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Research article

Assessing the availability of trusted health information in a rural Appalachia community using social network analysis

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ABSTRACT

The purpose of this study was to investigate how trusted health information is transmitted within a rural Appalachian community. Egocentric social network methods were used to identify and characterize influential community members ("alters") that participants ("egos") go to for trusted health advice. Friends and "other health professionals" were named most frequently as health advice alters, and health advice was described as frequent and helpful. Participants could count on their health advice network for multiple forms of social support. Understanding trusted sources of health advice will allow us to identify community members to serve as change agents for rural T2DM interventions.

1. Introduction

Appalachian Kentucky is part of a larger 13-state region that roughly follows the Appalachian mountain range but also includes areas such as northeastern Ohio and rural Alabama that share cultural features and have similar economic concerns [1,2]. Residents in Appalachian Kentucky counties tend to have lower educational attainment, lower income levels and higher unemployment rates, factors that collectively yield poorer health outcomes for many residents [2]. In the most rural parts of Appalachia, fewer than 15% of residents hold a bachelor's degree or higher [3] and some early estimates have suggested nearly 30% of Appalachian adults are functionally illiterate [4]. Taken together, these factors make health communication a particularly relevant concern when relaying important health information to individuals living in Appalachian Kentucky.

Complicating health communication, however, is the issue of medical mistrust and distrust. Distrust in the health care system is common among residents of the United States in general and has been associated with underutilization of medical services [5], lower utilization of screening uptake [6,7], and greater likelihood of self-reported fair or poor health [8]. Recent spikes in misinformation and disinformation, often spread through social media [9,10] have further entrenched medical distrust among many individuals. This concern is particularly salient in Appalachian Kentucky, where residents often reside in tightly knit, rural communities and carefully evaluate information from non-local sources to determine its trustworthiness and how it could be applied in the community [11]. This evaluation also extends to health information given by regional medical providers, with Appalachian residents noting providers often

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rely on negative stereotypes of Appalachian residents, leading to lower perceived health care quality [12] among patients.

High levels of medical mistrust are associated with overall physician mistrust [13] and poorer communication with providers [14], and individuals with lower health literacy have been shown to have lower trust in physicians and the health care system in general [15]. Cumulatively, these factors underscore a need for non-traditional communication networks outside of health systems to promote disease management in Appalachian Kentucky, where local knowledge and collectivism are prevalent [16]. Previous research found that rural mid-South residents often rely on social connectedness, utilizing informal communication in settings such as faith communities, barbershops, and community organizations to convey health information, particularly when formalized support groups or networks [17] are unavailable or perceived to be lacking in quality. Given that Appalachian residents often place a high value on interpersonal communication, it is likely interventions that leverage trusted sources of information (i.e., family, friends, faith leaders) to deliver health communication in rural Appalachian communities might hold promise.

Characterized as the examination and interpretation of relational connections, social network analysis (SNA) is an innovative approach to understand trusted sources of information, as well as health behavior, disease transmission, health communication, and dissemination [18,19]. Using SNA, researchers can map non-traditional communication networks such as those observed in Appalachian communities, with a focus on specific relationships between individuals [20]. SNA allows researchers to identify potentially influential individuals based on their position within social networks, known as key players.

Rural communities are often prone to higher levels of misinformation [21,22] that can exacerbate disparities across multiple health outcomes. It is critical to understand how health information is transmitted and disseminated by individuals in rural communities to determine the most appropriate and effective channels for communicating health promotion messages and dispelling misinformation. Accordingly, the objective of this study was to use social network analysis to evaluate how trusted health information is transmitted within a rural Appalachian Kentucky community and to determine the main providers of this information so as to better inform future regional interventions.

2. Methods

2.1. Study participants and recruitment

For this study, eligible study participants were adults (≥18 years) who lived in a designated rural county in Appalachia Kentucky. Initially we intended to use a snowball method of recruiting study participants for this community-level social network assessment. To conduct snowball recruitment, individuals who participated in the study would take flyers and encourage people they knew to contact the research team to participate. Unfortunately, this method of recruitment did not yield many participants. We then enlisted the help of a community liaison who lived and worked within the community to help with recruitment. This method proved to be more effective and yielded the majority of participants included in this analysis.

Once community members showed interest in participating, the community liaison would facilitate scheduling a study visit with the research team. All study participants completed written informed consent prior to enrollment in the study. Each participant engaged in one study visit (cross sectional) in the form of a semi-structured interview and completion of surveys with validated measures. At the completion of the study visit, participants were given $15 to compensate for their time. All study procedures were approved by the University of Kentucky institutional review board (protocol #45777) prior to data collection.

2.2. Social network data collection and measures

The social network methods and analysis conducted in this study use egocentric or personal social network analysis. This type of social network analysis involves identifying people in an individual's life and characterizing those people (referred to as "alters" or "network members") and the relationships between them and the individual (referred to as the "ego"). This creates an egocentric or personal network for the individual. Often, the relationships between alters or network members are also characterized. By providing information on the composition and structure of individual networks, egocentric network methods identify important resources and influences in individual's lives and may also be used to identify important members of a community when multiple community members are interviewed using egocentric methods.

In this study, we interviewed participants using an interview guide and script. We started by reiterating the purpose and goal of the interview and explaining that they are not required to answer questions that make them uncomfortable. From there we ask participant basic demographic questions and then move into open-ended questions about their experiences within the community (e.g., "Can you share with me any stories of something that has happened to you or someone you know that prevented good health management or healthy lifestyle?"). Then, we got more specific and asked participants to provide context to their relationships in the community by responding to the following question: "Please identify 3 people in your community who you believe are influential and who you trust and go to for good or reliable health advice." The resulting list of up to three names is considered the individual's egocentric network for this study. A series of questions characterizing the relationships between the ego and their network members are asked, providing values for types of social support received from these alters, frequency of overall contact, frequency and quality of alter provision of information on healthy lifestyle, and relationship between alters. This approach provides an understanding of 1) which *specific* community members are trusted sources of health advice, 2) *what are the characteristics* of community members who are identified as trusted sources of health advice, and 3) *the relationships* between community members and these trusted sources of health advice. We then use this information to understand whether community members are identifying the same people, sets of people, or roles people serve in the community as trusted sources of health advice, allowing us to optimally identify trusted community members to serve as change agents for rural T2DM interventions.

The egocentric networks collected in this study included measures of characteristics of 1) the *ego* (age, gender, race, highest level of education or qualification, marital status, employment status, type of health insurance coverage, and difficulty with understanding spoken English or reading written English), 2) the *alters and relationships between alters and ego* (provision of social support, frequency of contact, quality and frequency of provision of health information, role or relation to ego), and 3) *relationships or ties between alters*. Ego measures are collected as standard survey questions. Alters are identified in egocentric network research using a name generator. In this study, the name generator is, as mentioned above: "Please identify 3 people in your community who you trust and can go to for good or reliable health advice." This list of names is then used throughout to characterize alters and relationships between alters and ego and between alters.

Social support received from each alter is measured by asking the respondent to "please indicate whether you get each kind of support from them" with the following prompts for types of support: 1) "Count on to listen to you when you need to talk?", 2) "Count on when you generally need help for reasons other than an emergency?", 3) "Count on to give advice, guidance or useful suggestions that would help you to avoid mistakes?", 4) "Count on to support you in major decisions or plans you make?", 5) "Trust with a secret or information that could get you into trouble?", and 6) "Count on when you are ill?" Provision of social support *from ego to alters* is measured with one prompt: "Come to you if they had a need or problem?" [23]. *Overall frequency of contact* is a single-item measure asking ego to assign a score to each alter based on the amount of contact they have with them in which 1 is the least amount of contact and 10 is the most amount of contact. An additional item measures the *average number of days in a week* the ego talks to each alter via phone calls, text, email, or any form of communication. *Frequency and value of health communication* are measured by asking ego to indicate the frequency with which each alter provides ego with information on healthy lifestyle (Not Frequently, Frequently, Very frequently) and the "value of the information" each alter provides "that helps you with healthy lifestyle" (Not valuable, Valuable, Very Valuable).

Finally, *the type of relationship between ego and each alter as well as between alters* named are measured by asking "Are the persons you have identified connected to you or each other in any way? If so, please indicate how they are connected." A list of 21 possible relationship roles (e.g., spouse/partner, coworker or colleague, friend, neighbor, Doctor) and 3 additional activity-based relationship types (fellow church member, belongs to same club or social group, do leisure activities with) are provided to participants. Participants can indicate whether this role or type of relationship exists between themselves and each alter as well as between each of the three alters names. For all data collection procedures, trained interviewers read each question aloud to study participants to reduce any misunderstandings or bias related to literacy level or English proficiency.

2.3. Social network data analysis

This analytic approach is designed to understand 1) *what are the characteristics* of community members who are identified as trusted sources of health advice, 2) *which specific* community members are trusted sources of health advice, and 3) *the relationships* between community members and these trusted sources of health advice. These questions are explored through descriptive egocentric (individual-level) network analysis conducted in ENET, an egocentric network analysis software program [24]. Finally, on a community level, we wanted to identify 4) *who community members trust* for health advice and *whether community members are identifying the same people* or roles of trusted people in the community. To this end, we created a community-level network map or connected network map using sociocentric or complete network analysis using UCINET, a software program for complete network analysis [24].

First, frequencies and descriptive participant characteristics were calculated and reported. A single egocentric network with up to three alters was created for each participant in the study. Descriptive network analyses were performed to report network size (number of alters in the network, here the range is restricted to 0–3) for each participant and average size for the sample.

To meet the aim of understanding the characteristics of community members identified as trusted sources of information and participants' relationships to these individuals, the number of alters in each network (mean and standard deviation, mode) and proportion of networks comprised of alters reflecting each measured variable are calculated and reported. Average frequency of network members and proportion of networks comprised of each relationship type, each type of social support provided, average frequency of contact using both the single-item measure and the reported average number of days per week of communication (mean, SD), and the frequency and quality of health information provided by alters are reported. Average relationship type between alter and ego and between network members are calculated and reported. All egocentric analyses are completed using ENET.

Community Network Ties. To identify specific individuals in the community who are named by multiple community members as trusted sources of health information, we created a complete network sample by matching ego and alter names across ego networks, creating as many connected components as possible. This larger, more connected network comprised of the ego networks is called a sociocentric network. Each node in the network represents a person who was either a participant in the study (ego) or an alter named by an ego in the study. Some individuals hold both ego and alter positions in the network. We calculated the degree (number of times a person is identified as a source of trusted health information) for each node, and the average degree for the entire network. We calculate and report network size and other descriptive network statistics. All sociocentric network analyses were conducted using UCINET.

This approach provides an understanding of 1) which *specific* community members are trusted sources of health advice, 2) *what are the characteristics* of community members who are identified as trusted sources of health advice, and 3) *the relationships* between community members and these trusted sources of health advice. We can then use this information to understand whether community members are identifying the same people, sets of people, or roles people serve in the community as trusted sources of health advice, allowing us to optimally identify trusted community members to serve as change agents for rural T2DM interventions.

Participant characteristics. A total of 68 participants have been included in this preliminary analysis. Three cases were dropped from the analytic sample due to repeat interviews. In each of these cases, data from the participant's first interview were kept for analysis. The total analytic sample included 68 participants (see Table 1). Participants were majority female (n = 45, 66%) with a mean age of 43.8 (SD 15.7). Most participants were employed full (n = 32, 47%) or part time (n = 8, 12%), with 22% (n = 15) of the sample unemployed and 12% disabled/unable to work (n = 8). Most (97%) of participants were insured, with 39% covered privately (n = 25), 25% through Medicaid (n = 16), 14% through Medicare (n = 9), and 19% through some other insurance (n = 12). The majority of participants (75%) had a Year 12 equivalent education or less (n = 47), although few reported ever having trouble reading (n = 8, 12%) or speaking (n = 3, 4%) English. About 27% of the sample were married at the time of the interview (n = 18); most participants were never married (n = 22, 33%), or were separated or divorced (n = 21, 31%).

Characteristics of trusted health advice alters and relationships between ego and alters. When asked to identify three people in their community they trust and can go to for good or reliable health advice, most participants (82%) provided three names, with an average of 2.72 (0.67) alters named.

On average, participants reported talking to their health advice alters via phone calls, text, email, or any form of communication 3.51 days a week (SD 2.02) and rated their overall frequency of contact with alters as 7.15 (SD 2.05) on a scale of 1–10, with 10 representing the most amount of contact.

Nearly half (48%) of all participants reported that at least one health advice alter provided "very valuable" information "that helps you with healthy lifestyle," with 28% reporting that *all three* of their health advice alters provide very valuable information. Interestingly, one participant rated the information from all three of their health advice alters as "not valuable," but only 9% of the sample overall rated *any* of their health advice alters as providing information that they did not find valuable. About 73% of participants reported that at least one of their alters provide information on healthy lifestyle "frequently," and 22% "very frequently," but the distribution of frequency of health information provided varies across networks. Distribution of value and frequency of information provided by health advice networks is shown in Fig. 1.

Table 1
Characteristics of community members (N = 68).

Participant characteristics (N = 68)	n (valid %) or mean (SD)
Female	45 (66.2)
Age in years	43.8 (15.7)
Highest qualification (n = 63)	
Year 12 or equivalent	28 (44.4)
Diploma or advanced diploma	11 (17.5)
Bachelor's degree	10 (15.9)
Graduate certificate/diploma	2 (3.2)
Master's degree	4 (6.3)
Doctoral degree	0
None of these	8 (12.7)
Marital status (n = 67)	
Never married	22 (32.8)
Married	18 (26.9)
Sep/divorced	21 (31.3)
Widowed	6 (9.0)
Insurance (n = 64)	
None	2 (3.1)
Private	25 (39.1)
Medicare	9 (14.1)
Medicaid	16 (25.0)
Other insurance	12 (18.8)
Current employment status	
Employed Full Time	32 (47.1)
Employed Part Time	8 (11.8)
Unemployed	15 (22.1)
Unable to work/disabled	8 (11.8)
Retired	5 (7.4)
Trouble speaking English	
Never	65 (95.6)
Rarely	1 (1.5)
Sometimes	0
Often	0
Always	2 (2.9)
Don't know	0
Trouble reading English	
Never	59 (86.8)
Rarely	2 (2.9)
Sometimes	4 (5.9)
Often	1 (1.5)
Always	1 (1.5)
Don't know	1 (1.5)

Many networks also provide social support to participants. Displayed in Table 2 are the average proportion of participants' health advice networks that provide each type of social support, as well as the proportion of the total sample that indicate each type of support for 0, 1, 2, or 3 network members. Overall, participants indicated that they could count on 75% of their health advice network when they are ill, and count on 73% of their network "to give advice, guidance or useful suggestions that would help you to avoid mistakes," and "to listen to you when you need to talk." Participants also indicated, on average, that 73% of their health advice network would "come to you if they had a need or problem," demonstrating some reciprocity in support. Slightly lower proportions of network members could be counted on if the participant may "generally need help for reasons other than an emergency" (70%), "to give advice, guidance or useful suggestions that would help you to avoid mistakes" (67%), or to "trust with a secret or information that could get you into trouble" (64%).

Participants were most likely to name friends as health advice alters, with 52% of the sample defining at least one health advice network member as a "friend," and within a network, on average, 29% of ties are defined as friends (Table 3). After friends, "other medical professional" was the most prevalent type of relationship tie in the sample. Nearly one-third of the sample (32%) had at least one "other medical professional" in their network and within networks, on average, 17% of a participant's network was defined as "other medical professional." Doctors, religious leaders, and religious community members were less frequently named as community health advice network members in this sample. Dividing networks into kin and non-kin ties, on average, participants had 1.07 (SD 1.06) total kin ties in their networks and 2.07 (SD 1.52) non-kin ties.

Community network ties. Every alter named in this study was named as a trusted source of health advice. However, some community members were named by multiple participants as health advice alters. We created a preliminary connected map of all participants and alters by matching names of alters across participants (Fig. 1). While this connected network cannot represent all ties between the participants and alters in the study, it can show us whether certain community members were frequently named as trusted health advice alters.

In the figure, the small pink circles each represent a participant in the study. The squares represent a health advice alter named by a participant. Each edge or arrow pointing to a square is one participant naming that person as a health advice alter. The size and color of the squares represent the number of participants who named that person as a health advice alter: the larger and darker color the square is, the more participants who have named that person as a health advice alter.

There were a total of 185 alters named. There are four alters named most frequently as providing trusted health advice in the community. In the figure, these health advice alters (HA) are marked as "HA1," "HA2," "HA3," and "HA4." HA1 (large dark red square) was named by 10 participants as a provider of trusted health advice, HA2 (large bright red square) was named by 9 participants, and HA3 and HA4 (medium bright red squares) were named by 4 participants each. There are four individuals who were named by 3 participants each (small dark pink squares), and seven individuals who were each named by 2 participants (smaller light pink squares). All other alters (smallest light blue squares) were named by only one participant.

Of these four most frequently nominated alters, three were women. They were characterized by the egos that nominated them as other medical professional (n = 18 times); friend (n = 7), coworker (n = 4); relative (n = 2); priest, minister, or rabbi (n = 2); doctor (n = 1); and in-law (n = 1). These four alters did not differ significantly from the others in how they were characterized by participants regarding trust, the value or frequency of health information provided, or in support provided. However, these top nominated alters were significantly more likely than the other alters to be named as an "other health care provider" (67% of nominations in top alters versus 11% in other alters, X^2 46.99, $p < .001$), and participants reported a lower average amount of contact on a scale of 1–10 with the top alters (mean 4.65, SD 3.38) versus the other alters (mean 7.48, SD 2.68); t (179) = 4.79, p = .045).

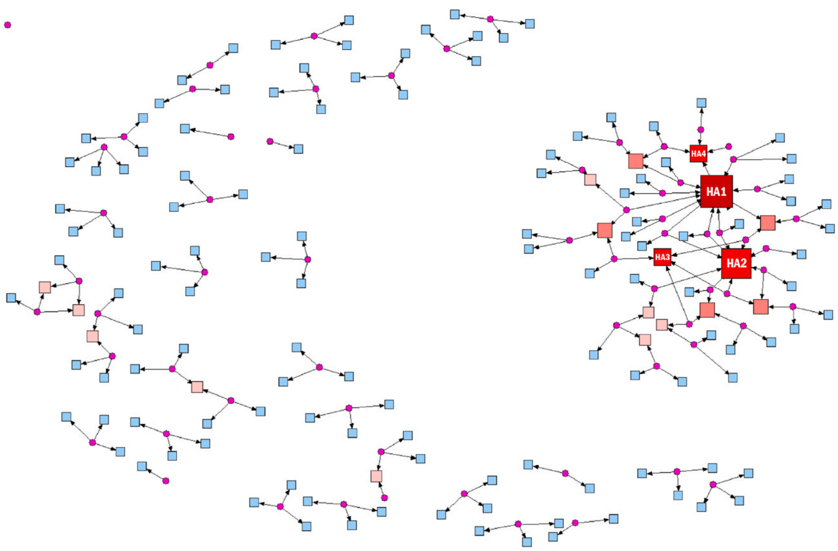

Fig. 1. Social network map of health information in a rural Appalachia community.

Table 2
Characteristics of networks and network members (N = 68).

Variable	n (valid %) or mean (SD)				
Network member characteristics	Mean % network for sample	n (%) of sample that indicated response for each number of network members			
		0	1	2	3
Network size (average degree)	2.72 (0.67)	1 (1.5)	5 (7.4)	6 (8.8)	56 (82.4)
Social support					
Count on when you're ill	75.0	2 (2.9)	17 (25.0)	11 (16.2)	38 (55.9)
Count on to give advice, guidance	73.0	3 (4.4)	19 (27.9)	8 (11.8)	38 (55.9)
Come to you if they had a need or problem	73.0	4 (5.9)	16 (23.5)	11 (16.2)	37 (54.4)
Count on to listen to you when you need to talk	72.5	2 (2.9)	21 (30.9)	8 (11.8)	37 (54.4)
Count on when you generally need help	69.6	2 (2.9)	21 (30.9)	14 (20.6)	31 (45.6)
Count on to support you in major decisions or plans	66.7	3 (4.4)	23 (33.8)	13 (19.1)	29 (42.6)
Trust with a secret/info that could get you in trouble	63.7	7 (10.3)	22 (32.4)	9 (13.2)	30 (44.1)
Health related information	Mean % network for sample	n (%) of sample that indicated response for each number of network members			
		0	1	2	3
Value of health-related information					
very valuable	37.3	35 (51.5)	10 (14.7)	3 (4.4)	20 (29.4)
valuable	48.0	27 (39.7)	7 (10.3)	11 (16.2)	23 (33.8)
not valuable	4.9	62 (91.2)	3 (4.4)	2 (2.9)	1 (1.5)
Frequency of health information					
very frequently	11.3	52 (76.5)	11 (16.2)	3 (4.4)	2 (2.9)
frequently	49.5	19 (27.9)	16 (23.5)	14 (20.6)	19 (27.9)
not frequently	29.4	31 (45.6)	19 (27.9)	13 (19.1)	5 (7.4)
Frequency of any contact	Mean (SD)				
Average amount of contact with each person, scale of 1–10 (n = 65)	7.15 (2.05)				
Average number of days in a week you talk to each person (n = 56)	3.50 (2.02)				

Table 3
Relational characteristics of networks (N = 68).

Summary kin/non-kin ties	Mean (SD) for sample	
Average total kin ties in a network	1.07 (1.06)	
Average total non-kin ties in a network	2.07 (1.52)	
Relation to ego	**Mean % of a *network* comprised of this relationship**	**Mean % of *total sample* indicating this relationship as a tie**
Friend	29.41	35 (51.5)
Other medical professional	17.15	22 (32.4)
Sibling	8.82	16 (23.5)
Relative	8.33	14 (20.6)
Parent	6.86	14 (20.6)
Coworker	7.84	10 (14.7)
Spouse	4.41	9 (13.2)
Doctor	4.41	7 (10.3)
Priest/minister/rabbi	3.92	8 (11.8)
In-law	2.94	5 (7.4)
Child	2.45	5 (7.4)
Neighbor	1.47	2 (3.0)
Fellow church member	1.47	2 (3.0)
Employer	0.98	2 (2.9)
Aunt/uncle	0.98	2 (2.9)
Grandparent	0.97	2 (2.9)
Employee	0.49	1 (1.5)
Belongs to same club	1.47	1 (1.5)
Do leisure activities with	0.49	1 (1.5)

3. Discussion

In this study, we aimed to understand which *specific* community members are trusted sources of health information. In this study, alters HA1, HA2, HA3, and HA4 were noted as main sources of health information is this community (see Fig. 1). Common characteristics of community members identified as trusted sources of health advice included frequent or very frequent provision of information on healthy lifestyles and the provision of social support. Community members identified as trusted sources of health advice were also more likely to be friends or health providers who are not doctors.

Our findings are different from existing scientific literature that identifies doctors and family members as most trusted sources of health advice [25–28]. However, in rural contexts there have been findings that other community members (e.g., neighbors, friends, partners) are preferred sources given their prior experience with issues in common [29–31]. Our findings suggest that rural residents still rely on friends, but family members and doctors are not as trusted in some communities when considering trust health information.

In addition, the question used in this study to identify names ("Please identify 3 people in your community who you believe are influential and who you trust and go to for good or reliable health advice.") may lead to different responses than those of previous studies. In previous studies, the question posed to study participants included asking about the whole network or cohesive subgroups in the network, [27,31], which are different from our study. For this study, we emphasize that the alters must be "influential members of our community who you trust and go to for health advice." The wording of the question required participants to evaluate those they interact within their social network on the qualifier of *influence*, *trust*, and willingness to receive their *advice*.

The community members nominated most frequently only differed than the others in that they were primarily non-physician health care providers. This may reflect a growing number of community nurses and nurse practitioners in rural areas like Appalachian Kentucky and could identify an important group to target as change agents. The significantly lower average amount of contact reported by participants for these tops alters versus the others makes sense given that they were primarily health care providers. Still, additional research is needed to better understand what type of non-physician health care providers are deemed trusted sources of information, and furthermore, how can we leverage those relationships and networks to promote healthy lifestyles in rural Appalachia communities. Overall, we can then use these findings to understand whether community members are identifying the same people, sets of people, or roles people serve in the community as trusted sources of health advice, allowing us to optimally identify trusted community members to serve as change agents for desired health behaviors.

This research has provided insights on how a rural Appalachia residents choose their source of health information and health advice. The strengths of this study includes how we framed our research question to identify alters, which may have allowed for more specific responses that are useful for implementation in communities than previous studies. This is important because it provides a method to identify individuals within vulnerable populations, such as Appalachia, who are considered trustworthy and informal community leaders. By identifying these individuals, researchers could approach those individuals to be trained in chronic disease management and provide informational support. This is important because cultural norms regarding chronic disease management (e.g., diabetes, obesity) would lend itself to fatalistic attitudes and/or poor coping mechanisms that do not improve health outcomes and increase disease severity among these populations. Hence, empowering community members who are seen as trustworthy and informal leaders could be one way to help shift these cultural health beliefs. In other lay health worker and community health worker literature, these individuals are self-selected and may not be considered trustworthy by community members or have not have personal characteristics (e.g., personality traits) that are perceived to be favorable. Overall, this is a different way of assessing dissemination of trusted health information but also the potential for identifying or combating health-related misinformation in vulnerable communities.

It is also important to mention limitations of this study. First, participants were limited to three names, as that provides limited results, but the results are specific, which is a strength. Next, though our intention was to use a snowball method to identify community members, we were not able to do so. However, partnering with a community liaison was crucial to our recruitment efforts but could also contribute to only identifying community members who were convenient to the community liaison. Unfortunately, this may have led to some bias in community members' responses during the interview. Of note, the study is ongoing and there may be changes in the distribution of the sample population's characteristics for future analyses. Third, the study findings may not be generalizable to populations outside of the specific community where we recruited due to the heterogeneous nature of rural communities, even within Appalachia. Still, the goal of this research is to determine if using this method (e.g., social network analysis) is helpful to identify the availability of trust health information and who or what those sources of trusted information are. Once identified, researchers could develop various interventions or programs to leverage those sources of trusted health information. Alternatively, if no sources of trusted health information are identified, the charge would be to determine how to integrate sources of trusted health information into those communities. As such, though the implications of these study findings may not be generalizable, the methods could be useful in other communities. Lastly, our sample was primarily of those who identified as women; however, previous literature provides evidence that in Appalachian communities, women are more likely to seek and communicate health information than men [32]. Therefore, it is unsurprising that our sample is largely female.

Author contribution statement

Brittany Smalls: Conceived and designed the experiments; Performed the experiments; Wrote the paper.
Katherine Eddens: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Aaron Kruse-Diehr, Edith Williams: Analyzed and interpreted the data; Wrote the paper.
Courtney Ortz: Performed the experiments; Wrote the paper.

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Data availability statement

Data will be made available on request.

Additional information

Supplementary content related to this article has been published online at [URL].

Declaration of interest's statement

The authors declare no competing interests.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.heliyon.2023.e13774.

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