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RESEARCH ARTICLE

Embedded inequality: Personal network dynamics and mental health during COVID-19

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Abstract

Personal networks provide crucial support during crises, yet people are embedded in different network types that structure unequal access to such resources. The current study integrates these perspectives to examine whether—and how—network turnover contributed to disparities in mental health across socioeconomic status (SES) groups during the pandemic. Using two-wave panel data from the COVID-19 Pandemic and Social Network Panel Study (2020–2021), an egocentric network study of the college population in Wuhan, we employ random forests and spectral clustering to identify 7 types of core networks based on 43 network variables (i.e., *Family*, *Friend*, *Restricted*, *Family & Community*, *School & Career*, *Just Activity*, and *Homebody*). We find that as local social-distancing policies tightened, respondents increasingly shifted to *Family* and *Friend* networks and withdrew from *School & Career* and *Just Activity*. Individual fixed-effect models reveal that these network turnovers have heterogeneous mental health consequences net of observed and time-invariant unobserved confounders. Moving into *Family* and *Friend* networks yields the most favorable mental health outcomes for higher-SES groups, whereas benefits are less pronounced and even reversed among lower-SES groups. This pattern is consistent with SES-based differences in social support available in these network types. The current research advances an updated machine-learning approach for identifying personal network typologies. It also shows how the pandemic laid bare unequal resources embedded in personal networks and intensified health-related social inequality, underscoring the need to theorize network effects as contingent on individuals' social status and the contexts in which networks are formed and embedded.

Keywords: Social network typology; network dynamics; social inequality of health; socioeconomic status; COVID-19 pandemic

1. Introduction

The COVID-19 pandemic has caused more than a billion confirmed cases and more than 4 million deaths worldwide since first reported in Wuhan (World Health Organization, 2021). As a global crisis, the pandemic also disrupted daily life in terms of mental health, education, and social relationships (Usher *et al*., 2020). Indeed, personal networks are changed in part due to the restrictions imposed by social distancing policies (Weeden *et al*., 2021) and in part because of network adaptations to the pandemic-induced challenges, including those imposed by lockdowns and social distancing policies. Regarded as the intermediate-level social determinant of health (Lahelma, 2007), personal networks are also found to have strong associations with a wide range of health indicators, including morbidity, depressive symptoms, and physical health (Fiori

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et al., 2007; Li and Zhang, 2015). Although sociologists have long speculated about the impact of personal networks on social inequality (Granovetter, 1983), this has seldom been empirically examined (Shepherd and Garip, 2021). Given the complexity and multidimensional nature of personal social networks, it is also difficult for studies analyzing only a handful of network features to provide a sufficiently rich picture of the social network, and their results may be obscured by potential confounders (Shiovitz-Ezra and Litwin, 2012). Therefore, scholars have resorted to clustering techniques to construct a parsimonious measure of social network typology that could effectively capture network characteristics and their association with health. For example, network typology is commonly applied in gerontology research as a predictor for health among older adults (Maya-Jariego, 2021).

Despite growing interest in networks and health, few studies focus on young adults, who experienced the worst mental health declines among all age groups during the pandemic (Nwachukwu *et al.*, 2020). More importantly, extant research on network typology and its health implications faces several challenges both methodologically and theoretically. First, social networks are documented to vary systematically across individuals with different personal characteristics and from different cultural backgrounds. These factors may serve as confounders between network type and health (Cornwell, 2015; Li *et al.*, 2018). Second, due to the constraints of commonly used clustering algorithms (Kouiroukidis and Evangelidis, 2011), existing studies usually input no more than 10 original variables to generate network typologies, which could leave room for omitted variable bias (Antonucci *et al.*, 2010). Further, two lines of research on network dynamics and the network's effect on health inequality have yet to be combined, especially in the context of the COVID-19 pandemic, which lay bare the fault line of society (Perry *et al.*, 2021).

To fill in this gap, we use both waves of data from CovNetps-Wuhan to examine how network dynamics shape mental health outcomes during the pandemic. The CovNetps-Wuhan survey samples the total college population in Wuhan, the first pandemic epicenter, who faced campus closure and strict social distancing policies during the first wave outbreak in the Wave 1 survey, but have largely resumed normal life and returned to the campus in Wave 2. The goal of our study is threefold: (1) to develop a comprehensive network typology describing these students' core networks; (2) to investigate how network types change as the social distancing policy becomes stricter; (3) to estimate the heterogeneous effect of network types on mental health across different SES groups and highlight the moderating role of SES. We build on the clustering method developed by Giannella and Fischer (2016) (henceforward, G&F) that includes 43 network features to identify network types. Combining data from the Oxford Covid-19 Government Response Tracker, we employ a multinomial logistic model to find out how the pandemic changes network types and use fixed-effect models to reveal the moderating effect of SES on the relationship between network type and depressive symptoms.

2. Theoretical backgrounds

2.1 Developing a social network typology

A personal network is a set of individuals who are linked to each other in ways specified by social roles (Hall and Wellman, 1985). Traditional studies focusing on a single network aspect, nevertheless, ignore the multidimensional nature of social networks, and their findings would be confounded by the remaining aspects due to mutual interdependence (Li and Zhang, 2015). To address these methodological caveats, inductive network typology turns out to be an economic, comprehensive, and useful way to encapsulate the main characteristics of networks. Previous network-health studies consistently report four common networks that have cross-cultural validity, namely *Restricted*, *Friend*, *Family*, and *Diverse* (Li and Zhang, 2015). Besides, other distinct types have been identified among non-Western populations. For instance, the *Congregant* network, deeply involved in religious activities, has been reported in Korea and Israel (Litwin and Shiovitz-Ezra, 2011; Sohn *et al.*, 2017), and a *Distant Family* network focusing on extended kin has been found in a sample of older Chinese adults (Cheng *et al.*, 2009).

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These inconsistencies may, on one hand, stem from cultural heterogeneity across countries, and on the other hand, from different sets of network variables selected to train the clustering algorithm and different algorithms employed. In terms of criterion variable selections, two lines of research exist that differ in variable choice and the resulting typology, namely support classification and structural classification (Maya-Jariego, 2021). The former emphasizes support-related information, such as the number of supportive network members and composition of help providers, while the latter further includes structural indicators such as network size, homogeneity, and density. Most network typology-health research to date follows the support classification tradition that considers the location and resource feature yet ignores structural elements. Consequently, the typology obtained fails to comprehensively represent social networks, and subsequent analysis may suffer from omitted variable bias. To overcome these potential drawbacks, the current study selects criterion variables that cover both support and structural dimensions so that the typology "captures the holistic nature of networks" (Perry *et al*., 2018).

In terms of the algorithm, K-means clustering and the more recently developed latent variable modeling techniques are commonly employed to detect network typology (Park *et al*., 2018). Nevertheless, K-means clustering hinders researchers from including more criterion variables due to "the curse of high dimensionality" (Kouiroukidis and Evangelidis, 2011). Further, K-means and latent analysis are also sensitive to noise, outliers, and variable scales, which may obscure the discovery of robust network types (Giannella and Fischer, 2016). To overcome these obstacles, G&F use the random forest to construct network types because it can capture the most useful variables in characterizing distinctive network types. Also, it outperforms traditional clustering methods because of its compatibility with both continuous and categorical variables with different scales, robustness to outliers, incorporation of extraneous features, and adaptation to multicollinearity (Cutler *et al*., 2012). Hence, we build on G&F's method to identify network typology in this sample.

2.2 Pandemic and social network dynamics

The vast literature on network dynamics suggests personal networks are likely to change as pandemic-induced social distancing policies, such as public space closures, become more stringent. First, social networks are shaped by structural contexts. According to Feld (1981), personal networks evolve around *foci*, namely social entities, contexts, or organizations, such as the workplace, school, home, or voluntary clubs. They are also referred to as context or spatial composition, without which social interactions and joint activities are unlikely to take place, and social ties cannot be formed or sustained (Blau, 1977; Small and Adler, 2019). Social distancing policies change the accessibility of these foci by closing schools, restaurants, and other public spaces, but at the same time encourage staying-at-home behaviors, which make individuals switch network types. For instance, networks between Cornell University students became less dense, less connected, and more fragmented during the pandemic when on-campus teaching was replaced by a hybrid instruction mode (Weeden *et al*., 2021).

Second, personal networks change because they "adapt to the dynamic and uncertain environment" (Perry, 2021), which is exactly the case of the pandemic, and especially during lockdowns. Previous research found that individuals endeavor to activate their network ties for help in times of crises, and rely heavily on kinship ties for resources in contexts such as Hurricane Katrina (Hurlbert *et al*., 2000) or the Gulf War (Shavit *et al*., 1994). Friendship networks among students have also proved to be robust in the context of COVID-19, as nominations for informational and emotional assistance increased modestly (Elmer *et al*., 2020). Changes in network types also occur as the ego's needs evolve or when alters self-activate to offer help upon perceiving the ego's difficulties (Perry and Pescosolido, 2012; Small, 2021). In the case of Wuhan, a large number of volunteers from local neighborhoods formed non-kin networks during the lockdown to meet local residents' needs of grocery deliveries, medicine purchases, basic health services, and so on (Miao *et al*., 2021). Therefore, we have the following hypotheses about network turnover that contextualize social inequality in mental health during the pandemic.

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H1: Individuals tend to withdraw from network types centered at school, work, and other public spaces as the pandemic-induced policies become more stringent.

H2: Individuals are more likely to have network types related to a high level of support, particularly networks with a focus on families, friends, or both, as the pandemic-induced policies become more stringent.

2.3 Network types, health, and SES

Among commonly reported network types, *Restricted* networks are characterized as being limited in every supportive aspect of networks and thus associated with the worst mental health profile (Cheng *et al*., 2009; Litwin, 2001; Litwin and Shiovitz-Ezra, 2011). On the contrary, *Diverse* networks are considered a more beneficial type for health (Moore *et al*., 2009). The superiority of *Friend* vis-à-vis *Family* networks remains debated. Some studies suggest that *Friend* networks yield better mental health (see, Antonucci *et al*., 2010), whereas other research, especially those conducted in East Asian contexts, finds that *Family* networks are either among the healthiest types or similar to friend-focused types (Cheng *et al*., 2009; Fiori *et al*., 2008, 2007).

Although individuals' network types are strong predictors of health outcomes (Litwin, 2001), estimated effects in previous research may be confounded by personal- and macro-level background factors. First, according to the social convoy theory, personal background factors including age, personality, life and family history (e.g., divorce, unemployment, imprisonment), all affect individuals' network types (see, Antonucci *et al*., 2010; Kahn and Antonucci, 1980), and yet they are also important social determinants of health (Phelan *et al*., 2010). Second, the macro-level context that individuals are embedded in, such as cultural background and level of regional economic development, shapes both their social network types and mental health simultaneously (Li *et al*., 2018). Therefore, the current study uses fixed-effect models to rule out these observed and unobserved confounders and examines the health effect of network types.

More importantly, the impact of network type on life outcomes may not be universal or constant. Instead, it tends to be contingent on the SES of the ego according to the strand of study on social capital and network inequality (Shepherd and Garip, 2021). On the one hand, high-SES individuals have more resource-enriching personal networks. For instance, Campbell *et al*. (1986) demonstrated that network members' educational level, job prestige, and family income are positively related to the SES of the ego. These network deficits make low SES groups less likely to have the resources they need in their networks (Lai *et al*., 1998), which has been used to explain why poverty is self-perpetuating (Granovetter, 1983). On the other hand, higher-SES individuals are more capable of accessing the resources in personal networks than their low-SES counterparts, even if the resources embedded in their networks are similar. For example, research in social capital activation has found that weak ties are beneficial for job status only for high SES individuals (Lin *et al*., 1981). By contrast, low-status individuals are often denied assistance even though they already have alters in their networks who wield the resources needed. They also have difficulties mobilizing social ties for resources due to the "functional deficit" of personal networks, especially in low SES neighborhoods and among low-wage occupations (Smith, 2005). This leads to our central hypothesis on the heterogeneous protective effect of networks across SES groups.

H3: The effect of network type on mental health is conditioned on SES.

In terms of why personal networks impact health, previous literature proposed three mechanisms, namely, social support, social capital, and behavioral diffusion (McCarty *et al*., 2019). Most network typology-health studies rely on the first framework that highlights the benefit of embedded social support on buffering life stressors and facilitating resilient coping strategies (Cohen *et al*., 2000; Song *et al*., 2011), which the present study follows to explain the network health disparities. Though scholars have long articulated the multidimensional nature of social support,

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which consists of actual support and perceived support according to the degree of subjectivity, only a few empirical studies take both aspects into consideration (Lin and Peek, 1999; Song *et al.*, 2011). Even if individuals are embedded in networks with abundant resources, they could still feel lonely, disconnected, and unsatisfied with the current network conditions (de Jong Gierveld *et al.*, 2009). Hence, the paper also examines different levels of social support embedded in each network type to help make sense of our central hypothesis on the network effect heterogeneity across SES groups.

H4: Mental health disparities associated with different network types can be explained by different degrees of social support embedded in the networks.

3. Data and methods

3.1 Data

The data for this study are the Wuhan subsample of COVID-19 and the Social Network Panel Study (CovNetps-Wuhan), a web-based survey with a representative sample of the college population in Wuhan city. Respondents are drawn proportionately according to the five-tier system developed by the Ministry of Education (MOE), a classification system that ranks the higher educational institutions (HEI) from the most selective national universities to local vocational colleges (see Section A1, Supplementary Material). The first wave of CovNetps-Wuhan was collected between March and May 2020, at the end of the first wave outbreak in China, to fully capture the network consequences of pandemic exposure. A total of 2,047 respondents participated in the study, who were then residing in all provincial-level administrative regions of China during the pandemic. The second wave was conducted from January to February 2021, three months after the reopening of the campus following MOE's administrative order. In total, 524 respondents participated in the follow-up survey. All qualified participants in Cov-Netps study meet the following screening criteria: (1) currently being enrolled in one of Wuhan's HEI; (2) aged 17 or above; (3) choose the "I agree to participate in this study" option; (4) manage to pass two filtering questions; and (5) spend an average of at least 3 s on each item. In this research, we further employ list-wise deletion on less than 5% of the respondents who reported missing or unmatched information. CovNetps-Wuhan applies egocentric network study methods to capture an individual's core networks through a two-step process similar to Fischer (1982). First, a name generator asked respondents to recall "people you typically do these sorts of things with, or other social things as well, such as going shopping, out for sports, studying together, chatting, or people who are important to you (both online and offline)", and then the survey recorded up to six names reported. Next, in the following name-interpreting stage, respondents were requested to describe their relationship with alters, the characteristics of each alter, and the connections among alters. These items offer detailed knowledge on personal networks, paving the way for our network typology development.

3.2 Measures

Social network types. Social network typology is derived from the 43 network indicators listed in Table S1, Supplementary Material. These variables are selected or constructed to cover different network aspects to obtain a comprehensive typology (Moren-Cross and Lin, 2006).

Depressive symptoms. As a dependent variable, we use the nine-item version of the Center for Epidemiologic Studies-Depression Scale (CES-D) to measure depressive symptoms and represent respondents' mental health status (Santor and Coyne, 1997). The depression scale asks respondents the number of days in the past week that they experience certain emotions (e.g., sad, depressed, happy), and we recoded the scale so that a higher score indicates a higher level of depressive symptoms.

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The pandemic and social distancing. We use the data from the Oxford Covid-19 Government Response Tracker that captures government policies related to space closure and social distancing (Hale *et al.*, 2021). The database includes seven indicators of social distancing policies, which can be used as proxies to capture the disruptions caused by the pandemic. These include the closure of schools, closure of workplaces, cancellation of public events, limits on gatherings, closure of public transport, stay-at-home requirements, and restrictions on travels between cities/regions (0 = no measures, 1 = recommend closing, 2 = require closing only some levels, 3 = require closing all levels), and we use the factor score of these items to measure the strength of local social distancing policies.

Actual and perceived support. Social support is considered in both actual support and perceived support dimensions, which are considered equally important (Moren-Cross and Lin, 2006; Wethington and Kessler, 1986). Actual support is measured by the number of alters with whom respondents confide personal matters, exchange pandemic-related information, discuss entertainment topics, and from whom they receive substantial help. The second dimension, perceived support, reflects the self-rated quality of social support or how satisfied respondents are with their current networks. It is measured by three dichotomous questions asking whether they hope to meet more friends to confide, hang out, and provide practical help (0 = Hope to know more, 1 = Enough for now). A higher score indicates the respondent is more satisfied and has a higher level of perceived social support. In alignment with the literature, Confirmatory Factor Analysis demonstrates that our two-factor model of social support fits the data well ($\chi^2 = 59.196$, $df = 13$, RMSEA = 0.037, CFI = 0.990, TLI = 0.983), which is superior to a traditional single-dimension construct ($\Delta\chi^2 = 2312.827$, $p < 0.001$).

SES and other control variables. The MacArthur scale of subjective socioeconomic status (SES) is used to measure SES. Sociodemographic covariates are age, gender, single or not, educational status, and college type in the five-tier system. In terms of the pandemic's impact, we also control the cumulative confirmed cases (log-transformed) and respondents' COVID experience. For subsequent analysis, the fixed-effect model has already held all time-invariant confounders constant. The descriptive statistics of all variables are presented in Table 1, and the sociodemographic profile of different network types is reported in Table 2.

3.3 Analytical strategy

Developing a network typology. We build on the network typology methodology developed by G&F and further adopt the streamlined version as demonstrated by Laier *et al.* (2022). The original G&F methodology is a multi-stage iterative process: it begins with an unsupervised random forest model on 43 raw network indicators to create a similarity matrix, then uses agglomerative clustering to partition observations into groups, followed by a supervised random forest model to assess prediction accuracy and filter out clusters with high prediction errors (> 20–25%). Next, it creates composite variables through principal component analysis using only observations from these "coherent" clusters, reducing the 43 indicators to approximately 10 composite dimensions. Finally, the entire process—unsupervised random forest, clustering, and validation—is repeated using these composite variables to arrive at the final network types. This approach involves two complete clustering cycles with an intermediate filtering and dimensionality reduction step.

Following Laier *et al.* (2022), we tested whether skipping the intermediate steps (initial clustering, filtering, and PCA on filtered data) would affect results. Our analysis reveals that directly creating composite variables from all observations and clustering once on these composites yielded very similar cluster assignments. Therefore, we adopt this streamlined methodology: (1) reduce 43 network indicators to 10 composite variables using principal component analysis on all Wave 1 observations, (2) apply unsupervised random forest on these composite variables to generate a similarity matrix, (3) perform spectral clustering to partition observations into groups,

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Table 1. Descriptive statistics of wave one and wave two data

	Wave one ($N = 2047$)		Wave two ($N = 524$)	
Variable	Mean	SD	Mean	SD
Age	21.20	2.43	21.12	2.09
Gender				
Male	0.56	0.50	0.55	0.50
Female	0.44	0.50	0.45	0.50
Single or not	0.82	0.39	0.69	0.46
Socioeconomic Status	5.45	1.64	5.51	1.55
Education				
Undergraduate	0.96	0.19	0.74	0.44
Graduate	0.04	0.19	0.13	0.34
Gap year	0.00	0.00	0.02	0.12
Already worked	0.00	0.00	0.12	0.32
College type	3.57	1.63	3.28	1.72
Confirmed cases (log)	7.15	1.90	7.61	1.93
COVID experience	0.46	0.50	0.06	0.23
Received Support	6.48	4.58	6.79	4.36
Perceived Support	4.19	1.22	4.05	1.15
Depression (CES-D)	17.87	12.32	16.62	11.71

and (4) use supervised random forest to validate prediction accuracy, retaining only clusters with prediction errors below 20%. This simplified approach produces seven network types substantively identical to those from the original method while significantly improving computational efficiency, reducing processing time to one-sixth of that of the original approach. For Wave 2 observations, we use the algorithm trained on Wave 1 data to perform out-of-sample prediction (for methodology details, see Section A2, Supplementary Material).

Moreover, we improve G&F's method by applying the spectral clustering method in step two instead of hierarchical agglomerative clustering (HAC), which is used by previous research. Spectral clustering does not make *a priori* assumptions about the shape of the clusters (Von Luxburg, 2007). It also performs better in this case and meets our research goal to obtain several distinctive, small, intuitive, and robust clusters. By contrast, HAC fails to fulfill our goal because the size of the resulting clusters tends to vary greatly in size (i.e., a few extremely large clusters and many small clusters), and this algorithm cannot revoke previously made decisions (Cheng *et al*., 2011; Maimon and Rokach, 2010; Smoliński et al., 2002). Figure 2 highlights how these two methods differ and how spectral clustering's flexibility enables it to learn the data's internal patterns more effectively. While HAC tends to maintain fixed clustering membership before the next split, the spectral clustering method allows making a "regret decision" that could change the individual's cluster membership in the future split. Therefore, spectral clustering has the advantage of balancing the size of different clusters and thus generates a more desirable result for the task of clustering.

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Table 2. Background characteristics, socioeconomic status, and depressive symptoms by seven network types

Variables	Social network types								Test stat.
	Family & community	Family	Friends	Homebody	Restricted	JustActivity	School & career	Total sample	(χ^2/F)
Sample Size	182	413	576	17	180	191	322	1881	
Gender									79.82***
Female or Others	53.30%	54.24%	49.65%	41.18%	39.44%	28.80%	29.50%	44.60%	
Male	46.70%	45.76%	50.35%	58.82%	60.56%	71.20%	70.50%	55.40%	
Single or not									36.49***
Not Single	26.37%	13.56%	22.92%	0.00%	15.56%	9.95%	17.39%	18.02%	
Single	73.63%	86.44%	77.08%	100.00%	84.44%	90.05%	82.61%	81.98%	
Education									1.05
Graduate or above	2.75%	4.12%	3.99%	5.88%	3.33%	3.66%	3.73%	3.77%	
Undergraduate	97.25%	95.88%	96.01%	94.12%	96.67%	96.34%	96.27%	96.23%	
Age, *M* (SD)	20.90 (1.70)	21.21 (2.55)	20.91 (2.11)	21.59 (3.10)	20.86 (1.98)	22.11 (3.52)	21.22 (2.12)	21.15 (2.38)	150.18***
Socioeconomic Status, *M* (SD)	5.36 (1.46)	5.54 (1.66)	5.18 (1.51)	5.53 (2.38)	5.00 (1.73)	6.22 (1.66)	5.56 (1.57)	5.43 (1.63)	16.92**
Depressive symptoms									
CES-D, *M* (SD)	17.67 (12.03)	16.58 (13.05)	17.69 (11.70)	16.00 (16.23)	18.97 (12.44)	19.30 (12.38)	17.63 (12.79)	17.71 (12.42)	9.73

Notes: Only 1,881 of 2,047 Wave One respondents embedded in coherent network types (prediction accuracy >80%) are included. *M* = mean; SD = standard deviation. *** $p < 0.001$, ** $p < 0.01$.

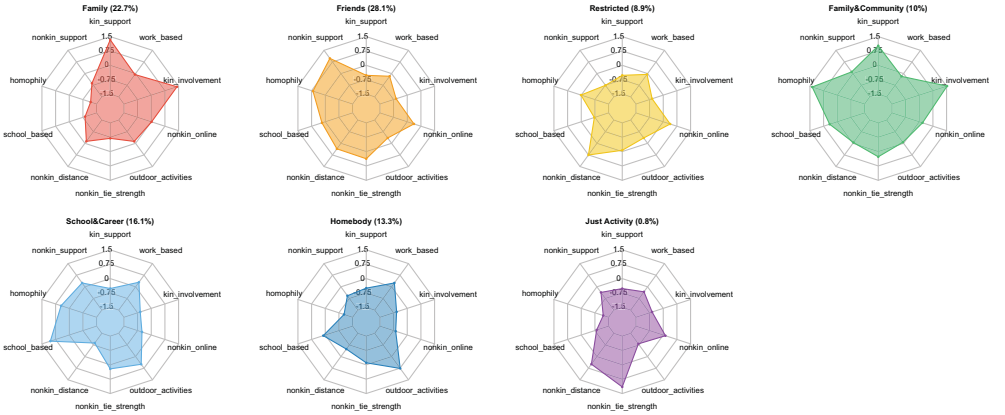


Figure 1. Radial graph mapping social network types on ten composite variables.

Fixed effect models. The fixed effect model takes all time-invariant variables into account (e.g., personality, family history, regional development), which are likely to correlate with both social network type and depressive symptoms. Since every respondent was treated as his/her own control in this model, fixed effect regression makes use of within-person variation observed in repeated measures, and the estimated effect reports the depressive symptoms outcome that would ensue should an "average" individual's network type change (Boone-Heinonen *et al.*, 2011; Rabe-Hesketh and Skrondal, 2008). To confirm our model selection, the Breusch–Pagan Lagrange multiplier test indicates pooled regression is biased for panel data analysis ($\chi^2 = 76.41$, $df = 1$, $p < 0.001$), and the Hausman test result ($\chi^2 = 30.89$, $df = 14$, $p < 0.001$) suggests that fixed effect model is more favorable over random effect model in the current study (Greene, 2008). Last but not least, we implement inverse probability weighting (IPW) in all panel fixed-effects analyses to address potential bias arising from selective attrition between the two survey waves. Specifically, we first estimate each respondent's probability of being observed in Wave 2 as a function of Wave-1 characteristics. We then weight the fixed-effects models by the inverse of this predicted retention probability, so that individuals who were under-represented among Wave-2 respondents receive greater weight in the estimation. This procedure rebalances the analytic sample to more closely resemble the original Wave-1 population and mitigates bias due to differential attrition that is correlated with observed characteristics. Importantly, IPW corrects for selection on observables rather than assuming random attrition, while preserving the within-individual identification afforded by the fixed-effects design.[1]

4. Results

4.1 Social network typology

In general, the clustering algorithm successfully identifies the network type for 1,881 out of 2,047 respondents in the first wave, with 92% "prediction accuracy" (i.e., accuracy in guessing cluster membership), suggesting that clusters are sufficiently distinctive. It generates 10 composite variables out of the 43 initial criterion variables, each of which reflects an important network dimension, namely kin support, kin involvement, non-kin support, non-kin tie strength, non-kin online, non-kin distance, homophily, school-based, work-based, and outdoor activities. Based on these composite variables, we find seven robust network types whose characteristics are visualized in Figure 1 and described below (for further explanations, see Section A3, Supplementary Material).

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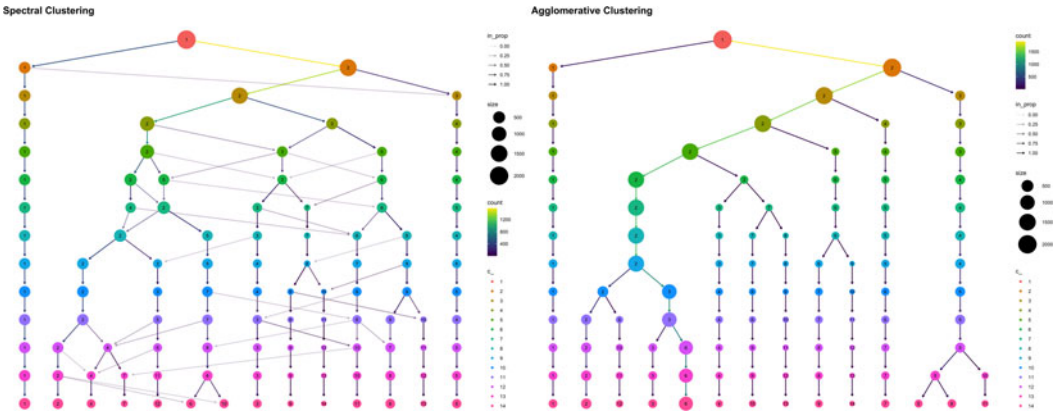


Figure 2. Visual comparison between spectral clustering and agglomerative clustering.

1. *Family* networks (22%) exhibit the highest levels of both kin support and kin involvement compared to other networks, whereas several key indicators representing non-family-oriented network activities, including non-kin support, non-kin tie strength, school-based, and homophily, are far below average.
2. *Friend* (31%). This friend-focused network demonstrates the highest non-kin involvement, in terms of non-kin support, homophily, and non-kin tie strength, while having lower-than-average scores for kin-related dimensions. Individuals embedded in this type of network have a stronger online rather than offline presence, which is probably due to the obstacles of face-to-face non-kin interactions posed by the pandemic.
3. *Restricted* networks (10%) are significantly limited regarding both kin and non-kin involvement. Moreover, except for strong online activities and living far away from their peers, all other network features remain at the average level.
4. *Family & Community* networks (10%) have outstanding levels of kin support, kin involvement as well as homophily, and above-average scores in terms of non-kin tie strength, school-based, and yet the support by non-kin members is only near the average level. Individuals with this network type are likely to have relatively frequent contact with peers of the same age and same educational background.
5. *School & Career* networks (17%) are characterized by the highest levels of connections with schoolmates and colleagues at work. It shares a similar pattern with the *Friend* network regarding non-kin support, homophily, and non-kin tie strength, but they tend to live closer and involve more frequent outdoor activities with non-kin members. Also, the level of support received from kin and non-kin is lower than the *Friend* network.
6. *Just Activities* (10%). The hallmark of this network is that it evolves around outdoor social activities with diverse groups. However, only a constrained amount of support from both the kin and non-kin members exists due to the nature of these social ties.
7. *Homebody* (1%) is a small cluster. As homebodies, they seldom engage in outdoor activities. Instead, individuals mainly rely on online social interactions with strong ties and live relatively far from non-kin members. Limited support is found in this type of network.

Table 2 summarizes the sociodemographic and health profiles of these network types, showing strong associations between core network types and mental health. However, we can also find that network types are not randomly distributed among individuals with different backgrounds, such as gender, marital status, age, and SES, which suggests further analysis is needed to address potential confounding factors.

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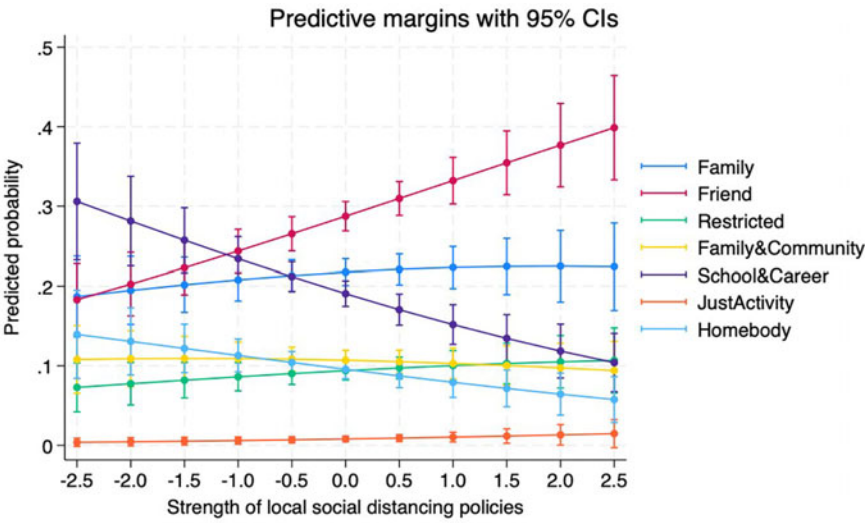


Figure 3. Predicted probability of having a certain network type by social distancing policies, both waves.

4.2 Social distancing policies and changes in personal network type

To investigate the role of the pandemic-induced social distancing policies, we employ multinomial logistic regression to predict the probability of having certain network types with the strength of social distancing policies, setting the above demographic covariates and COVID experience (i.e., the number of cases, knowing someone tested positive) as controls (see Table S7, Supplementary Material). The results based on both waves' pooled data are visualized in Figure 3, where a greater score of the strength index suggests the local pandemic is more disruptive, such as more regulation on public space opening, outdoor gathering, etc. There is a clear downward trend in the possibility of *School & Career* networks, which indicates that such a network type relies heavily on the availability of spaces in schools and in workplaces, and the lockdown and school closure drive individuals to withdraw from them. By the same token, the possibility of having *Just Activity* networks also declines as the pandemic forces the cancellation of public gatherings and outdoor activities. On the contrary, the possibility of the *Friend* network rises dramatically, which could be explained by resource-seeking behaviors such as the frequent usage of online contact and communication to exchange pandemic-related information. However, *Family* networks only demonstrate a slight increase as the social distancing policies become more stringent. This is probably because mutual support among family networks is usually an obligation as constrained by social context. Hence, they tend to be stable regardless of whether individuals are in normal circumstances or difficult times (Offer and Fischer, 2017).

4.3 Fixed-effect models predicting mental health by networks

We use personal fixed effect models to predict the buffering effect of social networks on health, and the results are reported in Table 3. Unlike other regressions, researchers only need to control time-varying confounders in fixed effect models. Relationship status, education, socioeconomic status, and COVID-related experience are factored into our model to control their potential impacts on mental health. Time-fixed effects are also included in our models. Model 1 estimates the effect of each network type on depressive symptoms, setting the *Restricted* network as the reference group. Results reveal that *Family* and *Friend* networks have the strongest buffering effect on mental health, followed by *School & Career* networks. Moreover, as shown by the negative

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Table 3. Fixed effect models predicting the level of depressive symptoms

Variables	(1)	(2)	(3)	(4)
Social network type				
Family	−4.03*	10.64^{+}		
	(1.934)	(5.942)		
Friends	−3.61*	11.48*		
	(1.789)	(5.768)		
Family & Community	−1.21	8.39		
	(1.950)	(5.654)		
School & Career	−2.79	0.86		
	(1.810)	(6.019)		
Just activity	−1.97	4.77		
	(2.397)	(7.865)		
Homebody	−5.19	12.15		
	(6.241)	(29.44)		
Rank of network type			−1.36^{+}	6.40**
			(0.719)	(2.341)
SES	−0.26	1.34	−0.255	3.184**
	(0.454)	(0.858)	(0.447)	(1.155)
Rank of network type × SES				−1.44***
				(0.428)
Network type × SES				
Famiy × SES		−2.67*		
		(1.050)		
Friends × SES		−2.82*		
		(1.106)		
Fam. & Comm. × SES		−1.74^{+}		
		(1.002)		
Sch. & Car. × SES		−0.618		
		(1.092)		
Just Act. × SES		−1.15		
		(1.433)		
Homebody × SES		−3.33		
		(4.707)		

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Table 3. *Continued*

Variables	(1)	(2)	(3)	(4)
Single	0.17	0.19	0.19	0.13
	(1.148)	(1.158)	(1.140)	(1.137)
Education				
Graduate or above	−0.39	−1.03	−0.69	−1.32
	(1.714)	(1.763)	(1.693)	(1.761)
Gap year	14.93**	14.13**	16.03***	15.44***
	(4.781)	(4.271)	(4.789)	(4.260)
Already got a job	−1.66	−1.36	−1.44	−1.21
	(1.849)	(1.862)	(1.862)	(1.874)
Wave				
Second wave	−1.77^{+}	−1.45	−1.84*	−1.58^{+}
	(0.927)	(0.936)	(0.938)	(0.942)
COVID experience				
Confirmed cases (log)	−0.58	−0.91	−0.34	−0.51
	(1.714)	(1.656)	(1.725)	(1.696)
Know someone tested positive	0.26	0.41	0.24	0.29
	(1.144)	(1.129)	(1.148)	(1.123)
Strength of social distancing	0.31	0.43	0.27	0.37
	(0.575)	(0.583)	(0.567)	(0.564)
Constant	26.25*	19.59	25.10*	7.669
	(12.59)	(12.46)	(12.58)	(13.23)
Observations	928	928	928	928
Number of egos	464	464	464	464

Notes: (1) Standard errors in parentheses. (2) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$. (3) Results are IPW-adjusted to account for potential panel attrition bias. (4) Reference groups: Restricted, Not single, Undergraduate, Wave one, Don't know someone who tested positive.

coefficients of all networks, *Restricted* is among the least healthy networks that yield the highest level of depressive symptoms.

However, these general effects are contingent on SES, and thus Model 2 further includes the interaction term between each network type and SES. The result shows that the interaction effect between SES and *Family* networks and *Friend* networks is statistically significant, which indicates that the health benefit of changing into these network types will be considerably amplified if individuals belong to a higher SES group. The heterogeneous health impact of different network types is visualized in Figure 4. It can be discovered that changing network types into *Family* and *Friend*, as a response to the pandemic, only brings mental health benefits for higher status individuals, which become more pronounced as their SES increases. For those whose SES score ranks below average (5.4), such changes in network types do not have protective effects and may even

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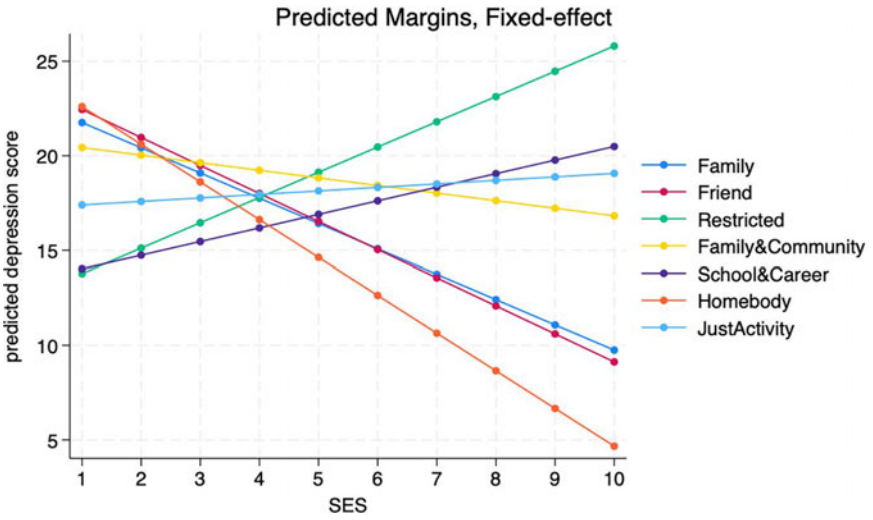


Figure 4. Predicted level of depressive symptoms by network type and SES, both waves.

incur mental health penalties. This stark contrast unveils how people with low SES fail to mobilize satisfying social support from their families and friends during the pandemic.

How do we make sense of the heterogeneous effects of network types on individuals' mental health? Prior research suggests that social support is a key mechanism linking social networks to mental health. We therefore examine whether the mental health effects of network types align with the supportive resources embedded in each type. Using Table 2, we rank network types by their combined levels of actual and perceived support. Support is highest in *Family*, *Friends*, and *Family & Community* networks, all of which show above-average levels on both dimensions. At the other end, *Restricted* networks are the least supportive, with below-average levels of both actual and perceived support. *School & Career*, *Just Activity*, and *Homebody* networks fall in between: each is relatively high on one dimension of support but low on the other. In Model 3, we replace the categorical network types with this continuous "network supportiveness" rank to more directly assess the role of embedded support. The fixed-effects estimates indicate that moving into a more support-enriching network type is generally associated with improved mental health. Adding an interaction between network supportiveness (rank) and SES in Model 4 yields a similar conclusion: the mental-health benefits of moving into a more supportive network type accrue primarily to individuals with higher SES. The negative interaction term further implies that the same shift may be detrimental for low-SES individuals. To probe the mechanisms underlying these patterns, we also conduct a conventional path analysis linking network types, social support, and mental health to confirm our findings. Mediation analysis reveals that perceived and actual support fully accounts for the mental health disparities among 5 out of 7 network types, resulting in a partial mediation effect between core network type and depressive symptoms. This validates that our modeling results are robust and consistent (see Section A4, Supplementary Material).

5. Discussion and conclusion

The present study applies random forest and clustering algorithms to identify 7 coherent social network types that comprehensively encapsulate important aspects of network properties. Our analysis reveals that individuals withdraw from two network types closely related to the context of public spaces, namely *School & Career* and *Just Activity*, as the pandemic becomes more disrupted. In other words, Hypothesis 1 has been supported. However, Hypothesis 2 only receives partial support, because though *Friend* networks become more prevalent, the probability of having *Family* and *Family & Community* networks that are high in kin or nonkin support does not

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change to a great extent. When it comes to mental health, SES moderates the effect of network type, and social support also largely accounts for such effects. Therefore, Hypotheses 3 and 4 are confirmed. Though the partial mediation effect of social support suggests that it is not the sole mediator, and implies that network types may impact health through other mechanisms such as diffusion (Shiovitz-Ezra and Litwin, 2012), which warrants further study. In addition, with regard to previous findings in East Asian contexts supporting or rejecting the superiority of a *Friend* or *Family* network (e.g., Cheng *et al*., 2009; Park *et al*., 2018), we discover that they both generate similarly desirable levels of mental health outcomes for higher-SES individuals. This may not seem surprising given that extant literature seldom considers personal and structural backgrounds that can prevent individuals from enrolling in *Friend* networks (Jain *et al*., 1999; Li *et al*., 2018).

The current paper contributes to the line of network typology-health study in several ways. First, we derive a network typology among younger adults that comprehensively represents the main network properties suggested by related theories. Based on the original method developed by G&F, we find that spectral clustering could help obtain more refined and intuitive results for identifying network types. Future researchers can draw from this typology framework as a convenient tool to characterize personal networks and follow the guidance and code we provide to implement this algorithm for their own studies. Second, the results reveal how individuals change their network types as the pandemic becomes more disruptive and shed light on the health consequences of such dynamics. Since individuals increasingly turn to *Friend* networks for support and resources as a response to the pandemic's challenges, the mental health benefit for changing into these types is reserved only for the higher SES groups, suggesting that the advantage groups are more capable of mobilizing their networks to cope with the pandemic while their lower status counterparts failed to do so and may even receive health penalty. This has profound implications that the pandemic lays bare the inequality embedded in networks along the SES line and further exacerbates social inequality in health due to the heterogeneous protective effect associated with such network dynamics. Third, our findings of social support echo the burgeoning literature that not only actual but also perceived support has implications for mental health outcomes. We thereby highlight the importance of social support as a two-dimensional construct and a mechanism underlying networks and mental health outcomes. The paper provides useful information for post-pandemic recovery for health practitioners and policymakers by highlighting how personal network deficits widen the chasm between the rich and the poor during the pandemic.

Admittedly, this study has several limitations. First, we experienced attrition between the two waves, an expected challenge given the constraints of data collection during COVID-19 outbreaks. An attrition analysis (Supplementary Material A5; Table S5) shows that attritors and completers were largely similar at baseline in depressive symptoms, SES, education, and network-type distributions, though attritors and completers have systematic differences in pandemic-related factors: completers lived in areas with higher COVID-19 prevalence, faced stricter policies, and were more likely to know someone tested positive. To address potential selection bias from these observed differences, we apply inverse probability weighting (IPW) in all main fixed-effects models and control for these baseline characteristics; the results are substantively unchanged. While response bias cannot be fully ruled out, the fixed-effects design mitigates confounding by focusing on within-person change over time. Second, it's worth noting that our attrition diagnostics are most consistent with a health-selection pattern, if any, meaning that respondents who dropped out at Wave 2 tend to have better-resourced networks and lower depressive symptoms. If such selective attrition occurred, it would suggest that our findings underestimate the true network effect. In other words, such possible bias from health-based selection would tend to make our estimates conservative, implying that the true mental-health benefits of moving into more supportive network types (and the associated inequalities across SES groups) may be at least as large as what we report, rather than reversing our conclusions. Despite these constraints, CovNetps-Wuhan remains, to our knowledge, the only egocentric network panel study available in China during the pandemic, offering rare leverage for studying crisis-induced network turnover and mental health

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inequality in this special period. Third, focusing on the college population may raise generalizability concerns. Network studies drawing on student samples usually report larger friendship networks, yet the size of global networks (i.e., the combination of all personal networks) remains the same as the general population (Wrzus *et al.*, 2013). Since our results focus on the heterogeneous health consequences across networks within different SES groups, the current findings may be even more pronounced in the general population. Finally, these conclusions are mainly applicable to young adults in the Chinese context, whose mental health has been hit most heavily during the pandemic. Nevertheless, as social convoy theory suggests, the impact of social network types varies across different age groups and cultural contexts. Therefore, we encourage future studies to replicate this research on older age groups or in other cultural contexts.

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Data availability statement. Replication code and the CovNetps-Wuhan dataset are available under data sharing agreements in Harvard Dataverse: Su, Zhixiang. 2021. "Replication Code for: Embedded Inequality: Personal Network Dynamics and Mental Health during COVID-19." https://doi.org/10.7910/DVN/8NSPFA.

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Ethical approval. Ethical approval was obtained from the Human Subjects Ethics Sub-Committee of the School of Social and Public Administration, East China University of Science and Technology.

Note

[1] The IPW applies a stabilized inverse probability weight to account for attrition effects, namely weight $= \bar{p}/\hat{p}_i$. The numerator is the unconditional probability of retention ($\bar{p}$), and the denominator is the conditional probability of retention given baseline covariates ($\hat{p}_i$), as predicted by the logistic regression.

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