TEC resilience

Using Social Network Analysis to Link Community Health and Network Strength

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ABSTRACT

Social network analysis (SNA) is a technique used to analyze social networks, whether it be composed of people, organizations, physical locations, or objects. It is being increasingly applied across a variety of sectors to gain insight into patterns of behavior and connectivity, the flow of information and behaviors, and to track and predict the effectiveness of interventions or programs. A key area associated with network strength using SNA is the health and wellness of individuals and communities. Both network strength and health and wellness are measured in many ways, which can obfuscate the association, so more consistency and further research is required. Despite this, the existing research using SNA to link characteristics of social networks to health and wellness find that stronger, more connected networks tend to be associated with better health outcomes. These results also present opportunities and insights for effective program implementation in response to disasters, to increase resilience, and to improve outcomes for individuals and communities.

INTRODUCTION

A social network is composed of a series of individuals or units, often referred to as nodes, that are interconnected by one or more relations (Scott & Carrington, 2011). Social network analysis (SNA) is a research method used to study these social relationships and the patterns of communication, interaction, and information flow among individuals, groups, or organizations. It is conducted by recording data on who is connected to whom (Valente et al., 2015). The analysis of these networks can reveal important information about the social structure and the roles of individuals within it and can be used to identify key individuals or groups within a network, measure the strength and frequency of connections, and identify patterns of communication and information flow (Hawe, 2004). It can be applied to a wide range of fields, including sociology, psychology, anthropology, political science, business, and public health. Outcomes related to network strength are many and varied, including many key outcomes surrounding health and wellbeing of individuals and communities.

In many fields, including public health, community development, sociology, business development, and many more, SNA can and has been used a valuable tool for providing insight and guidance (Lawlor & Neal, 2016; Neal & Neal, 2017; Scott, 2011; Valente et al., 2015; Varda, 2011). This holds true in many contexts, including at community, city, or state levels, as well as by private organizations or non-profits, whether they wish to look internally at their own network or externally at a group they may be seeking to emulate, work with, or assist. It may be used by practitioners to "assess the overall composition of their networks, strengthen collaborations with other community partners, and evaluate network function" (Kothari et al., 2014). It can also be used to track outcomes, behaviors, progression of disease, and resources throughout a network, thereby informing policy or program implementation (Valente et al., 2015). These measures of social network can then be linked to health and wellbeing for analysis in different ways. It can be used to directly measure the association with such outcomes as obesity, smoking, or STI transmission (Christakis & Fowler, 2007; Périssé & Nery, 2007; Zhang et al., 2018), or with more social outcomes, like happiness or educational attainment (Fowler & Christakis, 2008; Keim-Klärner et al., 2023).

Overall, social network analysis provides a powerful tool for understanding the social structure of relationships and communication patterns within and between individuals, groups, or organizations. This understanding of networks and their strengths may allow vital insights into some of the factors influencing the health and wellbeing of individuals and their communities.

MEASURES IN SOCIAL NETWORK ANALYSIS

There are many methods of social network analysis, and a correspondingly wide and varied set of terms and measures. The following are terms and measures in SNA that tend to be used when describing relationships with health and wellbeing outcomes. They are not exhaustive of the vocabulary and measures used in SNA, but describe those commonly used to promote understanding.

Nodes or Actors

Individual units being measured within the network are referred to most commonly as nodes or actors (Hawe, 2004), or as vertices (Butts, 2008). These may be individuals, groups, or organizations. It is their connectivity to each other that is being measured.

Links and Relationships

A link between one actor and another is key to social network analysis. This may be called a link, tie, line, or relationship (Hawe, 2004), and also commonly known as an edge (Butts, 2008). An actor having multiple ties to others is known as multiplexity, while an actor having no ties, but still being considered part of the network or community, is considered an isolate (Hawe, 2004). If a relationship between actors goes both ways (i.e. both actors are considered to be connected to each other), then it would be an instance of reciprocity, whereas if two actors that are connected to each other are also connected to a third actor it is known as transitivity (Valente et al., 2015). The tendency for actors to be connected to those like themselves (i.e. to others exhibiting the same behavior, like smoking) is known as homophily (Scott & Carrington, 2011).

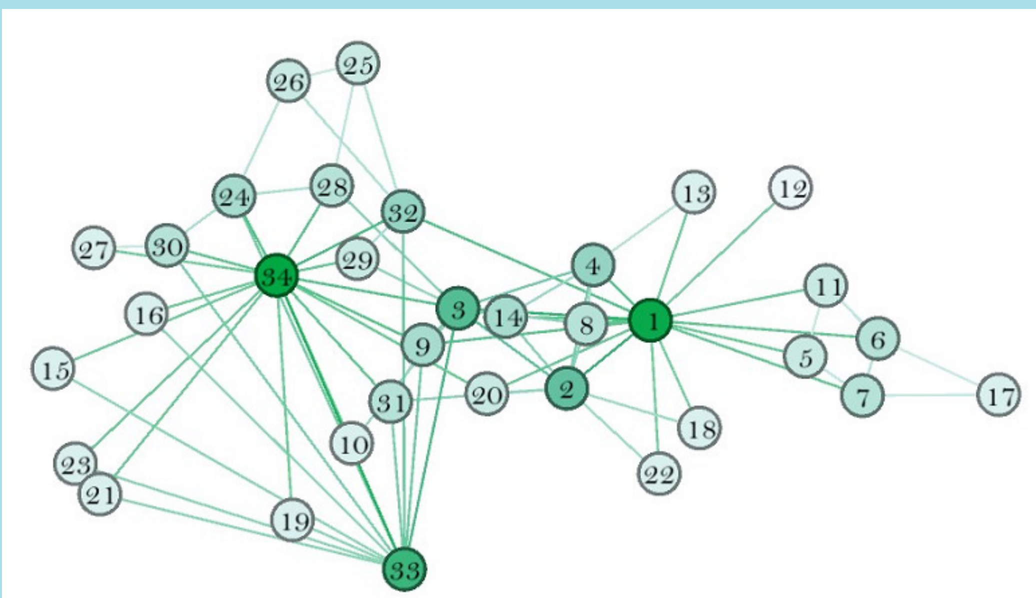
Communities, Subgroups, and Modes

The entire network analyzed may be known as a group or community, and it may be defined either as those contained within a single defined community, known as socio-centric, or perhaps by those related to a central actor, known as ego-centric or personal networks (Hawe, 2004). The network may have just one center, known as a mode, or multiple (Hawe, 2004). It may also be broken down into important subgroups. A component is a subgroup of actors that are reachable by any number of steps (with isolates being considered as individual components) (Hawe, 2004; Valente et al., 2015), and clustering and cliques (a cluster wherein every actor is connected to each other) may also be observed (Hawe, 2004; Valente et al., 2015). Measuring and analysis of the amount of clustering or cliques within a network is a common form of SNA (Butts, 2008), and may be informative about the structure and flow of information within a network (Valente et al., 2015).

Network Size

The size of the network may also be measured in a few ways. It may refer to the number of actors or connections, or the maximum number of connections possible within the network (Scott & Carrington, 2011). It may also be measured by the diameter, which refers to the shortest path between actors the furthest from each other, or the "longest shortest path" (Bae et al., 2015). The size of a network can have an impact on what is possible to detect and influence other measures of SNA, including centrality (Butts, 2008).

Figure 1. An Example of Social Network Analysis



GIS&T Body of Knowledge https://gistbok.ucgis.org/bok-topics/social-networks

Cohesion

The cohesion of a network describes the interconnectedness of a network, and is measured in a few ways (Hawe, 2004). Most frequently measured in SNA is density, which is the number of connections present divided by the total number of connections possible (Hawe, 2004). Having a high network density can be beneficial to a network as it can aid a high speed of information sharing, but can also be disadvantageous by making a network too insular and inhibiting the introduction of new ideas (Valente et al., 2015). Cohesion can also be measured by calculating the distance, or number of connections between actors in a network (similarly to calculating the diameter) and the reachability of actors, by measuring whether and how actors are related or "reachable" by each other (with isolates having a reachability of 0) (Hawe, 2004).

Centrality

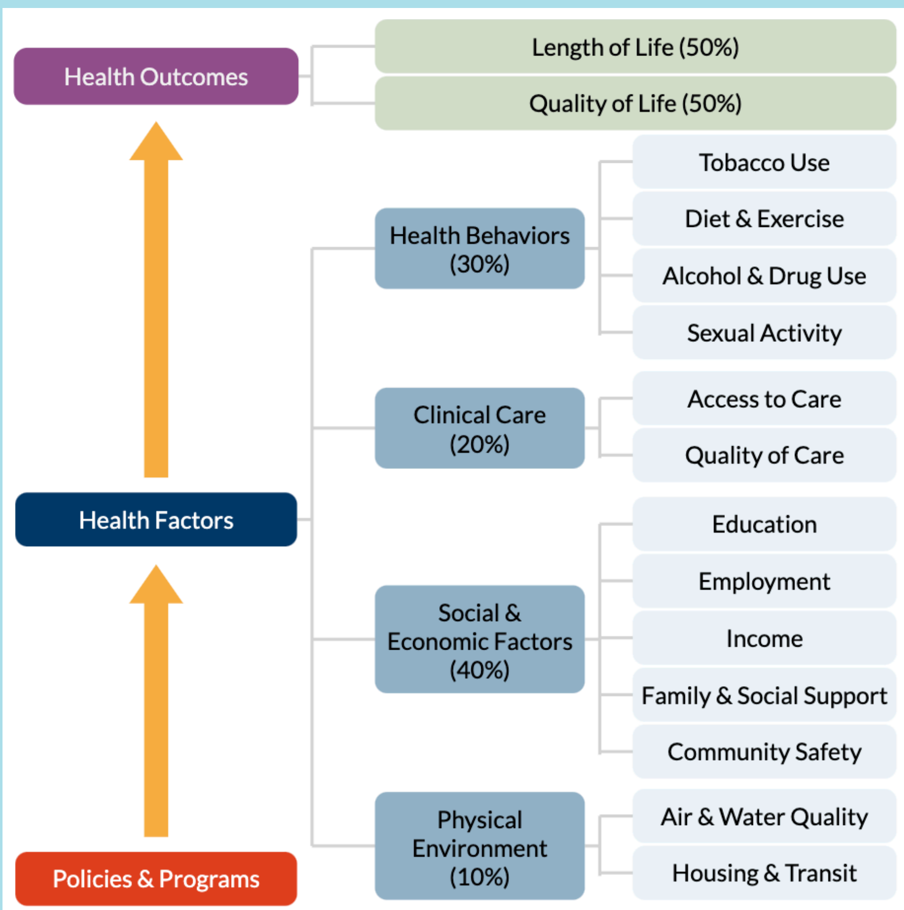
Social network analysis commonly uses centrality measures to understand the connections, influence, and accessibility of actors within a network. Centrality assesses an actor's position in the network (Bae et al., 2015), with more central actors being more influential compared to those on the peripheral (Valente et al., 2015). The three main types of centrality measures are degree centrality, betweenness centrality, and closeness centrality. Degree centrality is the sum of the direct connections an actor has within the network (Hawe, 2004). Betweenness centrality measures the degree to which an actor acts as the connection between others that would not otherwise be connected, giving those with high betweenness centrality greater control over the flow of information (Hawe, 2004). Lastly, closeness centrality indicates how close an actor is to others by measuring how many direct connections to actors within the network, indicating those with higher levels of closeness centrality have better access to other actors in the network (Ostovari & Yu, 2019). These measures can be used to identify key providers who play critical roles in the network and to understand how information flows within the network.

MEASURES OF HEALTH AND WELLBEING

Health and wellbeing of an individual or community may be measured and defined in a variety of ways. The WHO defines health as a "state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (World Health Organization, 1946). This implies many potential methods for measuring health. In the context of social network analysis, a plethora of measures of health and wellbeing have been utilized as an outcome to track the relationship between a network measure and an element of health.

At the individual level, this may include the presence of chronic or infectious disease, affordability of healthcare, or social factors like happiness or mental wellbeing. At a community level, it may be more difficult to define. SNA tends to analyze individual-level outcomes, rather than population-level, within the context of the network.
For the purposes of this paper, we will follow the framework laid out by the County Health Rankings Model to describe community-level health outcomes (County Health Rankings, 2023).

Figure 2. County Health Rankings Model



County Health Ranking Model © 2014; https://www.countyhealthrankings.org/explore-health-rankings/county-health-rankings-model

The County Health Rankings Model describes health outcomes for the community as made up of health factors within four categories, weighted for analysis. These are health behaviors, clinical care, social and economic factors, and the physical environment (County Health Rankings, 2023). Not all of these categories and their components have been analyzed as an outcome for SNA in the readily available literature, although many have. Common measures for health behaviors have included such outcomes as tobacco use, obesity, alcohol and drug use, and sexually transmitted infections. Measures of clinical care include access to care, which has been measured by the amount of primary care physicians and the affordability of healthcare, as well as the quality of care, which has been measured by avoidable hospital visits. Social and economic factors have been measured by such outcomes as employment, income, economic living standard or minimum wage, and education. Finally, measures of the physical environment are less commonly analyzed as outcomes of SNA.

All together, components of three categories (weighted in the model to represent 90% of factors contributing to community health outcomes) comprising health factors according to the County Health Rankings Model are represented as outcomes in SNA in the available literature. These measures, along with those that represent purely individual-level outcomes, comprise the health and wellbeing outcomes for social network analysis in the literature.

SNA TO IMPROVE A COMMUNITY'S HEALTH AND WELLBEING: AN EXAMPLE FROM MISSOURI

A 2006 study used social network analysis to examine Missouri's public health emergency system, focusing on the connections local public health emergency planners use to facilitate emergency planning and response (Harris & Clements, 2007). During the study period, 31 public health emergency planners contracted to The Center for Emergency Response and Terrorism (CERT) at the Missouri Department of Health and Senior Services were administered a survey regarding their experience working with emergency preparedness in addition to their work at the agency and emergency planning and response in the state. Some of the factors assessed were communication among public health emergency planners in the state, partnerships between planners and local entities, communication between public health emergency planners and hospital planners, and who public health emergency planners communicate with, seek expertise from, and exchange guidance with regarding Strategic National Stockpile (SNS) planning and All-Hazards Planning (AHP).

The findings revealed that local public health planners maintained regular communication, with some planners having a greater degree of centrality and influence in the network. Interestingly, the region in which a planner worked had a significant impact on their connectivity and influence within the network, while experience in emergency preparedness did not have any notable impact (Harris & Clements, 2007). The study also revealed that planners communicated more frequently with those in their own region, but some acted as bridges between various regions. Additionally, most local planners communicated at least monthly with their assigned regional planner, and more than half communicated with both regional planners (Harris & Clements, 2007). The majority of planners worked with hospital planners and various local entities, with emergency management being the most common.

The study utilized two measures of centrality, degree and betweenness centrality, to analyze the network. The range of degree in this network was 1-14, with 6 being the median. The higher the degree, the more central and active the planner was in the network. Planners with higher betweenness had more control over the flow of information in the network. A significant difference was found between regions when comparing the mean betweenness, indicating that the region in which a planner worked significantly impacted their connectivity and influence within the network (Harris & Clements, 2007).

Overall, this study highlighted the critical role that relationship building plays in Missouri's public health emergency system. Effective communication and partnerships are essential for successful emergency planning and response efforts. For example, during a power outage in St. Louis in the summer of 2006, emergency planners relied on their networks to secure backup generators for hospitals, provided them with supplies, and staffed nurses at cooling centers. The study emphasizes the power of social network analysis as a tool and provides valuable insight into the type of information that it can uncover.

SOCIAL NETWORKS AND THE HEALTH AND WELLBEING OF INDIVIDUALS AND THE COMMUNITY

Across the literature, the measures of network strength and connectivity have been associated with a variety of health outcomes. Findings vary as there are almost as many measures of SNA that may be analyzed as there are health outcomes to be measured, resulting in an inconsistency in reportings and findings. Despite this, the association between network strength and connectivity and outcomes associated with health and wellbeing have been described, with the findings reported in the following sections in alignment with the categories of the County Health Rankings Model.

Health Behaviors

Tobacco and Smoking

Tobacco use, both among adults and minors, is a health outcome commonly analyzed in SNA. It has been associated with a variety of SNA outcomes and measured in a few ways, including prevalence and frequency of smoking (Jeon & Goodson, 2015; Patterson & Goodson, 2019). A systematic review of college-aged student's behaviors found tobacco use to be significantly associated with a variety of network measures, along with drinking and aggression (Patterson & Goodson, 2019). Similarly, among adolescents, tobacco use, in particular the frequency of use, was found to be increased when close friends, as well as friends separated by 1 or 2 degrees (as measured as a factor of cohesion) smoked as well (Jeon & Goodson, 2015). In a study of drinking and tobacco use among fraternity members, smoking behavior was highly associated with a measure of homophily within the network, with smokers tending to "hang out" with each other, forming cliques of smokers and nonsmokers within the network, supporting this finding (Phua, 2011). Among adults, a SNA on smoking behaviors within the Framingham Heart Study (FHS) echoed that smokers tended to form cliques, but also noted that, in quitting behaviors, entire cliques tended to cease smoking together (Christakis & Fowler, 2008). This provides evidence of the power of social networks to influence bad health behaviors, but also provides insight into the dynamics influencing such behaviors and highlights a potential avenue for intervention.

Adult Obesity and Physical Activity

Obesity as a health concern is rising, with recent estimates putting obesity among US adults at over 40% and severe obesity at almost 10% (Tucker & Parker, 2022). Obesity and physical activity, in both adults and adolescents, has been analyzed with SNA many times, with obesity and overweight being associated with homophily among social groups and cliques, among other social measures, not mediated by geographic proximity (Powell et al., 2015; Zhang et al., 2018). Namely, like tends to be connected to like within a network, where BMI is concerned. This was found to be particularly prominent among same-sex siblings, spouses, and close friends or co-workers (as defined by a measure of cohesion) in an analysis over time of networks within the Framingham Heart Study (Christakis & Fowler, 2007). To address the ever-increasing epidemic of obesity, one team used SNA modeling on longitudinal data from the FHS to understand and predict the spread of obesity and physical activity among the observed clusters and into the surrounding network (Bae et al., 2015). They observed, using SNA modeling, that losing weight with close friends, while initially successful, would eventually be counteracted by the surrounding pressures of the more extended network. To address obesity, they suggested SNA-informed solutions like focusing social interventions on a few people that are well-connected within their network or prioritizing resources on maintaining a healthy weight among a small subgroup of a network, which their models showed would stabilize the spread of obesity in the network and work to counteract it (Bae et al., 2015). These insights and solutions to improve the health of entire communities are an example of how the power of social networks can be harnessed for public health.

Alcohol Use and Abuse

Alcohol use and overuse is a health behavior most commonly studied in adolescents and young, college-aged adults (Knox et al., 2019). It is another health behavior found to be common within subgroups, with those who drink more having more connections with each other (displaying greater homophily). This was observed among college-age students (Patterson & Goodson, 2019) and fraternity members, although to a lesser degree than with smoking (Phua, 2011). Unlike smoking, in Phua, 2011, alcohol use tended to diffuse throughout the network, with the drinking behaviors of those central to the network becoming the same as the rest of the network over time. Along these lines, college students who self-identified as being heavier alcohol consumers were more likely to identify close friends with the same behavior (Russell et al., 2021). This aligns with findings about alcohol use among adolescents, where those with higher popularity or centrality (i.e. more friends or relationship) were more likely to drink alcohol (Jeon & Goodson, 2015). Conversely, one study focused on individuals recovering from alcohol abuse found that those with more social connections (i.e. higher centrality or popularity within their network) were able to maintain sobriety significantly longer than their less-well connected peers (Patterson et al., 2021). Among adults observed in the FHS, similar patterns within an actor's network observed with smoking or obesity (heavily associated with the same behavior among individuals within 3 degrees of relation) were observed with drinking (Rosenquist et al., 2010). While little research exists on addressing alcohol consumption as a public health problem via SNA, these similarities imply that there may be some overlap in approach between alcohol consumption, obesity, and smoking.

Drug and Illicit Substance Abuse

The social networks surrounding illicit substance abuse have long been a subject of study for those attempting to understand and intervene in the spread of these behaviors. One early study noted that the presence of a family member did not have a significant effect on substance abuse while having a partner did, and noted that larger size and density of the individual's drug subnetwork was associated with increased frequency of drug injection (Latkin et al., 1995). Similarly to alcohol abuse, many studies focus on drug abuse in adolescent populations, with a more recent study reviewing the impact of homelessness and foster care experience within an individual's social network on methamphetamine use. They found that having individuals with foster care experience within the network increased the likelihood of methamphetamine abuse, suggesting intervening in the foster system may help to indirectly affect this health outcome (Yoshioka-Maxwell et al., 2015). Further studies reviewing intervention techniques to prevent substance abuse among adolescents have found that leveraging social networks, by applying such techniques as peer-lead groups, is more effective than other evidence-based techniques (Jeon & Goodson, 2015). Whether among adults or adolescents, social networks have been shown to be related to the spread and intervention of substance abuse.

Sexually Transmitted Infections

Sexually transmitted infections (STI), like other infectious diseases, have long been studied through social network analysis. Understanding the dynamics between people and how they interact is often key to tracking the spread and understanding the mechanism of disease (Wang et al., 2021). The spread of STIs in particular depends on close human contact and relationship, and so is naturally linked to a social network (Périssé & Nery, 2007). One study noted that the endemicity and outbreaks of STIs has to due with the structure of the social network, with the peripheral clusters in the network keeping it circulating and outbreaks occurring when it spreads to the larger, more densely connected subgroups at the center of the network (Jolly et al., 2001). A further study used SNA to identify individuals, with high centrality within their networks, acted as bridges transmitting an STI within their network (De et al., 2004). Overall, SNA has been used frequently to address STD's, either to identify, contain, or respond to outbreaks, explain differences in STD rates among different populations (a high STD rate may be maintained disproportionately in some populations if there is a high degree of clustering), or to identify key influential actors within a network where an intervention may be the most influential (Périssé & Nery, 2007).

Additional Measures of Health Behaviors Measured in Social Network Analysis

There are many health behaviors not identified in the County Health Rankings Model. Social network analysis has been applied to many of them, with a few notable instances listed here. As with substance abuse, many studies have focused on adolescent and child obesity rather than simply adults. One systematic review of these described high homophily among adolescent friend groups when it comes to physical activity levels, as well as high levels of cluster, suggesting some methods for intervention (Macdonald-Wallis et al., 2012). These findings were echoed by another review which found largely studies focused on adolescents, adding a significant degree of homophily as well for BMI and body type (Zhang et al., 2018). Additionally, sexual activity among adolescents has been analyzed with SNA, with consistent results indicating having close friends (by a measure of cohesion) that engaged in sexual activity made individuals more likely to be engaging in the behavior or else more likely to begin within the next year (Jeon & Goodson, 2015).

Among adults, contraceptive uptake among married women has also been analyzed with SNA. One study found networks to be highly dense and homophilic, with those choosing to use injectable contraceptives to be very connected to a central, influential agent and to be very similar to each other within their subgroup (Akinyemi et al., 2019). SNA has also been used frequently to analyze epidemics of infectious diseases and the response. It has been used by the CDC and related agencies to track the influence of network structure on the spread of information and disease, the impact of individual behavior, the influence of different types of communication strategies, immunization strategies, outbreak response strategies, and many other factors (Wang et al., 2021).
In all, social network analysis has been used extensively to describe health behaviors and related outcomes for a variety of factors. It has been used to describe the network and transmission, find commonalities and key points of influence, and design and test interventions.

Clinical Care

The County Health Rankings Model describes the two major elements of clinical care contributing to community health as the access to and quality of care provided. Networks of providers, agencies, and social services, known as social care networks, describe healthcare services and can improve access and quality for individuals and communities who may otherwise face barriers to accessing care (Conrad et al., 2003). These networks within clinical care are key targets of social network analysis so that we may better understand the dynamics, where successes and failures are occurring, and how to intervene

Access to Care

Access to care can help prevent and manage health conditions, ultimately leading to better health outcomes (Pollack et al., 2015). As social networks provide a coordinated and integrated system of care, they can help reduce healthcare costs by avoiding unnecessary hospitalizations and emergency room visits, promoting preventive care and ensuring appropriate use of healthcare services (Barnett et al., 2012). As higher regional healthcare spending has consistently been shown to be unrelated with better health outcomes within the community, lower healthcare costs is objectively desirable (Barnato et al., 2010; Yasaitis et al., 2009). The connectedness of a physician within their social network, whether it be their hospital or a larger physician-sharing network, is associated with fewer unnecessary healthcare expenditures. A 2012 study found that higher betweenness centrality of primary care providers within the studied hospital networks was associated with lower healthcare spending on items such as imaging and tests, with a 14.7% decrease in specialist visits (Barnett et al., 2012). In a further study, patients treated by physicians in larger patient-sharing networks as well as those treated by physicians with higher network centrality (more connected within their network), had lower overall health care spending and fewer hospitalizations than those treated by physicians in smaller networks (Landon et al., 2018).

Access to care is also defined in the model as having a greater availability of primary care providers. Primary care providers have been found to be central points of contact within their care network, and correspondingly, have been associated with emergency department visits and unplanned hospitalizations (Ostovari & Yu, 2019). SNA has been used to show that communities with a higher proportion of primary care providers had fewer specialist visits and emergency department visits (Landon et al., 2018). Other studies have not consistently found this association, with one only showing no association with hospital readmission and having a primary care provider in the care network (Geva et al., 2019), but overall, SNA has been able to show a distinct relationship between the strength and connectivity of a primary care provider within the care network and positive health outcomes.

Quality of Care

Quality of care was defined in the model, among other measures, as the amount of avoidable hospital visits. Rate of unplanned hospitalization is a key outcome of an effective healthcare system that has been measured by social care analysis. In a 2019 study, the degree of connectedness and higher access of providers in the community was analyzed, finding higher social connectivity to be significantly associated with reduced inpatient hospitalization and emergency department visits (Ostovari & Yu, 2019). Among patients with diabetes mellitus, reduced rates of 30-day readmissions and lower odds of potentially avoidable complications was associated with having a provider with higher density within their network, although not among patients with congestive heart failure and chronic obstructive pulmonary disease (Pollack et al., 2015).

Additional Measures of Clinical Care Measured by Social Network Analysis

Improved health outcomes may include hospitalizations or specialist visits for more severe care, but may also include any incidents of adverse events. In a 2015 study, Pollack et al. found that patients of providers with a higher care density (higher number of shared patients) had lower rates of adverse events compared to other patients (Pollack et al., 2015). Higher closeness of the provider was also associated with lower unplanned hospitalizations, and consistently was shown to be protective against poorer outcomes (Ostovari & Yu, 2019).

Social and Economic Factors

The last category within the County Health Rankings Model with outcomes consistently analyzed by social network analysis is the social and economic factors. This includes income, socio-economic status (SES), and education level and availability, among other measures. The findings within the literature describing social networks and their roles, either as a moderating effect on the health outcome or as a mediating effect were summarized in a 2023 scoping review by Keim-Klärner, et al.

Figure 3. Representation of the ways social networks interact with social and health outcomes

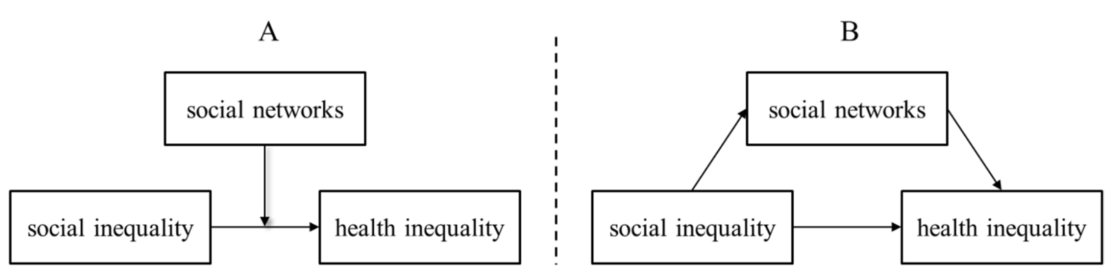


Fig. 1 Schematic representation of moderator (**A**) and mediator (**B**) effects of social networks on health inequality. Source: own display

Keim-Klärner et al. International Journal for Equity in Health (2023) 22:74

As with other categories, findings of applying SNA to social and economic factors influencing health were inconsistent, especially as the SNA measures used were rarely the same across studies.

Income, Socio-Economic Status (SES), and Poverty

Having a higher level of connectivity within the social network was found to be beneficial for those experiencing poverty, as it moderated (provided a buffer against) the effects of poverty on associated health outcomes (Keim-Klärner et al., 2023). This effect of having a higher connectivity or centrality within the network was observed either at a higher level or only observed at all among those living in poverty relative to those with a higher income level in the considered studies (Keim-Klärner et al., 2023). Being at a higher SES status or not experiencing poverty were also found to be beneficial in being able to actively participate in a social network and leverage the associated resources. This was exceptionally impactful on health as analyzed studies found a significant percentage of self-rated, subjective health inequities due to SES to be mediated by an individual's social network (Keim-Klärner et al., 2023). These findings suggest that the impact of poverty on health outcomes may be more complicated than simply limiting resources and availability, but may also be limiting on social opportunities and the related benefits.

Education

The association between network strength and education level was more complicated than with other social and economic factors. Findings were inconsistent, although the available literature suggests that having a denser social network for those with lower levels of education was associated with higher health risks, in particular when combined with higher BMI (Keim-Klärner et al., 2023). Authors proposed theories including higher homophily among the social networks of those with lower education which, in combination with higher network density, may be acting to prevent the introduction of beneficial new ideas and having a detrimental effect on health (Valente et al., 2015).

Additional Social Factors Measured by Social Network Analysis

Additional social and emotional factors measured in social network analysis not included in the County Health Rankings Model include happiness and subjective emotional wellbeing. While a systematic review of friendship quality and subjective wellbeing in adolescents found little relationship between the size of the social network and reported happiness, loneliness, or depression, perceived social support was highly associated (Alsarrani et al., 2022). A further study utilizing the FHS cohort identified similar patterns as observed with obesity and smoking. Happiness and unhappiness over time displayed clustering, with happiness being more likely to those with high centrality within their network and appearing to spread outward to up to 3 degrees of separation away. Unlike what has been observed with obesity and smoking, geographic proximity was a high indicator about the impact of happiness's spread through the network, with the greatest effect being observed among those who live within a mile (Fowler & Christakis, 2008). These additional factors, among many others, display the utility of social network analysis in quantifying factors that impact quality of life and wellness and their spread throughout a population.

Conclusion

Health is a difficult concept to fully measure and define. It has many elements and can look very different for each individual, community, network, or group. No matter how health is defined, it is irrevocably related to the network in which the individual or community exists. Social network analysis is a powerful tool that is increasingly being harnessed across multiple sectors. It can, and has, been used to quantify relationships and define how the structure and dynamics of the network impacts health and wellbeing across many measures. Some key findings are as follows:

Dense and closely connected networks have been shown to be highly associated with the spread of important information and health outcomes, like illicit substance use, alcohol abuse, and quality of healthcare (Latkin et al., 1995; Pollack et al., 2015; Rosenquist et al., 2010). However, a dense network can also prevent the introduction of new ideas, particularly when combined with low education and poverty (Keim-Klärner et al., 2023; Valente et al., 2015). How central an actor is to their network impacts how influential they are in the spread of information, disease, or care, as well as influencing how protected they are from damaging factors like poverty (Barnett et al., 2012; De et al., 2004; Harris & Clements, 2007; Keim-Klärner et al., 2023; Landon et al., 2018). Furthermore, SNA has been used to trace the spread of health behaviors throughout a network, measuring how far outcomes like happiness or obesity may spread from a single actor throughout the network (Christakis & Fowler, 2007; Fowler & Christakis, 2008; Zhang et al., 2018).

These findings can be used to design interventions to address and improve the health of individuals and communities as a whole. Historically, SNA has been used commonly to predict the spread of infectious disease and plan effective countermeasures (Wang et al., 2021). Others are attempting to utilize models to predict the effectiveness of measures to counter certain health outcomes like obesity (Bae et al., 2015). Still further, interested parties are using SNA to inform program implementation to identify the most effective populations, programs, and strategies to achieve the best outcomes possible (Valente et al., 2015).

Despite the utility of SNA as it is now, many researchers and practitioners are calling for necessary changes to the field. As noted above, there are a wide variety of measures that can be used when analyzing social networks. This leads to inconsistent results and reporting, hindering the creation of a conclusive body of evidence. Researchers call for a more consistent standard when approaching SNA so that results are more actionable (Keim-Klärner et al., 2023). There is also a need for more longitudinal studies allowing for measurement of the evolution of social networks over time, rather than relying on inference from a single point in time, as well as the tracking of the effectiveness of interventions (Alsarrani et al., 2022; Keim-Klärner et al., 2023; Valente et al., 2015).

In conclusion, social network analysis is a powerful technique that is increasingly being used to inform and predict many elements of health and wellness of individuals and communities. It is an evolving field with applicability to health programs, community development, emergency response, and many other areas. As a relatively young field of analysis, it is being actively used in many fields as well as undergoing advancement and refinement. Social network analysis is an important and effective tool for researchers and program implementers alike, and has high potential for the future.

Tech Enabled Community Resilience (TEC Resilience) is a model for building community resilience by incorporating technology to create a more robust approach powered by real-time data. It offers a way for communities to measure, respond, and adapt to changes they face. TEC Resilience is designed to harness the power of networks in a community ecosystem to drive community outcomes by using such techniques as social network analysis. This model is a key example of the potential of social network analysis to measure and make actionable the power of social networks.

Learn more at https://www.tecresilience.com/

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