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HOW DO PERSONAL NETWORKS AFFECT ADHERENCE TO EPIDEMIOLOGICAL MEASURES, VACCINE HESITANCY, AND THE RISK ASSESSMENT OF COVID-19?

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Since the beginning of the COVID-19 pandemic, adherence to epidemiological measures was proved related to the information exchanged through personal networks. However, there is still limited evidence on the effect of specific network properties. Using data from a randomised national sample of adults in Croatia (*N* = 765), we examine the role of various personal networks attributes with regard to three dependent variables: risk assessment of COVID-19, adherence to epidemiological measures and intention to avoid vaccination. We propose "pandemic discussion networks" as personal networks that encompass social contacts with whom respondents exchange pandemic-related information. Network heterogeneity in terms of the discussants' education level contributed to more protective behaviour, while network heterogeneity in terms of age contributed to an inclination towards vaccination. These associations were confirmed independently of behavioural homophily in terms of risky health behaviour, which was also found.

Keywords: COVID-19, discussion networks, demographic network heterogeneity, vaccination, social pressure

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INTRODUCTION

The study of COVID-19 examined many important aspects of spreading information and misinformation about the virus, regarding the psychological properties (Kwon et al., 2022; Betta et al., 2022; Li et al., 2022), sociodemographic factors which explain the affinity to accepting conspiracy theories (Ančić & Cepić, 2021), and technological properties of news outlets and social media (Huang, 2022). However, the aspect which remained understudied concerns the role of personal networks in spreading the news related to the COVID-19 pandemic. Certainly, psychological properties such as a tendency towards anxiety and anger, levels of interpersonal and generalised trust, sociodemographic attributes which include education level or economic vulnerability, or technological properties of social media, are all deemed important in explaining pandemic attitudes and behaviour (Kwon et al., 2022; Betta et al., 2022; Li et al., 2022; Ančić & Cepić, 2021; Huang, 2022). But how are COVID related information and narratives transmitted via personal non-virtual channels? In this paper we have studied the latter through social network analysis. Using the name generator on the national representative sample from Croatia, we examined who do people directly exchange information on the pandemic with. This is relevant as the composition of information networks is likely to influence the formation of pandemic attitudes and behaviour.

Social network analysis (SNA) has been widely used in COVID research, regarding the transmission patterns (Saraswathi et al., 2020; Fraser & Aldrich, 2021) and visualisation (So et al., 2020), policy implications (Jo et al., 2021), social support (Cugmas et al., 2021; Bian et al., 2020; Radey et al., 2022) and loneliness (Kovacs et al., 2021). Furthermore, regarding the topics closer to the COVID "infodemic", SNA was used to study the reporting of COVID on social media (Ahmed et al., 2020; Westmoreland et al., 2021; Zhao et al., 2022; Singh et al., 2022; O'Leary et al., 2022; Luo & Ren, 2022; Faccin et al., 2022), which, however, still makes up only a fraction of the overall human communication. Past studies of epidemics found that "information from trusted personal ties was more effective in changing health behaviours than centralised information campaigns" (Fraser & Aldrich, 2021), while peer endorsements and health advice from friends and acquaintances were found to be effective at facilitating population-level behaviour change (Quinn, 2020). Therefore, the question of how COVID news is transmitted via personal non-virtual networks is very relevant. This has been especially the case given the reported trend towards "information avoidance", which occurs when a person diverts attention away from news coverage and skips social media newsfeeds to evade the topic (Qu et al., 2023).

From the research of COVID, it is known that personal networks not only provide emotional support but they also may foster virus-preventive behaviours (Qu et al., 2023). However, a specific contribution of our research is that we examine the role of personal networks attributes, including network size, composition, and the effect of network homophily with regard to three dependent variables: attitudes towards the COVID-19 pandemic, adherence to epidemiological measures and the intention to avoid vaccination. Following this research perspective, we propose pandemic discussion networks as a special subset of personal network that encompasses social contacts with whom respondents exchange information related to the COVID-19 pandemic.

Information sharing and personal networks in the COVID-19 pandemic

One of the main postulates of social epidemiology is that humans are not just hosts for viruses, but are actively involved in social contact with others, and therefore, how humans form social networks affects the overall state and structure of the spread of infection (Jo et al., 2021; Quinn, 2020). However, the aspect of social networks which was of primary interest for us in this paper concerned the sharing of information. In the research on COVID-19, this aspect of personal networks has been mostly studied in comparison to other sources of information, such as state authorities, science and health experts, news outlets, and social media (Westmoreland et al., 2021; Amiri et al., 2022; Ahmadinia et al., 2022; Baker et al., 2022; Freeman et al., 2022; Yang et al., 2022). This is relevant insofar as people's perceptions of risk can be amplified or weakened depending on the channels through which they receive risk-related information, as Zhao and Wu explain using the social amplification theory (Zhao & Wu, 2021). Nevertheless, what remained unclear in the literature on the COVID-19 pandemic were the specificities of personal, non-virtual information sharing networks and the effects of personal network properties (such as network size, composition and degree of heterogeneity) on personal attitudes towards the pandemic, risk perception and protective behaviour.

For instance, Westmoreland et al. (2021) used a US national cohort study to analyse sources of trusted information about COVID-19, including official and unofficial sources. The top three responses were immediate family (77.1%), close friend/someone you see or talk to regularly (69.8%), and partner/significant other (56.1%). These findings are consistent with Fraser and Aldrich (2021) and Quinn (2020), regarding the high importance of personal ties in information sharing. News media present official information regarding the risks, whereas personal networks offer unfiltered and sometimes unique information from grassroots that may not be available in other channels (Zhao & Wu, 2021). Furthermore, the literature suggests that people usually perceive less psychological distance with those who are socially proximal, and interpersonal discussions about risks often involve personal stories and experiences — therefore the information from such channels will be deemed as more trustworthy (Zhao & Wu, 2021). However, what remains unclear from these studies is the effect of various network properties and mechanisms, such as homophily and transitivity.

An important step in this direction is the study of Qu et al. (2023) on information avoidance and personal networks. According to this study, the relationship of network size with information avoidance followed a U-shape curve, showing that discussion networks both too small and too large may encourage individuals to avoid information related to COVID-19. In addition, network heterogeneity with respect to perceived severity was an important predictor of pro-information behaviour. This study, however, did not explore the effect of personal networks on other aspects of behaviour and attitudes related to the COVID-19 pandemic, including adherence to epidemiological measures or intention to avoid vaccination, which we have sought to do in this paper.

HYPOTHESES

Network size refers to the number of alters in a personal network and is related to the amount of social support one receives from one's personal community. Besides that, network size is related to information diversity: the greater the number of people with whom one communicates, the greater the probability of obtaining diverse information (Wellman & Wortley, 1990; Chua et al., 2011). For instance, some research suggests that smaller interpersonal networks may lead to a health knowledge gap (Askelson et al., 2011). In the case of COVID-19, broader, more diverse social networks boost the spread of quality information on how to keep community members from contracting the virus (Fraser & Aldrich, 2021). Therefore, we hypothesise that individuals with larger personal networks are less prone to conspiracy theories related to COVID-19 and are more likely to adhere to epidemiological measures introduced by the authorities.

H1: Network size is positively related to the adherence to epidemiological measures.

When it comes to network composition, the proportion of strong and weak ties is one of the most widely used indicators in network research. This network property is also related to the network size, in the sense that larger personal networks usually contain more weak ties. While strong ties are an important source of emotional support, their above-average representation in relation to more diverse weak ties may result in densely knit homogeneous networks in which disinformation may circulate easily (Burt, 2009; Granovetter, 1973). Therefore, it can be assumed that areas characterised primarily by strong bonding social ties and low heterogeneity of network would lack diverse sources of information from experts and outsiders. This is in line with findings from two studies of the spread of antivaccination beliefs (Campbell & Salathé, 2013; Salathé & Bonfoeffer, 2008), which showed that such beliefs spread more easily in a clustered social network composed of bonding, overlapping ties. Hence, we expect that deeper reservoirs of bridging and linking ties, containing alters with diverse demographics might facilitate the spread of quality information. In line with that, residents who discuss the topic with different social groups should be more likely to adhere to epidemiological measures (e.g. implement physical distancing, personal protective equipment, and hand washing); less likely to be vaccine hesitant; and more likely to perceive COVID-19 as exceptionally dangerous.

H2a: Higher share of weak ties is positively related to adherence to epidemiological measures.

H2b: Higher share of weak ties is negatively related to vaccine hesitancy.

H2c: Higher share of weak ties is positively related to the risk assessment of COVID-19.

H3a: Higher network demographic heterogeneity is positively related to adherence to epidemiological measures.

H3b: Higher network demographic heterogeneity is negatively related to vaccine hesitancy.

H3c: Higher network demographic heterogeneity is positively related to the risk assessment of COVID-19.

From the network theory perspective, there are different mechanisms through which personal relations create more complex networks. A number of empirical studies have identified homophily as a ubiquitous principle of social organisation, both at micro and macro levels (Kadushin, 2012; McPherson et al., 2001; Cepić & Tonković 2020). Basically, this mechanism assumes that people who socialise together are more likely to have similar attitudes, values and behaviours. In the context of the COVID-19 pandemic, we can expect that people who do (or do not) adhere to protective behaviour are more likely to socialise with others of similar behaviour.

H4a: The presence of alters who do not exercise protective behaviour is negatively related to adherence to epidemiological measures.

H4b: The presence of alters who do not exercise protective behaviour is positively related to vaccine hesitancy.

H4c: The presence of alters who do not exercise protective behaviour is negatively related to the risk assessment of COVID-19.

DATA AND METHODS

Sample

We used the survey data collected from 765 respondents in the second wave of the "Panel survey of attitudes and experiences related to the COVID-19 pandemic among Croatian residents: How do we live during the pandemic?" (Matković et al., 2024), collected between March 4 and April 11, 2021. The initial sample was realised in autumn 2020 using phone interviews based on the land-line phone register supplemented by members of the agency-recruited panel, while the follow-up wave was enacted with consenting participants from the initial wave, using web-based self-completion questionnaire with computer assisted telephone interview as a backup collection mode.

In line with the object of our inquiry, we further constrained our analysis to the sub-sample of 506 respondents who named at least two alters with whom they discussed the pandemic, since most of the network measures that we used as covariates are defined only for networks of 2 or more alters. In the total sample, 12.9% did not name any alters in the name generator, and 20.9% named only one alter, introducing additional bias, as men and respondents with 3-year vocational education or less were more likely to be in this group (pseudo $R^2 = 0.02$). Furthermore, 83 of those respondents included at least one "collective entry" as an alter (for example, "Friends", "Colleagues" or "Mirela, Branko and Suzana"), introducing noise alongside other valid entries with regards to attributes of those alters. The mainstay of our analysis is constrained to 423 respondents whose every response to the name generator was discernible as an individual, since exclusion of such alters from the analysis while keeping the respondents would render networks incomplete. The logistic regression of exclusion due to collective responses on the three dependent variables and the demographic variables (gender, age group, education level, and the occupation category) did not show significant differences.

Descriptive statistics of all variables used in the analysis of the focal sub-sample of 423 respondents are shown in Table 1. Regarding the demographic structure, the average age of 50 years closely corresponded to the average age of adults in Croatia according to the 2021 population census (51 years), while women (60 versus 51 percent) and persons with tertiary educational attainment (44 versus 23 percent) were overrepresented relative to the adult population. While underrepresentation of younger cohorts present in the first wave was counterbalanced by attrition in the follow-up, the initial education bias towards the more educated was intensified in the follow-up wave, and by exclusion of respondents with less than two alters. In an attempt to account for this, weights were constructed to account for age, gender, education and region disbalance both in the initial sample and subsequent attrition.

TABLE 1
Descriptive statistics

Quantitative variables		*Mean* (*SD*)
Index of adherence to epidemiological measures and recommendations		7.0 (1.9)
Age (years)		50.1 (14.3)
Network size		3.7 (1.8)
Share of weak ties		0.2 (0.3)
Network gender heterogeneity		0.3 (0.2)
Network age group heterogeneity		0.5 (0.2)
Network education level heterogeneity		0.3 (0.2)
Categorical variables		*f* (%)
Vaccine hesitancy	Vaccinated or intends to get vaccinated	310 (73.5%)
	Does not intend to get vaccinated	112 (26.5%)
Risk assessment of COVID-19	Not perceiving the virus as exceptionally dangerous	295 (69.7%)
	Perceiving the virus as exceptionally dangerous	128 (30.3%)
Gender	Male	166 (39.2%)
	Female	257 (60.8%)
Education level	Without high school	19 (4.5%)
	High school	212 (50.1%)
	Higher education	192 (45.4%)
Been infected	Not been infected	375 (88.7%)
	Been infected	48 (11.3%)
Social proximity to hospitalized and/or deceased	No	154 (36.6%)
	Yes, weak tie	183 (43.5%)
	Yes, strong tie	84 (20.0%)
The presence of alters who do not exercise protective behaviour	No	397 (93.9%)
	Yes	26 (6.1%)
N		423

The highest intercorrelation among the quantitative covariates was 0.43 (between network age group heterogeneity and network size) and the average intercorrelation was 0.10.

Network measures

The name generator was used to elicit the discussants with whom respondents "over the last few weeks had talked most often about the COVID-19 pandemic (for example, about epidemiological measures, consequences of the pandemic, decisions of the civil protection headquarters, etc.)". The respondents could list up to 10 alters. For each of the alters listed, the respondents were asked about the alters' demographics (age group, gender, and education level); and the ego's relationship with the alter on a 9-degree scale, with degrees arranged on a pre-supposed scale of the relationship's closeness ("1" being "Partner", "8" being "Neighbour", "9" being "Other"). Furthermore, the respondents were asked to assess how much the alter "abides by the epidemiological measures and recommendations (for example, avoiding contacts, physical distance, wearing masks)" on a 4-degree scale ("1" being "Does not abide at all", "4" being "Abides completely").

Network size was measured by the number of discussants listed by each respondent for whom the respondent also stated age group, gender, and education level.

Share of weak ties was measured by the ratio of the number of alters for whom the respondent stated one of the degrees of the relationship's closeness that were deemed as substantially more distant ("Acquaintance [from common activities, hobbies, etc.]", "Acquaintance [from social media, for example Facebook]", "Colleague from work or college", "Neighbour", "Other") than the degrees we deemed as close ("Partner", "Immediate family member", "Extended family member", "Close friend") and the network size.

Network demographic heterogeneity was measured by three Blau indices (Blau, 1977), the most commonly used measure to capture group diversity on a categorical scale (Harrison & Klein, 2007), pertaining to gender, age group and education level. The Blau index expresses the probability that any two alters in a network (excluding ego) belong to different categories of a categorical variable and thus theoretically ranges from 0 (completely homogenous network) to 1 (completely heterogeneous network).

$$Blau = 1 - \sum_{i=1}^{k} p_i^2$$

In the formula, k is the number of categories of the variable and p_i is the proportion of the i-th category in the network size which is squared (multiplied by itself) to express the probability that two independent events occur, i.e. that any two alters belong to the same category *i*. The sum of the squared proportions of all categories is subtracted from total probability of belonging to different categories (its value set at 1), which means that the more categories there are and, at the same time, the more equal their proportions in the network, the larger is the probability that any two alters belong to different categories (since squaring numbers less than 1 and closer to zero results in smaller numbers to be subtracted from total probability). There were two gender categories in the network gender heterogeneity measure (which means that this measure has a theoretical maximum of 0.5), six age groups of alters (up to 29, 30-39, 40-49, 50-59, 60-69, 70+) in the network age group heterogeneity measure and three groups of alters' education levels (no high-school, high-school, higher education) in the network education level heterogeneity measure.

The presence of alters who do not exercise protective behaviour was operationalised by a simple indicator of whether an ego assessed for at least one of the listed alters that he or she did not abide by epidemiological measures and recommendations, which was a relatively rare occurrence in the sample (6.1%).

Dependent variables

All dependent variables were developed by the project research team (Matković et al., 2024).

Index of adherence to epidemiological measures and recommendations (IAEMR) was constructed as a sum index of 9 binary items where "0" is "No" and "1" is "Yes" (for example, "You wash or disinfect your hands more often than usual", "You avoid public transport [tram, bus, train]") (Cronbach Alpha = 0.75). The higher result on this index meant higher adherence.

Vaccine hesitancy was constructed as a binary recode of an ordinal variable ("0" being "I am already vaccinated", "I will surely get vaccinated", and "I shall probably get vaccinated"; "1" being "I shall probably not get vaccinated" and "I will surely not get vaccinated"), whereby 26.5% in the focal sub-sample stated they did not have the intention to get vaccinated.

Risk assessment of *COVID-19* was constructed as a binary recode of an ordinal variable whereby only the last degree was counted as "1" ("[Virus]exceptionally dangerous, the consequences may be fatal for many people"), chosen by 30.3%. The preceding degrees, counted as "0", were "Quite dangerous, but the consequences will not be fatal for a vast majority of people" (53.0%), "Dangerous to some extent, but the fear and caution are an overreaction" (13.0%), "Danger to a smaller extent, coronavirus is like the flu" (3,6%) and "No danger at all, coronavirus actually does not exist" (0.2%).

Control variables

Among the control variables were the standard demographics in social research (age, gender and education level), also confirmed as predictors of the attitude towards the pandemic and the epidemiological measures (Ančić & Cepić, 2021; Morales et al., 2022). The other two control variables were chosen following the notion that the direct or indirect salient ("serious") experience with the pandemic might influence the dependent variables. Direct experience with the pandemic was operationalised as personally having been infected (11.3%), while the indirect "serious" experience with the pandemic was operationalised through social proximity to hospitalised and/or deceased, i.e. knowing someone who suffered grave consequences. The respondent could either be not knowing anyone who was hospitalised or died from the consequences of COVID (36.6%), having a weak connection to someone with those outcomes (acquaintance, colleague, neighbour, someone else) (43.5%), or having a strong connection with someone with those outcomes (partner, family member or friend) (20.0%).

Analytical strategy

In the regression analyses of the three dependent variables, in each case we start with the null model including the control set of ego's characteristics only, then proceed by adding three blocks of network characteristics measures successively: network size, network composition (share of weak ties and demographic heterogeneity), and finally the presence of alters who do not exercise protective behaviour (models 2-4 in Tables 1, 2 and 3). The rationale for adding the blocks of network characteristics successively are intercorrelations between the network characteristics which could obscure contributions of each set of variables to the explanation. Therefore, not only individual covariates, but also changes of model fit statistics are of interest in the results' interpretation.

Network size is added in the first block of network characteristics as the most basic network characteristic with relatively larger correlations with network heterogeneity measures (from 0.14 with the gender heterogeneity to 0.43 with the age group heterogeneity) among all intercorrelations of the network measures (the average correlation being 0.13). This is followed by a block of more complex network composition traits with hypothesised associations with the outcome. Finally, we assess whether the introduction of a covariate indicating behavioural homophily of alters with the observed outcome (the presence of alters who do not exercise protective behaviour) demonstrates the expected association, or moderates the effects of network size and composition introduced in prior steps.

Among the three dependent variables, Poisson regression was used in the case of IAEMR, since it is a count variable, while logistic regression was used in the case of the other two, binary dependent variables. We used heteroskedasticity-robust standard errors.

Respondents with missing values in the case of social proximity to the hospitalised and/or deceased (2 respondents) and vaccine hesitancy (1 respondent) in the focal sub-sample were deleted listwise in the three sets of models shown in Tables 2-4.

Given the bias of our sample, the use of survey weights in modelling was considered. While survey weights may help to address the potential estimates' bias, they tend to reduce the estimates' efficiency (Bollen et al., 2016). To test if survey weights are needed, the method proposed by Pfefferman and Sverchkov (2007) was used as the only consistently applicable test in our case among all the tests mentioned in a review (Bollen et al., 2016). The method entails regressing the weight variable on the dependent variable and the covariates, whereby a significant association of survey weights with the dependent variable indicates that the weights make a substantial difference to the estimates and are therefore needed. In three OLS regressions (one for each dependent variable), there were no significant associations with the dependent variables ($p(\mathrm{t}) > 0{,}05$) and it was decided not to use the survey weights.

A robustness check of the regression results was made by comparing the significance patterns in the focal sub-sample (shown in Tables 2-4) and in the larger sub-sample of 506 respondents that listed collective entries as alters, where such respondents were retained in analysis, but only with alters for whom the ego had stated the age group, education level and gender in the name interpreters (the "noisy" sample).

RESULTS

Network size was not associated with adherence to epidemiological measures and recommendations (H1) in the linear regression analyses (Table 2).

Among network composition variables, the share of weak ties was not connected to adherence to the measures and recommendations (H2a). Network heterogeneity in terms of education level significantly and positively contributed to the ego's adherence to epidemiological measures and recommendations (H3a): having all the alters with different education levels as opposed to having all the alters with the same education level (a unit change in the covariate) meant on average about 1 point more on the IAEMR. Network gender heterogeneity was negatively associated with IAEMR (H3a) before adding the presence of the alters who do not exercise protective behaviour.

Behavioural homophily in terms of risky health behaviour was found, as the presence of alters who do not exercise protective behaviour had a significantly negative and relatively strong association with the ego's own risky behaviour (H4a), substantially improving model fit (as indicated by lower information criteria values) and decreasing the ego's adherence to measures and recommendations for somewhat less than 2 points (on a 0-9 scale) on average.

Significance pattern of the findings related to network heterogeneity and behavioural homophily in terms of risky health behaviour held also in the "noisy" sample that included those respondents who named "collective entries" as alters, though the effects were smaller.

TABLE 2
Hierarchical Poisson regression analyses for adherence to epidemiological measures and recommendations

	(1) b (SE)	(2) b (SE)	(3) b (SE)	(4) b (SE)
Female (Ref: Male)	0.03 (0.03)	0.03 (0.03)	0.02 (0.03)	0.01 (0.02)
Age	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Education level (Ref: High school)				
No high school	-0.03 (0.06)	-0.03 (0.06)	-0.02 (0.06)	-0.00 (0.06)
Higher education	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.03 (0.02)
Been infected (Ref: No)	-0.05 (0.05)	-0.05 (0.05)	-0.06 (0.05)	-0.05 (0.05)
Social proximity to hospitalised and/or deceased (Ref: No)				
Yes, weak tie	0.03 (0.03)	0.03 (0.03)	0.02 (0.03)	0.02 (0.03)
Yes, strong tie	0.02 (0.03)	0.02 (0.03)	0.01 (0.03)	0.02 (0.03)
Network size		0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)
Share of weak ties			0.13 (0.12)	0.09 (0.12)
Share of weak ties # Share of weak ties			-0.12 (0.14)	-0.09 (0.14)
Network heterogeneity: gender			-0.13* (0.06)	-0.09 (0.05)
Network heterogeneity: age group			0.07 (0.07)	0.08 (0.07)
Network heterogeneity: educ. level			0.14* (0.06)	0.15* (0.06)
The presence of alters who do not exercise protective behaviour (Ref: No)				-0.31** (0.10)
Constant	1.63*** (0.07)	1.62*** (0.07)	1.62*** (0.08)	1.60*** (0.08)
Observations	421	421	421	421
AIC	1839.3	1841.2	1845.7	1835.0
BIC	1871.6	1877.6	1902.3	1895.7

Robust standard errors in parentheses; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

In the logistic regressions of vaccine hesitancy (Table 3), the share of weak ties was associated with less vaccine hesitancy (H2b), albeit non-linearly; those having about half of their ties were somewhat less prone to express vaccine hesitancy, though this pattern was not pronounced (Figure 1). Among the network heterogeneity measures (H3b), only the network heterogeneity in terms of age group was significantly associated with the intention to get vaccinated (a negative sign), albeit not in the "noisy" sample. Naming all alters different in terms of age group as opposed to naming all alters as belonging to the same age group meant about 70% less chance of stating the intention to not get vaccinated (expressing the log-odds as the odds-ratio: exp(-1.27) = 0.28). The presence of alters who do not exercise protective behaviour was significantly and positively associated with vaccine hesitancy (H4b), increasing the odds of vaccine hesitancy for about 2.8 times (exp(1.03) = 2.80).

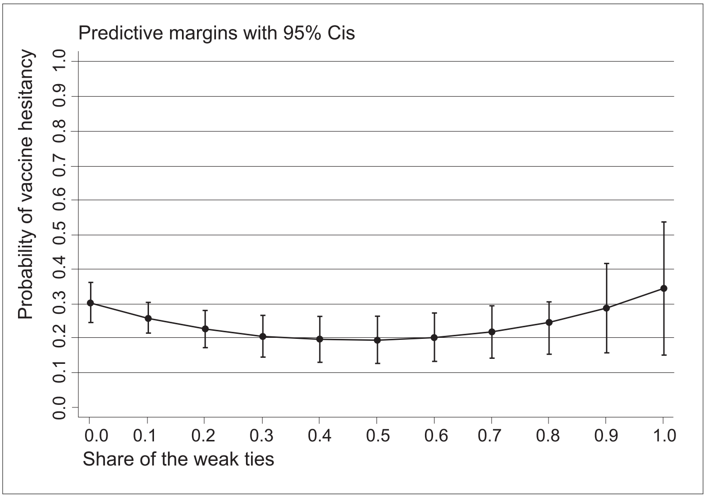
➊ TABLE 3
Hierarchical logistic regression analyses for vaccine hesitancy (log-odds)

	(1) b (SE)	(2) b (SE)	(3) b (SE)	(4) b (SE)
Female (Ref: Male)	0.42 (0.25)	0.43 (0.25)	0.54* (0.25)	0.58* (0.25)
Age	-0.04*** (0.01)	-0.04*** (0.01)	-0.04*** (0.01)	-0.04*** (0.01)
Education level (Ref: High school)				
No high school	1.00 (0.53)	1.00 (0.53)	0.97 (0.56)	0.90 (0.59)
Higher education	-0.07 (0.24)	-0.06 (0.24)	0.02 (0.25)	-0.01 (0.25)
Been infected (Ref: No)	0.29 (0.36)	0.32 (0.36)	0.44 (0.37)	0.39 (0.37)
Social proximity to hospitalised and/or deceased (Ref: No)				
Yes, weak tie	-0.19 (0.26)	-0.18 (0.26)	-0.18 (0.26)	-0.21 (0.27)
Yes, strong tie	-0.77* (0.34)	-0.76* (0.34)	-0.81* (0.34)	-0.81* (0.34)
Network size		-0.05 (0.07)	0.07 (0.08)	0.05 (0.08)
Share of weak ties			-2.84* (1.26)	-2.70* (1.28)
Share of weak ties # Share of weak ties			3.05* (1.47)	2.95* (1.50)
Network heterogeneity: gender			-0.02 (0.61)	-0.17 (0.61)
Network heterogeneity: age group			-1.20* (0.61)	-1.27* (0.61)
Network heterogeneity: educ. level			-0.21 (0.55)	-0.23 (0.55)
The presence of alters who do not exercise protective behaviour (Ref: No)				1.03* (0.44)
Constant	1.01* (0.50)	1.15* (0.55)	1.39* (0.59)	1.48* (0.59)
Observations	420	420	420	420
AIC	462.7	464.1	464.2	461.7
BIC	495.0	500.5	520.8	522.3

Robust standard errors in parentheses; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

In the logistic regressions of the high risk assessment of COVID-19 (Table 4), none of the network heterogeneity measures nor the share of weak ties were significantly associated with perceiving the virus as an exceptionally grave danger (H2c, H3c).

➲ FIGURE 1
Adjusted predictions of vaccine hesitancy according to the share of weak ties



➊ TABLE 4
Hierarchical logistic regression analyses for Risk assessment of COVID-19 (log-odds)

	(1) b (SE)	(2) b (SE)	(3) b (SE)	(4) b (SE)
Female (Ref: Male)	0.52* (0.23)	0.52* (0.23)	0.53* (0.23)	0.52* (0.24)
Age	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)
Education level (Ref: High school)				
No high school	1.00 (0.55)	1.00 (0.55)	0.99 (0.53)	1.13* (0.51)
Higher education	-0.09 (0.23)	-0.11 (0.24)	-0.11 (0.24)	-0.05 (0.24)
Been infected (Ref: No)	-0.01 (0.38)	-0.05 (0.38)	-0.05 (0.39)	0.02 (0.39)
Social proximity to hospitalised and/or deceased (Ref: No)				
Yes, weak tie	-0.13 (0.25)	-0.16 (0.26)	-0.12 (0.26)	-0.09 (0.26)
Yes, strong tie	0.02 (0.31)	0.01 (0.31)	0.03 (0.31)	0.07 (0.32)
Network size		0.08 (0.07)	0.07 (0.08)	0.09 (0.08)
Share of weak ties			-0.53 (1.23)	-0.75 (1.25)
Share of weak ties # Share of weak ties			0.28 (1.49)	0.45 (1.53)
Network heterogeneity: gender			-0.18 (0.61)	0.00 (0.62)
Network heterogeneity: age group			0.84 (0.65)	0.85 (0.66)
Network heterogeneity: educ. level			-0.42 (0.56)	-0.34 (0.57)
The presence of alters who do not exercise protective behaviour (Ref: No)				-1.64* (0.71)
Constant	-3.48*** (0.55)	-3.75*** (0.60)	-3.90*** (0.67)	-4.12*** (0.69)
Observations	421	421	421	421
AIC	487.2	487.5	494.6	488.9
BIC	519.6	523.8	551.2	549.5

Robust standard errors in parentheses; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

On the other hand, high risk assessment of COVID-19 was significantly negatively and relatively strongly associated with the presence of alters who do not exercise protective behaviour (H4c), which was also found in the "noisy" sample; naming at least one alter who did not adhere to the measures meant about 80% less chance to assess the danger as exceptional (exp(-1.64) = 0.19).

DISCUSSION AND CONCLUSIONS

Previous studies of COVID related communication reported the importance of personal networks in comparison to other sources of information, such as state authorities, science and health experts, news outlets, and social media. However, the aspect which remained insufficiently studied concerned the structure of the personal, non-virtual information sharing networks. In this research, we were interested in the effect of personal COVID-19 information-sharing network properties. The overarching question was to what extent the crucial aspects of risk-aversive behaviour – including adherence to epidemiological measures, intention to get vaccinated, and perception of the virus as exceptionally dangerous – are a network-mediated phenomenon. With this in mind, we sought to provide a more nuanced understanding of how behaviour in the context of the pandemic is shaped by horizontal social ties.

The size of the reported information-sharing network does not seem to be associated with any of the outcomes observed here. This lack of association is interesting and may indicate that a greater number of people with whom one communicates do not imply the greater probability of obtaining diverse information. This is partly in line with findings from Qu et al., 2023), as their research confirmed that the relationship between personal network size and information avoidant behaviour followed a U-shape curve. Similarly, previous findings from social support theory and research also imply that there is a curvilinear relationship between the network size and individual outcomes (KIm & Lee, 2011). However, what seems more important is the strength of ties and network heterogeneity.

As for the network characteristics, the share of weak ties was non-linearly connected to vaccine hesitancy, so those who personally shared COVID-19 information with both weak and strong ties were somewhat less likely to express vaccine hesitancy than respondents who communicated the topic mostly or exclusively with those they share either strong or weak ties. This does not conform to our expectations to the full extent. Also, this network characteristic did not turn associated with either adherence to epidemiological measures and recommendations or risk perception.

With respect to network heterogeneity, the pattern of effects varies regarding the observed outcome. The ego's adherence to epidemiological measures and recommendations is positively associated with education heterogeneity. Having all the alters with different education levels as opposed to having all the alters with the same education level meant on average about 1 point more on the index of adherence to epidemiological measures. This pattern being only the case with education heterogeneity, but not with age or gender heterogeneity of the discussion network, might be due to the education level being a stronger marker of societal distance, or the "bridging" characteristic of the social network, than the other two. However, only network heterogeneity with respect to age is associated with vaccination intent. This is not surprising as age is one of the key determinants of adverse outcomes from the COVID-19 infection.

Regarding behavioural homophily among the respondents participating in such networks, we found that if the network contains alter(s) not adhering to epidemiological measures and recommendations, the ego is substantially more likely not to be adhering to measures themselves, to be vaccine-hesitant, and not to perceive COVID-19 as exceptionally dangerous. Those findings, while expected and in line with previous studies that examine behaviour change with regard to the characteristics of personal networks (Valente & Pitts, 2017; Valente, 2015), are important as, in addition to demonstrating that attitudes and behaviour related to pandemics are a network phenomenon, they also suggest that it takes only one alter in the discussion network to make a difference. Though, the effects of the network characteristics remained robust after introducing behavioural homophily in the model, indicating an independent mechanism of action. In a context broader than the discussion networks, baseline models indicate that social proximity (strong ties) to someone who was hospitalised or deceased as a consequence of COVID was associated with the ego's higher vaccination propensity, but intriguingly no such association was found for their adherence to epidemiological measures and recommendations, or COVID-related risk assessment.

In light of the obtained findings, future research may benefit from exploring in more detail the effects of network structure, especially the effect of network closure mechanisms. In particular, transitivity is of special importance as it explains the creation of dense cohesive networks characterised by reciprocal relationships and mutual trust. In the pandemic context, this type of dense support network was identified as a special type of social capital – virus-combat social capital (Bian et al., 2020) which helps people deal with containment measures and prolonged stress. However, cohesive networks may also be more prone to spreading disinformation and, consequently, risky behaviour related to COVID-19. Besides that, future research may focus on complete networks instead of personal networks and thus explore the effect of different network metrics and positions in the network.

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Declaration of interests

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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Kako osobne mreže utječu na pridržavanje epidemioloških mjera, namjeru necijepljenja i procjenu rizika od COVID-19?

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Od početka pandemije COVID-19 dokazana je povezanost pridržavanja epidemioloških mjera s informacijama razmjenjivanim kroz osobne mreže. Unatoč tome, malo je dokaza o efektima pojedinih obilježja osobnih mreža. Koristeći se podacima iz slučajnoga nacionalnog uzorka odraslih u Hrvatskoj (*N* = 765), ispitujemo odnos raznih obilježja osobnih mreža s trima zavisnim varijablama: procjenom općeg rizika od COVID-19, pridržavanjem epidemioloških mjera i namjerom izbjegavanja cijepljenja. Predlažemo "pandemijske diskusijske mreže" kao osobne mreže sačinjene od sugovornica s kojima ispitanice razmjenjuju informacije ili raspravljaju o pandemiji. Obrazovna heterogenost mreža pridonijela je pridržavanju mjera, a dobna heterogenost mreža pridonijela je sklonosti cijepljenju. Ove su povezanosti potvrđene neovisno o ponašajnoj sličnosti prema rizičnom ponašanju, koja je također utvrđena.

Ključne riječi: COVID-19, diskusijske mreže, demografska heterogenost mreža, cijepljenje, socijalni pritisak