences.

How to Measure Networks

Since the review by Berkman et al. (2000), the field has seen a tremendous proliferation in the volume, content, and extent of network data collection, and these tools are now taking network research far afield from its origins in anthropological fieldwork. In addition to the use of survey data, several of the studies in this Special Issue leverage new and exciting methods of data collection for measuring the structure and contours of networks. For example, Pachucki et al. (this issue) employed novel technology based on radio-frequency identification (RFID) technology to capture the interaction networks of early adolescents at a private school in a California city. RFID tags worn by study participants enabled the research team to identify, with a 1.5 meter range and a 20 second time resolution, the social interactions of nearly all students in the sixth grade class at a single school. Then using traditional survey data collection, the authors analyzed the effects of these interaction networks on health outcomes. One key finding from this study is that depressive symptoms (self-esteem) among girls were associated with less (more) social integration and sociability -- while for boys, neither was associated with their propensity to interact. In contrast to previously published studies of adolescents, Pachucki et al. (this issue) did not find strong evidence of homophily in either depressive symptoms or self-esteem over time. Such novel data collection methods not only offer insight into key empirical debates in the research on mental health and networks but also raise important questions about how the ways we measure networks may influence our results.

New methods of data collection also raise important issues pertaining to appropriate methods of analysis and statistical inference. Papers throughout the Special Issue invoke a range of such novel methods. Paul et al. (2014), for instance, describe a new dyadic-dependence model that seeks to account for effect modification of the within-dyad effect of reciprocity and inter-dyad effects involving three (or more) actors. Put another way, the authors have developed a new statistical approach that they hope can better account for significant network effects by providing more nuanced estimates of dyadic and higher-order social processes. Applying their model to two datasets of physician influence and physician patient networks, the proposed statistical models confirm previous research on the

importance of organizational and geographic proximity for information sharing between clinicians but also shed new light on how such factors might influence (or be influenced by) higher order processes such as reciprocity or clustering.

Sociocentric network studies remain a mainstay of empirical research. In their systematic review, Perkins, Subramanian, and Christakis (this issue) attempt to identify all sociocentric social network studies conducted in low- and middle-income countries in order to understand how social networks are associated with health behaviors and health outcomes. The authors found that network composition and structure, and individual centrality, are associated with important health behaviors and health outcomes including family planning, diarrheal disease, and HIV infection. In terms of network measurement, the included studies used a wide range of methods for data collection. Name generators form the backbone for survey-based measurement of many types of social networks -- for example, Perry and Pescosolido (this issue) used a single name generator while the analysis by Shakya, Christakis, and Fowler (this issue) used 12 different name generators -- so this catalog may prove to be particularly useful for researchers new to the field as well as researchers preparing new data collection instruments.

Some high-risk populations -- such as sex workers and intravenous drug users -- are considered “hard to find” or “hidden.” To access or estimate such populations, network scientists have largely relied on snowball or “respondent driven sampling” (RDS) methods. Merli and colleagues (this issue) examine a crucial yet often neglected assumption at the heart of these sampling approaches: do RDS methods provide accurate estimations of the larger network populations? Their study combines data and insights from two studies of Chinese female sex workers to test this representativeness assumption. Using recent developments in simulation and exponential random graph modeling, Merli and colleagues (this issue) find that traditional RDS methods tend to oversample low-degree nodes and exhibit a geographic bias as well. These insights provide an important launching point for future studies of high-risk and hidden populations as well as the types of interventions based on such sampling methods.

From Mezzo to Micro: How Social Networks Affect Health and Mental Health

The majority of the submissions we received for the Special Issue focused on understanding how the shape, size, and characteristics of one’s network shape individual health, mental health, and health behavior. This area of research corresponds to the “from mezzo to micro” portion of the conceptual framework elaborated by Berkman et al. (2000). Accordingly, these papers examine a range of core putative mechanisms including social influence, homophily, and affiliation.

Cornwell and Laumann (this issue) conducted a longitudinal analysis of data from the National Social Life, Health, and Aging Project (NSLHAP) to understand how changes in social networks over a five-year span were correlated with health and psychological wellbeing. While previously published studies have focused on the health and mental health impacts of *net* changes in total network size and other aspects of social integration (Cerhan & Wallace, 1997; Eng et al., 2002; Tsai et al., 2014), the NSLHAP design permitted the identification of specific tie changes using a computer software-based procedure that tracked

ties from one interview to the next. Thus, the overall stability in average social network size masked considerable turnover in participants' networks. Importantly, the authors found that the adverse health effects of network loss could be counterbalanced by the addition of new network members.

Studying a similar population, Ellwardt, Van Tilburg, and Aartsen (this issue) used data from the Longitudinal Aging Study Amsterdam to examine how network complexity may be associated with slower cognitive decline among middle aged and older adults. While they did not measure specific tie changes from one interview to the next, they did make use of information about the different roles occupied by social ties. Reductions in network complexity over time were associated with declines in cognitive functioning, suggesting that more complex networks provide greater opportunities for social engagement and preservation of cognitive ability over the long term.

Perry and Pescosolido (this issue) adopted a different approach to understanding the relationship between social networks and health by examining the extent to which social network ties are *activated* in response to mental illness episodes (i.e., reaching out to others to talk about important health matters). Using an egocentric design, they found that tie activation is more likely in the context of more severe illness episodes and also more likely for specific kinds of ties. The authors also, in turn, found that higher quality of life was correlated with activating a greater number of ties and feeling closer to activated ties. Thus, their findings speak to the importance of not only aggregate network characteristics like network size and complexity but also the types of goal-directed interaction within networks.

The study by Shakya, Christakis, and Fowler (this issue) examined the association between social networks and latrine ownership in southern India. Using a publicly available dataset collected as part of a study examining the diffusion of microfinance (Banerjee et al., 2013; Jackson, Rodriguez-Barraquer, & Tan, 2012), the authors created a composite social network from twelve different name-generating questions. Their results suggest that individuals are more likely to own latrines when their social contacts also own latrines even after accounting for standard predictors of latrine ownership such as caste and education. In light of recent findings from India about individuals' *preferences* for open defecation compared to latrine use (Coffey et al., 2014), the authors' findings provide some evidence for key levers that could be used to inform intervention development to address this critical public health issue.

Papachristos, Wildeman, and Roberto (this issue) applied formal network methods to a health outcome rarely study within a network framework: gunshot victimization. Using five years of detailed arrest and shooting victimization data in Chicago, their study produces two important findings pertaining to the importance of networks and gun violence. First, gun violence is more severely concentrated *within* networks than it is within populations or places. Even within the highest-risk population for gunshot injuries -- including among young, black, male gang members -- being in a co-offending network exponentially increased one's risk of being a gunshot victim after adjusting for other well-known individual and neighborhood risk factors. Second, the authors found that exposure to other

gunshot victims in one's network further increased the probability of victimization above and beyond the traditional risk factors.

The final three papers in this section deal with substance use and delinquency among adolescents. Rees and Wallace (2014) used AddHealth data to examine *resistance* to negative health behaviors. While the authors did find evidence of classic peer influence -- in that non-drinking adolescents exposed to social networks where the majority of adolescents drink are then more likely to drink -- they also found that the presence of one or more non-drinking friends could have a moderating influence on the onset of drinking. Thus, their findings introduce important nuance into our understanding of how group norms affect adolescent health behavior.

While most of the studies in this Special Issue analyzed one-mode networks in which the nodes are the same type of object (e.g., networks of students or patients), Browning, Soller, and Jackson (this issue) adopt a relatively new approach to understanding two-mode networks -- an approach described as "ecological networks" or "eco-networks," which are the networks created as individuals share various activity spaces in their geographic neighborhoods (Browning & Soller, 2014). Their approach is evocative of the propinquity effect described by Festinger, Schachter, and Back (1950) and indirectly links individuals *through* their use of shared geographic resources such as parks, shopping malls, and so on. Theoretically, such an approach marries theories of social control and collective efficacy with a new focus on two-mode network data. Analyzing data from the Los Angeles Family and Neighborhood Survey, the authors found that eco-network reinforcement exhibits strong negative associations with adolescent substance abuse and delinquency.

Finally, the paper by Fujimoto and Valente (this issue) provides a novel example of how expanding the focus of the types of networks studied can shed new insight into important health behaviors. Different types of relations can be co-present between members of a dyad. This phenomenon, commonly described as "multiplexity," was emphasized by early network scholars (Boorman & White, 1976) and often discussed theoretically. Empirically, however, most network studies -- including many of the papers in this Special Issue -- tend to focus on a single type of network tie. In situations where multiple ties are observed, as described by Perkins, Subramanian, and Christakis (this issue) and as illustrated in one of the sensitivity analyses conducted by Shakya, Christakis, and Fowler (this issue), a common approach is to generate a composite network or to analyze each network separately. Doing so, however, runs the risk of ignoring network overlap or dependencies that are of substantive interest (Ahn, Bagrow, & Lehmann, 2010; Szell, Lambiotte, & Thurner, 2010). Fujimoto and Valente aim to address how network multiplexity influences drinking behavior among adolescents in a Los Angeles high school. The authors used friendship nominations and perceptions of popularity to create two one-mode networks based on friendship and perceived popularity. They then defined "multiplex congruity" as the extent to which the friendship and popularity nomination ranks were congruous with each other: a best friend who is perceived as popular by others has complete congruity. The authors found that exposure to drinking by multiplex-congruous ties (close friends who are popular) was associated with drinking. The implication is that consideration of these types of congruities can potentially boost the effectiveness of network-targeted interventions.

Harnessing the Power of Networks for Health Interventions

Three studies in this Special Issue provide glimpses of how the field can move beyond observational studies (i.e., linking social networks and health) to intervention studies that exploit network information for intervention targeting, delivery, or diffusion. In terms of intervention diffusion, Knopf et al. (2014) report the feasibility and acceptability of an HIV prevention intervention developed in rural Kenya to address partner concurrency, which has been identified as a critical factor that amplifies the spread of HIV (Morris & Kretzschmar, 1997). The single-session intervention is explicitly network-focused, with a group didactic component that describes how concurrency influences the spread of disease, and an individually tailored component that provides participants with a schematic of their own egocentric sexual network. The authors' focus group data suggest that social diffusion may translate into behavioral impacts, but this hypothesis would need to be tested in a more formal manner.

In terms of exploiting network information for intervention targeting or delivery, Schneider, Zhou, and Laumann (this issue) used information from 241 study participants' cell phones to generate a communication network of 4,991 men who have sex with men (MSM) in southern India. From this network, they selected candidate peer change agents on the basis of social network position and compared these candidates to actual peer-educator MSM working for a community-based HIV prevention organization. Candidate peer change agents selected on the basis of their bridging potential had consistently higher innovativeness scores, while the actual peer educators were more likely to engage in HIV transmission risk behaviors. Thus, the authors' strategy can potentially benefit HIV prevention interventions not only because their sociometrically-chosen peer change agents may be able to diffuse interventions more effectively within high-risk networks but also because existing strategies result in the selection of peer educators who may have limited utility for encouraging positive behavior change.

Computerized simulation approaches are becoming increasingly popular modes of inquiry given the logistical difficulty in conducting randomized experiments (Auchincloss & Diez Roux, 2008; El-Sayed et al., 2013). Zhang et al. (this issue) provide a unique perspective on social network interventions to reduce obesity. The authors use AddHealth data to derive parameter estimates for their agent-based model and then conduct simulation experiments. Importantly, they find that the strategies of stigmatization and network targeting may not be effective, and that peer influence may have a potential buffering effect on obesity rather than intensifying its spread.

Conclusions

Our aim in this Special Issue was to integrate new findings about networks and health, using the seminal essay by Berkman et al. (2000) to organize our discussion. Reviewing the contributions to this Special Issue, we observe that many of the key pathways outlined by Berkman et al. (2000) are better understood today than they were at the turn of the millennium. The field of network science has matured, and our network measures have matured along with it. Based on the papers included in this Special Issue, we now know

much more about the linkages between social networks, health and mental health -- along with potential intervening mechanisms and effect modifiers.

We are struck by two observations. First, our usual lurking bugbear, the inadvisability of making causal claims, is ever present. Certainly many of the observational studies published in this Special Issue include this caveat as a potential limitation on interpreting their findings. Unmeasured common cause variables, latent homophily (as well as other network formation processes that can masquerade as homophily, such as differential interaction opportunities (Feld, 1982; Kalmijn & Flap, 2001)), multiple peer effects, and the boundary specification problem all pose significant problems for researchers attempting to understand the phenomena of contagion and social influence (Berndt & Keefe, 1995; Laumann, Marsden, & Prensky, 1983; Manski, 1993; Shalizi & Thomas, 2011; Thomas, 2013). While some of the debates in this literature have taken an unnecessarily acerbic and "unrelentingly hostile" (Shalizi, 2012) (p.1) tone, fortunately this remains an active and, we hope, collegial area of ongoing research (Christakis & Fowler, 2013; Durlauf & Ioannides, 2010; VanderWeele, Ogburn, & Tchetgen Tchetgen, 2012). In the future, we expect the field will see more innovative and less expensive ways of collecting network-behavior panel data, as well as more sophisticated analyses of data from social media (Centola, 2013; Coviello et al., 2014). Consequently, our ability to make causal claims will increase.

Second, and related to the above, the findings from this rapidly growing literature argue for greater attention to be paid to developing interventions that harness the power of the social network in order to favorably influence health, mental health, or health behaviors. The simulation study by Zhang et al. (this issue) provides a tantalizing glimpse at what is possible, and the pilot studies included in this Special Issue hint at future findings to come. While some social network/social support interventions have not resulted in the expected salubrious outcomes (Berkman et al., 2003), other types of interventions may be possible, such as those that explicitly aim to achieve collateral benefits for social network ties resulting from interventions targeting an index participant (Halloran & Struchiner, 1991; Philipson, 2002) or those that capitalize on relational data to select recipients for intervention targeting (Valente, 2012).

Third, while the study of social networks draws our analytic gaze away from traditional "variables based" science and towards a relational focus on human behavior (Emirbayer, 1997), the real world is much more complex then simply thinking about *either* variables *or* behaviors and relationships. Networks interact with other sorts of processes, variables, and risk factors in complex ways that researchers are only just beginning to understand. Several papers in this Special Issue raise exactly such questions. How, for example, are social networks shaped by geographic space (adams, Faust, & Lovasi, 2012; Graif, Gladfelter, & Matthews, 2014)? New technologies appear to transcend the spatial dimensions often thought to hinder friendship and affiliation, and health information from across the globe is available on the Internet in just a few clicks. Nonetheless, propinquity has a highly significant roles in the relationships below form. Yet another pressing question is how social and economic conditions—such as poverty and inequality—affect the structure of one's social network, access to networks, or even how one mobilizes her own social capital within and across networks? Scholars have recently turned their attention to answer such complex

questions, both theoretically and empirically (Kelly et al., 2014), and this area promises to be one of the most important areas of research in the years to come.

Even during the final stages of production for this Special Issue, we were reminded of just how quickly network science has evolved and proliferated over the last 15 years. Dozens of papers on network theory, methods, applications, and interventions are no doubt already in press or making their way through various stages of review, already poised to advance the field. In another 15 years, some of the findings described in these articles may turn out to be so foundational as to seem trivial, while others may still have scholars scratching their heads. Nonetheless, the application of network science to the study of health and mental health has flourished and, if the papers in this Special Issue are any indication, shows no sign of slowing down. Our sincere hope is that the advancement of the field continues with the same rigor and excitement as it has over the past 15 years while innovating with new theories, data, and technology.

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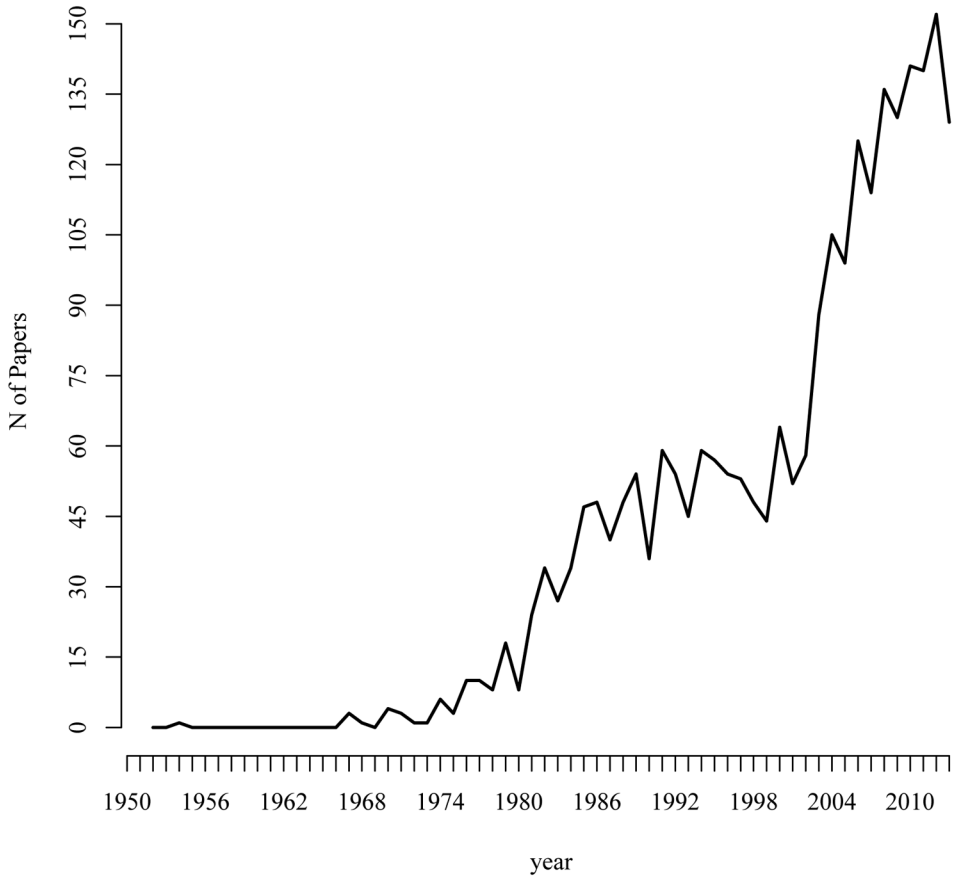

Figure 1.

Total number of articles appearing in selected epidemiological, public health, and medical journals with the term “social network” or “social networks” in the abstract or title.

Note: Journals searched include: *American Journal of Epidemiology, American Journal of Public Health, Annals of Internal Medicine, British Medical Journal, Epidemiology, International Journal of Epidemiology, Journal of the American Medical Association, Journal of Epidemiology and Community Health, New England Journal of Medicine, Public Library of Science Medicine, Proceedings of the National Academy of Sciences, and Social Science and Medicine.*

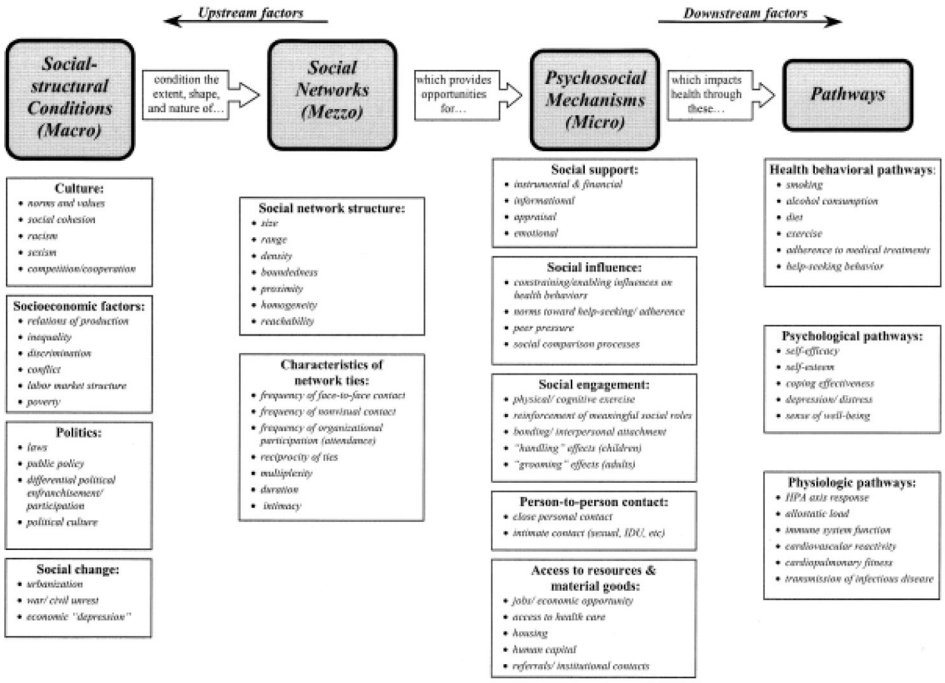

Figure 2.

Conceptual model of how social networks affect health, mental health, and health behaviors. Reprinted with permission from Berkman et al. (2000).