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Social network characteristics of COVID-19 vaccination and preventive health behaviors: Cross-sectional findings from the US northeast during the early COVID-19 pandemic

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ABSTRACT

Background: The link between individuals' vaccine attitudes and their social networks has been widely studied, but less is known about how these networks impact broader health behaviors like precautionary measures during the COVID-19 pandemic.
Methods: Egocentric social network data were collected from June 7–21, 2021, via an online survey by researchers based at the Brown University School of Public Health. The sample ($n = 173$) was recruited through Amazon's Mechanical Turk in Connecticut, Massachusetts, New Jersey, New York, and Rhode Island. Participants reported their COVID-19 precautionary behaviors and those of up to 5 of their closest social network contacts (SNCs, $n = 851$). The primary outcome was the mean of 13 CDC-recommended precautionary behaviors (PBS). Covariates included SNCs' COVID-19 testing, hospitalization, vaccination, disease experiences, social distancing adherence, and encouragement of participants' testing and vaccination. Associations between PBS and SNC attributes were assessed using chi-square tests, t-tests, and Generalized Estimating Equations (GEE).
Results: Eighty percent of participants had received at least one vaccine dose. The PBS ranged from 0.38 to 3.00 ($M = 2.3$) and was positively associated with SNCs' adherence to social distancing guidelines (0.33, $p < 0.001$), encouragement of social distancing (0.33, $p < 0.001$), encouragement of vaccination (0.25, $p = 0.001$), mask-wearing behavior (0.20, $p = 0.008$), receiving the vaccine (0.20, $p = 0.01$), and encouragement of testing (0.17, $p < 0.05$).
Discussion: The clustering of precautionary behaviors in social networks highlights the potential of leveraging these networks to promote public health interventions. The identification of clusters of unprotected communities at risk underscores the need to address disparities and integrate interpersonal factors into future pandemic responses.

1. Introduction

As of March 2024, the World Health Organization (WHO) has reported over 7 million deaths globally due to COVID-19 [1]. The U.S. alone accounts for 1.2 million of these reported deaths [2]. Despite the widespread availability of vaccines effective in reducing symptom severity and risk of adverse outcomes, vaccine uptake has been suboptimal, particularly during the pandemic itself [3]. From January 2021 to March 2022, an estimated 318,000 vaccine preventable deaths occurred in the US [4]. Moreover, though, to our knowledge, no comprehensive data exist on the specific number of vaccine-preventable deaths since March 2022, it is reasonable to infer that the number has likely increased. Factors contributing to this include persistent vaccine hesitancy, the waning of immunity over time, and the emergence of new SARS-CoV-2 variants that may partially evade immunity. These conditions create an environment in which unvaccinated or under-vaccinated individuals remain at higher risk of severe outcomes, leading to additional preventable deaths [5].

Suboptimal vaccine uptake is influenced by a range of complex interacting factors, including barriers to access, socioeconomic challenges, misinformation, medical mistrust, cultural beliefs, social norms, perceived risk, and systemic healthcare issues range of factors [6]. Vaccine hesitancy, an outcome of some of these interacting factors (including mistrust, misinformation, beliefs, norms, and risk

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perception), is a factor in low vaccine uptake, likely contributing to many deaths [7]. Vaccine hesitancy can be characterized by individuals' reluctance or refusal to accept vaccination despite the availability of safe and effective options [8]. Globally, vaccine hesitancy has undermined public health efforts to control vaccine-preventable diseases [9]. Within the United States (U.S.), it has proven an especially prevalent and challenging problem to address. One systematic review reported a vaccine acceptance rate of only 56.9 % in the U.S. during the early phase of the pandemic, one of the lowest among the 33 countries evaluated [10]. These findings are concerning, as low vaccination rates are associated with increased infections, hospitalizations, and deaths that are preventable by timely vaccination [11,12].

Vaccine hesitancy is a multifaceted phenomenon, and vaccine-hesitant individuals are a heterogeneous group with attitudes ranging from acceptance to complete refusal [13]. The determinants of hesitancy are highly variable and likely result from a complex interplay of several factors [14]. At the individual level, income, education status, age, and political persuasion are correlated with vaccine hesitancy [15,16]. Structural factors such as lack of access to healthcare services, healthcare system distrust, and inadequate vaccine distribution infrastructure also play substantial roles in shaping vaccine attitudes [17].

Beyond individual and structural factors, interpersonal determinants, such as social networks, also play an important role. Family, friends, colleagues, and romantic partners influence one another's health practices and can have a profound impact on vaccination [18–21]. Strong community ties and positive peer influences, for instance, may promote greater or lower vaccine acceptance, depending upon the belief systems of network members [22,23]. COVID-19 infections among friends and family are also correlated with vaccine uptake [19,20]. Social media platforms can amplify and extend the influence of these social networks as well. However, this phenomenon is not always a net positive, as the ease with which information can be spread directly facilitates the proliferation of misinformation and unscientific theories [24]. Social media platforms also allow like-minded users to more easily connect with one another and to create strongly clustered communities, which may result in "echo chambers" wherein pre-existing vaccine attitudes can be reinforced [25].

This final point is significant, as it suggests social relationships and health attitudes/behaviors have bidirectional influences on one another. That is, people may not just be influenced by their social network contacts but may also more inclined to form closer ties with others who already share their beliefs [26]. This observation that people cluster more strongly on individual attitudes, preferences, and behaviors than would be predicted by random chance alone [27] – a phenomenon termed homophily – has been found in diverse contexts (e.g., racial and ethnic mixing in sexual networks,[28] friendships among persons who smoke [29]) and is a key consideration when examining patterns of vaccine acceptance and protective behaviors, as well as planning effective future pandemic responses [30]. Despite their importance, the association of social networks with protective behaviors related to COVID-19 are not routinely examined, particularly in terms of how health behaviors and attitudes in networks impact individual behaviors such as masking, social distancing, isolating after a positive test, and vaccination.

To better understand the underlying factors contributing to vaccine hesitancy, the present study aims to address the following research questions: (1) How do individual, structural, and interpersonal factors influence COVID-19 vaccine hesitancy and adherence to preventive behaviors? (2) What role do social networks play in shaping vaccine-related attitudes and behaviors? Given the role of social networks in shaping health behaviors, we hypothesize that individuals will cluster in terms of their adherence to precautionary guidelines, and vaccination status, acceptance and hesitancy, indicating that social influence and homophily contribute to the observed patterns of vaccine uptake and resistance.

2. Methods

2.1. Data collection

A cross-sectional convenience survey was conducted in five Northeast US states – Connecticut (CT), Massachusetts (MA), New Jersey (NJ), New York (NY), and Rhode Island (RI)] – from June 18 − July 19, 2020 (n = 1185). Follow-up longitudinal survey and social network surveys were completed between June 7 − June 21, 2021. Detailed data collection methodology has been described previously [31]. To summarize, study participants were recruited using a de-identified, web-based survey on Amazon's Mechanical Turk (MTurk) platform [32]. The eligibility criteria were as follows: at least 18 years of age; resident of CT, MA, NJ, NY, or RI; and, having an Amazon Mechanical Turk (MTurk) account, as necessary for survey distribution. Data cleaning was performed to remove surveys that did not pass validity checks or were identified as duplicate responses, and quotas for age, gender, race, and ethnicity were instituted to obtain a diverse sample (described previously).[31].

For the social networks survey, participants were asked to report on their closest contacts in regard to their COVID-19 precautionary behaviors, particularly adherence to masking guidelines, COVID-19 testing history, vaccination attitudes, and vaccination status. The survey also included information on the contacts' substance use behaviors. As the social network survey was administered as part of the follow-up survey, only those who completed follow up and provided details on their social network could be included in analyses. Thus, participants in the current paper constitute a subset of the full sample, as detailed below. Participants received USD 5 via the MTurk system upon completion of the survey.

2.1. Analytic sample selection

A total of 1,155 participants answered the baseline survey questions. Of these, n = 1101 met the eligibility criteria and n = 1085 were used for the baseline analysis published previously [31]. Of those who completed one-year longitudinal follow up (n = 353), 173 participants also provided information on their adult social network contacts (SNCs), corresponding to a social network survey response rate of 49 % (173/353). Data on a total of 865 network contacts were reported. Fourteen of these reported contacts were minors (<18 years) and were removed from our analysis, resulting in a total contact network size of 851.

2.3.4. Outcome measures

The outcome variables represented self-reported adherence to 13 protective behaviors recommended by the CDC to mitigate COVID-19. We coded these on a scale from 0 (rarely/never) to 3 (always), such that higher scores represented better adherence [31]. The guidelines included the following: (1) "Wash your hands often with soap and water for at least 20 s especially after you have been in a public place, or after blowing your nose, coughing, or sneezing"; (2) "Use hand sanitizer that contains at least 60 % alcohol when soap and water was not readily available"; (3) "Avoid touching your eyes, nose, and mouth"; (4) "Avoid close contact with people who are sick"; (5) Remain at least 6 feet away from other people when in public; (6) "Stay home as much as possible"? (7) "Use a cloth face cover over your nose and mouth when in public"; (8) "Cover your mouth and nose with a tissue or use the inside of your elbow when you cough or sneeze". (9) "Throw used tissues in the trash"; (10) "Immediately wash your hands with soap and water for at least 20 seconds after coughing or sneezing; (11) "Clean and disinfectant frequently touched surfaces in your home (examples: tables, doorknobs, light switches, countertops, desks, phones, toilets, faucets)"?; (12) "Use detergent or soap and water to clean dirty surfaces before disinfection"?; (13) "When cleaning surfaces, how often did you use any of the following: a diluted household bleach, a solution that was at least 70 % alcohol, or another EPA-registered household disinfect?" The primary outcome was the average of these scores.

2.3.4. Covariates

The network covariates included the interviewed study participants' – i.e., "egos" [33] in social network analysis (SNA) terminology – reports of whether each of the network members: (1) had been tested for COVID-19 (and for those who had been tested, if they had tested positive or been hospitalized for COVID-19); (2) knew anyone who had been hospitalized for COVID-19; (3) knew anyone who had died of COVID-19; (4) had ever encouraged the participant to get tested for COVID-19; (5) followed social distancing guidelines; (6) had encouraged the participant to follow social distancing guidelines; (7) had received at least one dose of the COVID-19 vaccine (and if so, if the network member had a negative reaction or bad side effects after the COVID-19 vaccine or, if not, if the network member was open to receiving a vaccine); (8) had encouraged the participant to get the COVID-19 vaccine, (9) had discouraged the participant from getting the COVID-19 vaccine.

2.3.4. Analysis

First, given that prior research has shown that there are substantial individual differences between the decision and ability to follow preventive guidelines and become vaccinated,[34] we started by evaluating whether there were individual-level differences between the study participants who consented to provide network data ($n = 173$) and those who did not ($n = 912$). To do so, we compared sociodemographic and behavioral variables across both groups, including: age, gender, race, ethnicity, education, household income, essential worker status, household size, mean adherence to CDC recommended behaviors, testing for COVID-19, and testing positive for COVID-19. This comparison enabled us to assess if there were systematic differences between the sample of participants who provided network data versus those who did not.

Second, we compared the similarity of the network members between participants who were strongly adherent to the CDC guidelines to those who were less so. We stratified the study sample into four quartiles based on average CDC score. We then compared the differences in the same sociodemographic variables mentioned above, this time focusing on the network members on whom the participants detailed information (Table 2). This analysis assessed if there were systematic individual-level differences in the network members according to adherence scores reported by the study participants.

Third, to better understand the social network determinants of vaccination among the study participants who had received the vaccine ($n = 134$), we computed the homophily measure, which describes the extent to which study participants and their nominated social network contacts (SNCs) share the same vaccination status, or similar COVID-related behaviors or attitudes. We further analyzed the association of the vaccination status of participants (binary outcome, coded 0/1) with demographic and behavioral characteristics of their social network contacts, with respect to a range of behaviors, including each network member's: party/political affiliation; ever testing for COVID-19; knowing someone who was hospitalized for COVID-19; knowing someone who had died because of COVID-19; encouraged the participant to test for COVID-19; encouraged the participant to follow social distancing guidelines; received at least one dose of the vaccine; and encouraged the participant to get the vaccine. These variables were selected because they describe the network members' own attitudes and behaviors with regard to COVID-19 prevention and would likely be most closely correlated with the participants' characteristics.

Homophily by vaccination status is illustrated in Fig. 1. Following standard terminology from social network analysis, each study participant and their reported SNC is defined as a network "node", indicated by an anonymized label in the dataset. Pairs of participants and their SNCs are referred to as being connected by "links", or "edges", compiled in the form of an "edgelist". A visual of the network diagram was constructed from this edgelist, consisting of anonymized partners, their social network contacts, and the links connecting the two (Fig. 1). Each set of participants and their social network contacts appear as a "cluster" in the figure. Persons who had received at least one dose of the vaccine are colored green, and persons who had not received any doses of the vaccine are colored red. This figure illustrates the degree to which persons who had (or had not) received at least one dose of the vaccine cluster together.

Since the network members of a participant are not a random sample, the analysis of such data requires methods that account for the inherent dependencies. GEEs are a robust choice for analyzing

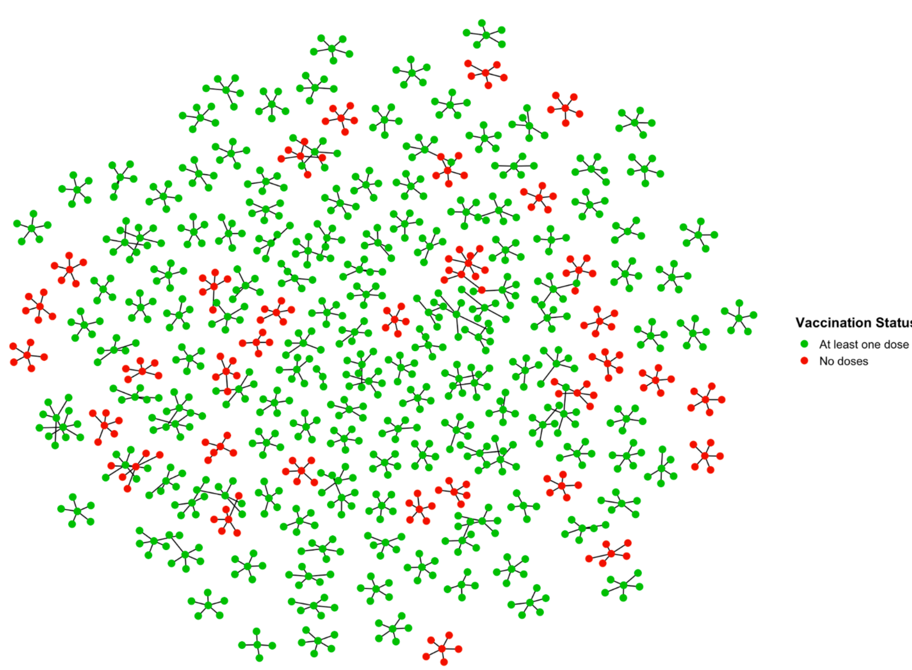

Fig. 1. Vaccination Status of Participants and Social Network Contacts (SNCs). This figure illustrates the degree to which persons who had (or had not) received at least one dose of the vaccine cluster together.

correlations arising from social network surveys because they are designed to account for the correlation within clustered or grouped data, such as the interdependencies among network members [35]. GEE models were fit using an "exchangeable" correlation structure, implying that all pairs of relationships in a cluster are equally correlated. In cases where this assumption is violated, GEEs still provide valid standard errors when the correlation structure is misspecified, ensuring reliable inference for our analyses [36]. The models adjust for all the network variables, thus providing a measure of the strength of statistical association even when other related variables are adjusted for.

We next considered the network correlates of the intention to receive the vaccine of the participants who were not yet vaccinated (n = 34). As above, we used GEE models with the exchangeable correlation structure to analyze this outcome. Given the small sample size of persons providing network data who had not received the vaccine, we used unadjusted models in this analysis.

2.3. Software Tools

All analyses were conducted in the R programming language (v4.2.2) [37]. The GEE analysis was conducted using the "geeM" package in R [38].

2.3. Ethical approval

The study was reviewed by the Brown University Institutional Review Board and exempted from requiring approval due to minimal risk. Written informed consent was obtained from all participants.

3. Results

2.3. Participants

Of the 1085 persons providing follow-up data, 173 consented to provide social network data, and 912 did not provide consent (Table 1). Participants who provided social network data did not differ significantly in age (43.5 vs. 43.8 years, p = 0.82), gender (54 % male in both groups, p = 0.88), or ethnicity (87 % vs. 84 % Hispanic, p = 0.65) compared to those who did not provide network data. There were no significant differences in race (p = 0.09) or education (p = 0.666). However, participants who did not provide network data were more likely to report annual household incomes below $25,000 (17 % vs. 8 %, p = 0.03). Both groups had similar proportions of essential workers (76 % vs. 77 %, p = 0.94) and household sizes (mean of 2.7, p = 0.78). The CDC adherence score was slightly (but non-significantly) higher among those who provided network data (2.3 vs. 2.2, p = 0.24). Notably, a significantly higher percentage of participants in the network group had received at least one vaccine dose (80 % vs. 67 %, p = 0.005).

Table 1
Comparison of Characteristics of Participant Characteristics based on Provision of Social Network Information.

Sample Characteristic	Participants providing network information (n = 173)	Participants not providing network information (n = 180)	Test Differences (p-value)
Age, mean (SD)	43.5 years (14)	43.8 years (14)	0.82
Gender, n (%)			0.88
Man	94 (54 %)	98 (54 %)	–-
Woman	79 (46 %)	78 (43 %)	–-
Nonbinary	0	4 (2.1 %)	–-
Race, n (%)			0.09
White	127 (73 %)	139 (77 %)	–-
Black	25 (14 %)	24 (13 %)	–-
Asian	20 (12 %)	9 (5 %)	–-
Other	1 (0.6 %)	32 (3.5 %)	–-
Not reported	0	12 (1.3 %)	–-
Ethnicity, n (%)			0.65
Hispanic	150 (87 %)	152 (84 %)	
Non-Hispanic	23 (13 %)	28 (16 %)	
Education, n (%)			0.666
Up to some high school	63 (36 %)	73 (41 %)	–-
High School Graduate/ Equivalent	74 (43 %)	69 (38 %)	–-
Some College or Higher	36 (21 %)	38 (21 %)	–-
Annual household income			0.03
< 25,000 USD	14 (8 %)	31 (17 %)	–-
25000-50000 USD	81 (46 %)	80 (44 %)	–-
>50000 USD	78 (45 %)	69 (38 %)	–-
Essential worker, n (%)			0.94
Yes	132 (76 %)	139 (77 %)	–-
No	41 (24 %)	41 (23 %)	–-
Household size: mean (sd)	Mean: 2.7 (1.3)	Mean: 2.7 (1.3)	0.78
CDC guideline adherence score, mean (sd)	Mean: 2.3 (0.5)	Mean: 2.2 (0.5)	0.24
Tested for COVID-19, n (%)			0.49
Yes	151 (87 %)	164 (91 %)	–-
No	20 (12 %)	15 (8 %)	–-
Unsure	2 (1.2 %)	1 (0.5 %)	–-
Received at least one vaccine dose, n %_			0.005
Yes	139 (80 %)	120 (67 %)	–-
No	34 (20 %)	60 (33 %)	–-

2.3. Social network contacts (SNCs)

We next stratified study participants into quartiles based on average CDC score and examined the characteristics of each group's SNCs. The first group, consisting of participants with the lowest 25 % of the mean CDC score (n = 44, mean CDC scores: 0.385–1.92), reported 217 SNCs. The second quartile, consisting of participants with scores higher than the first quartile but at or below the median score (n = 51, mean CDC scores: 2–2.38), reported 252 SNCs. The third quartile consisted of persons above the median but below the 75th percentile (n = 36, mean CDC scores: 2.46–2.62); these individuals reported 176 SNCs. Finally, the fourth quartile included participants above the 75th percentile (n = 42, mean CDC scores: 2.69–3), and this group reported 206 SNCs.

Overall, we observed that as the participant CDC adherence score increased, there was a significant reduction in the reported age of the SNCs (Table 2). As the participants' CDC score increased, there was also a reduction in the proportions of SNCs of Hispanic ethnicity and of lower annual household income (<25,000 USD), as well as a non-significantly decreasing proportion with Republication/Independent party affiliation. No such pattern was observed with regards to the gender composition, reported education level, or household size of network members. Among the SNCs, 72.1 % had received one dose of the vaccine, 18.1 % were unvaccinated (i.e., had not received any doses of the vaccine), and the vaccination state was unknown for 9.7 %.

2.3. Covariates associated with vaccination and intent to vaccinate

The homophily on vaccination state was about 72.4 %, i.e., of all pairings between study participants and SNCs, 72.4 % matched on vaccination status. This is shown in Fig. 1, where the vaccination states of study respondents and their nominated SNCs are highlighted, providing a visual representation of homophily on vaccination status. Adjusted GEE models revealed that the following network variables were significantly associated with increased odds of participants' receiving at least one dose of the vaccine: SNCs' annual household

Table 2
Characteristics of Reported Network Members Stratified by Participant's CDC Guideline Adherence Score Quartiles.

Sample Characteristic	First Quartile (n = 217)	Second Quartile (n = 212)	Third Quartile (n = 211)	Fourth Quartile (n = 211)	Test Differences (p-value)
Age (years), mean (sd)	51 (17)	48 (18)	46 (16)	47 (16)	0.003
Gender, n (%)					0.83
Man	98 (45 %)	114 (45 %)	87 (49 %)	91 (44 %)	–-
Woman	118 (54 %)	137 (54 %)	86 (49 %)	114 (55 %)	–-
Nonbinary	1 (0.5 %)	0 (0 %)	1 (0.5 %)	1 (0.5 %)	–-
Transgender	0 (0 %)	1 (0.4 %)	1 (0.5 %)	0 (0 %)	–-
N.R.	0 (0 %)	0 (0 %)	1 (0.5 %)	0 (0 %)	–-
Race, n (%)					
White	169 (78 %)	177 (83 %)	154 (78 %)	159 (78 %)	0.78
Black	20 (9.2 %)	17 (8.0 %)	29 (14 %)	16 (7.6 %)	0.09
Asian	28 (13 %)	24 (11 %)	24 (11 %)	25 (12 %)	0.13
Other	2 (0.9 %)	2 (0.9 %)	3 (1.4 %)	2 (0.9 %)	0.01
Ethnicity, n (%)					0.27
Hispanic	202 (93 %)	227 (90 %)	158 (90 %)	179 (87 %)	–-
Non-Hispanic	14 (6.5 %)	24 (9.5 %)	14 (7.9 %)	24 (12 %)	–-
N.R.	1 (0.5 %)	1 (0.4 %)	4 (0.2 %)	3 (1.5 %)	–-
Education					0.1
Up to High School	46 (21 %)	64 (25 %)	52 (30 %)	39 (19 %)	–-
Some College	39 (18 %)	37 (15 %)	37 (21 %)	36 (18 %)	–-
College Graduate/Beyond	126 (35 %)	146 (58 %)	85 (48 %)	124 (60 %)	–-
N.R.	6 (2.8 %)	5 (1.9 %)	2 (1.1 %)	7 (3.4 %)	–-
Annual household income (USD), n (%)					0.05
Up to 25,000	25 (12 %)	20 (7.9 %)	15 (8.5 %)	10 (4.9 %)	–-
25000-50000	45 (21 %)	60 (24 %)	54 (31 %)	45 (22 %)	–-
>50000	147 (68 %)	172 (68 %)	107 (61 %)	151 (73 %)	–-
Household size, mean (sd)	2.5 (1.2)	2.9 (1.5)	2.7 (1.2)	2.6 (1.2)	0.88
Political Party, n (%)					0.17
Democrat	97 (45 %)	119 (47 %)	74 (42 %)	114 (55 %)	–-
Republican	43 (20 %)	48 (19 %)	32 (18 %)	35 (17 %)	–-
Independent/Other	48 (22 %)	47 (19 %)	35 (19 %)	28 (14 %)	–-
N.R.	29 (13 %)	38 (15 %)	36 (21 %)	29 (14 %)	–-
Spouse or intimate partner, n (%)					0.45
Yes	29 (13 %)	33 (13 %)	25 (14 %)	37 (18 %)	–-
No	188 (87 %)	219 (87 %)	151 (86 %)	169 (82 %)	–-
Tested for COVID-19, n (%)					0.19
Yes	101 (47 %)	112 (43 %)	80 (46 %)	97 (48 %)	–-
No	64 (29 %)	91 (34 %)	68 (41 %)	78 (37 %)	–-
NA	52 (24 %)	49 (23 %)	28 (13 %)	31 (15 %)	–-
Tested positive, n (%)	217	212	211	211	0.13
Yes	20 (20 %)	15 (14 %)	8 (10 %)	21 (22 %)	–-
No	81 (80 %)	94 (86 %)	70 (90 %)	75 (78 %)	–-
Encouraged Testing, n (%)					0.02
Yes	36 (17 %)	56 (22 %)	52 (30 %)	53 (26 %)	–-
No	181 (83 %)	196 (78 %)	124 (71 %)	153 (74 %)	–-
Follows social distancing, n (%)					3.30E-06
Yes	146 (67 %)	208 (83 %)	137 (78 %)	182 (88 %)	–-
No	41 (19 %)	24 (9.5 %)	15 (8.5 %)	13 (6.3 %)	–-
N.R.	30 (14 %)	20 (6.3 %)	24 (14 %)	11 (5.3 %)	–-
Encouraged social distancing, n (%)					6.90E-07
Yes	98 (45 %)	139 (55 %)	115 (65 %)	144 (70 %)	–-
No	119 (55 %)	113 (45 %)	61 (35 %)	62 (30 %)	–-
Received at least one vaccine dose, n (%)					0.0001
Yes	147 (68 %)	190 (75 %)	113 (64 %)	164 (80 %)	–-
No	40 (18 %)	45 (18 %)	46 (26 %)	23 (11 %)	–-
N.R.	30 (14 %)	17 (6.8 %)	17 (9.7 %)	19 (9.2 %)	–-
Negative side effects if vaccinated, n (%)					0.41
Yes	24 (19 %)	33 (19 %)	13 (13 %)	33 (21 %)	–-
No	105 (81 %)	137 (81 %)	87 (87 %)	122 (79 %)	–-
Encouraged vaccination, n (%)					0.0008
Yes	90 (42 %)	135 (54 %)	91 (52 %)	126 (61 %)	–-
No	127 (59 %)	117 (46 %)	85 (48 %)	80 (39 %)	–-
Discouraged COVID-19 vaccine, n (%)					0.24
Yes	4 (1.8 %)	9 (4.3 %)	11 (5.2 %)	6 (2.8 %)	–-
No	213 (98 %)	203 (96 %)	200 (95 %)	205 (97 %)	–-

income > 50,000 USD, SNCs' knowing someone who had died of COVID-19, SNCs' receiving at least one dose of the vaccine, and SNCs' encouraging the participant to get vaccinated (Table 3). On the other hand, the following network variables were significantly associated with decreased odds of participants receiving the vaccine: SNCs' knowing someone who was hospitalized for COVID-19, or SNCs' having a Republican party affiliation (Table 3).

Among the participants who were not vaccinated, the following network variables were significantly associated with participants intent to vaccinate: SNCs' knowing someone who was hospitalized for COVID-

Table 3
Adjusted Generalized Estimation Model for Vaccination of Participants associated with Characteristics of Social Network Contacts.

Characteristics of SNCs	Estimates	Model SE	Robust SE	wald	p
(Intercept)	−1.07	0.73	0.77	−1.4	0.16
Age	0.014	0.012	0.012	1.2	0.22
Income (< $25,000)	Ref				
$25,000 − $50,000	1	0.51	0.58	1.7	0.09
> $50,000	2	0.48	0.54	3.7	0.0002
Political Party (Democrat)	Ref				
Republican	−0.85	0.36	0.37	−2.3	0.02
Independent/Other	−0.4	0.37	0.37	−1.1	0.29
Tested for COVID-19	−0.35	0.34	0.32	−1.1	0.28
Knows anyone hospitalized for COVID-19	−0.96	0.40	0.42	−2.3	0.02
Knows anyone died of COVID-19	0.86	0.42	0.42	2.0	0.04
Encouraged testing	−0.28	0.43	0.41	−0.68	0.5
Follows social distancing guidelines	−0.25	0.47	0.5	−0.50	0.62
Encouraged following social distancing guidelines	0.04	0.41	0.38	0.11	0.91
Received at least one dose of the vaccine	1.1	0.37	0.37	2.9	0.003
Encouraged vaccination	1.6	0.42	0.4	4.0	0.00006
Discouraged vaccination	−0.58	0.54	0.54	−1.1	0.28

19, SNCs' knowing someone who has died because of COVID-19, SNCs' encouraging the participant to test for COVID-19, following social distancing guidelines, SNCs' receiving at least one dose of the vaccine, and SNCs' encouraging the participant to vaccinate (Table 4).

4. Discussion

This study examined the social network correlates of vaccine hesitancy and broader health behaviors related to the prevention of COVID-19 infection in a northeast U.S. sample. As hypothesized, significant clustering of vaccine-related attitudes and precautionary behaviors was observed. Additionally, systematic individual-level differences in network members across a continuum of CDC adherence scores were found, along with several social network determinants of vaccination and intent to vaccinate.

Our findings highlight several key themes that are consistent with other studies, and provide novel insights into the association between social networks and health behaviors. Firstly, we found that higher socioeconomic status was positively associated with receiving one dose of the COVID-19 vaccine [39]. Second, we found that social influences, such as SNCs receiving the vaccine or encouraging vaccination, and salient emotional experiences, such as knowing someone who died of COVID-19, may incentivize vaccination or preventive behaviors [39]. However, determining causality in these instances is challenging due to the lack of temporal precedence. Third, our results underscore vaccination and preventive behaviors were correlated with political party affiliation [40].

Our study provides new findings in the social network correlates of intent to vaccinate among persons who had not received the vaccine. First, having SNCs who knew someone hospitalized for COVID-19, SNCs who had died because of COVID-19, or SNCs who encouraged testing for COVID-19 were significantly associated with the intent to vaccinate. This finding suggests that increased awareness of the dangers associated with the virus may have contributed to a heightened sense of vulnerability and, subsequently, worry about remaining unvaccinated. Participants with higher CDC adherence scores also generally had fewer social network contacts of Hispanic ethnicity or lower socioeconomic status. Their network contacts also tended to be younger on average. Additionally, we found several SNC characteristics associated with respondents' vaccination status. Having SNCs who: had annual household incomes greater than 50,000 USD, knew someone that died of COVID-19, received at least one dose of the vaccine, or encouraged the participant to get vaccinated were associated with increased odds of the respondent receiving at least one dose of the vaccine. Conversely, SNCs' knowing someone who was hospitalized for COVID-19 and SNCs' having a conservative political orientation were associated with decreased odds of the respondent being vaccinated.

There were some differences between persons who consented to provide network data and those who did not. Persons consenting to provide network data were, on average, older, more likely to report being an essential worker, and more likely to identify as White or Hispanic compared to individuals who did not provide network data. They were also more adherent to CDC guidelines and more likely to report ever being tested for COVID-19. However, they did not differ significantly from those who did not provide social network data in terms of education or household income. Consenting participants also had lower representation of individuals with minoritized racial identities, as well as individuals more likely to be vaccine hesitant, i.e., those who exhibited poorer adherence to CDC safety guidelines and lower rates of testing for COVID-19. These findings may indicate a selection bias, as individuals who consented to provide network data were more likely to be vaccinated or adhere to prevention guidelines.

Our findings have important implications for public health practice. The clustering of unvaccinated individuals within certain social networks may create pockets of communities that are particularly vulnerable to COVID-19 outbreaks. These clusters could exacerbate the spread of the virus and lead to more severe health outcomes, particularly in areas with low vaccine coverage. Identifying these at-risk communities through social network analysis could enable public health officials to prioritize interventions more effectively. Moreover, leveraging social networks to promote vaccination could be a key strategy in addressing vaccine hesitancy. By engaging influential community members or peers who have positive attitudes toward vaccination, public health campaigns could enhance their reach and impact, fostering more widespread

Table 4
Unadjusted Generalized Estimation Model for Vaccination of Participants associated with Characteristics of Social Network Contacts (pretty/very positive vs not).

Characteristics of SNCs	Estimates	Model SE	Robust SE	wald	p
Age	0.004	0.017	0.013	0.31	0.76
Income (< $25,000)					Ref
$25,000 − $50,000	Did not converge				
> $50,000	Did not converge				
Political Party (Democrat)					Ref
Republican	−0.91	0.57	0.56	−1.62	0.11
Independent/Other	−0.96	0.61	0.61	−1.58	0.11
Tested for COVID-19	0.46	0.49	0.49	0.95	0.34
Knows anyone hospitalized for COVID-19	2.5	0.67	0.66	3.8	0.0001
Knows anyone died of COVID-19	2.2	0.62	0.62	3.5	0.0004
Encouraged testing	1.0	0.48	0.48	2.2	0.03
Follows social distancing guidelines	2.1	1.05	1.04	2.0	0.04
Encouraged following social distancing guidelines	0.42	0.41	0.41	1.0	0.3
Received at least one dose of the vaccine	1.3	0.55	0.55	2.3	0.02
Encouraged vaccination	1.0	0.43	0.43	2.4	0.02
Discouraged vaccination	Did not converge				

vaccine acceptance. Additionally, understanding the social network dynamics that contribute to vaccine hesitancy could inform the development of targeted communication strategies to address misinformation and build trust in vaccines. Given the potential for future COVID-19 surges or the emergence of new variants, our findings also suggest that public health efforts should not be limited to vaccination alone. For communities where vaccine hesitancy is deeply entrenched, other interventions, such as promoting the use of therapeutics like Paxlovid, could be more acceptable and effective in mitigating the impact of the virus. Anticipating which communities will be most heavily impacted by COVID-19 surges can guide resource allocation and inform the focus of public health campaigns, ensuring that interventions are both timely and culturally appropriate.

We note several limitations in our study. Our results are from data collected in June-July 2021 and may not be generalizable to later phases of the pandemic. Our study's reliance on self-reported survey data collected may introduce recall bias, potentially affecting the accuracy of the findings. Our geographical focus on five Northeast states with the highest rates of COVID-19 infection and deaths at the time of data collection may also limit the generalizability of the results to other regions or populations with different demographic characteristics or healthcare infrastructure. A key limitation of our study is the use of a convenience sampling method through Amazon Mechanical Turk (MTurk), which may have resulted in a non-representative sample. This sampling method likely skewed our sample towards individuals who are more health-conscious, technologically savvy, and have greater access to vaccination, as evidenced by the higher vaccination rates in our sample compared to the general U.S. population at the time. This overrepresentation may limit the applicability of our findings to the broader U.S. population.

It is also important to note that at the time of our study, about 65 % of Americans had received at least one dose of the COVID-19 vaccine [41], whereas approximately 80 % of our study participants who consented to providing network data had received at least one dose (and about 73 % including those who did not consent to provide network data). This discrepancy may indicate that our sample was more health-conscious or had greater access to vaccination, which could limit the generalizability of our findings to the broader U.S. population. Relatedly, our reliance on network data from a subset of consenting study participants may have introduced selection bias, as demonstrated by the difference in annual income between the consenting group and the broader study sample. Finally, while efforts were made to control for confounding variables, the observational nature of the study limits the ability to establish causality between social network characteristics and vaccination behaviors.

Despite these limitations, this study provides valuable insights into the multifaceted nature of vaccine hesitancy and underscores the need for further research to address the complexities of social influences on health behaviors. The identification of significant clustering of vaccine-related attitudes and precautionary behaviors, alongside the social network determinants of vaccination or intent to vaccinate underscore the influence of social networks in shaping individual health decisions. Overall, findings from the present study contribute to our understanding of the determinants of vaccine hesitancy and highlight the importance of considering interpersonal factors, in addition to individual and systemic factors, when forming public health interventions and devising future pandemic responses. Ongoing work from our group is considering how social networks can be leveraged to promote testing and vaccination among persons who tend to have lower rates of vaccination and are less able or willing to adhere to preventive guidelines.

Ethics approval and consent to Participate

The study was reviewed by Brown University Institutional Review Board and exempted from requiring approval due to minimal risk. Written informed consent was obtained from all participants.

CRediT authorship contribution statement

Aditya S. Khanna: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mollie A. Monnig:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Data curation, Conceptualization. **Samantha E. Clark:** Writing – review & editing, Writing – original draft. **Peter M. Monti:** Conceptualization, Funding acquisition, Methodology, Writing – review & editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The datasets analyzed are confidential. The analysis code is publicly available at https://github.com/khanna7/CLC-PROJECT-5.

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