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Construction of vaccination network and influencing factors: a case study of Chongqing, China

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Vaccination is a fundamental tool in preventing infectious diseases. However, due to the wide array of vaccines available, comprehending the entire vaccine landscape can be a daunting task. To tackle this complexity, this study employs advanced network analysis methods capable of capturing the intricate relationships within multivariate datasets. The objective is to investigate how the vaccination landscape has evolved both before and after the COVID-19 pandemic. This study examined vaccination data in the Nanan District of Chongqing, China, spanning from 2016 to 2022. Additionally, the network topological characteristics were computed and scrutinized across 2326 sliding windows. The investigation focused on assessing alterations in the topological structure of the vaccination network before and after the COVID-19 pandemic, encompassing analyses at both macro and mesoscale levels. Furthermore, at the micro level, this study delved into the correlation degrees of selected vaccine nodes within the vaccination network. The analysis unveiled that the correlation and activity within the vaccination network showed a noticeable enhancement in strength in the wake of the COVID-19 pandemic, especially during the spring and winter months. However, the community structure and the average interactions between vaccines displayed a diminishing trend post-pandemic. Among the analyzed vaccines, the HepA vaccine emerged as the one with the highest average node-degree centrality rank. A closer examination of the node-degree centrality ranking chart within the vaccination network disclosed fluctuations in the rankings of various vaccine types across different time periods and seasons. In contrast, vaccines incorporated into NIP exhibited a remarkable degree of consistency, which is attributed to children adhering to a fixed vaccination schedule, rendering NIP vaccines less susceptible to disruptions and enhancing their stability within the vaccination network. This study offers valuable insights into the dynamics of the vaccination network, shedding light on the impact of the COVID-19 pandemic, seasonal variations, and the ever-shifting correlation patterns among different vaccine types. These discoveries enrich our comprehension of vaccination trends and have the potential to guide forthcoming endeavors aimed at refining vaccination strategies and enhancing public health outcomes, not only in the Nanan District but also in analogous settings.

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Introduction

Throughout history, epidemics have caused great harm to human societies. Today, the risk of epidemics continues to persist, with the COVID-19 pandemic having a profound impact on the global healthcare system (Abbas, 2021; Akande and Akande, 2020; Czabanowska and Kuhlmann, 2021; Jakovljevic et al., 2020). Vaccination has long been acknowledged as an essential measure for preventing and reducing the impact of epidemic diseases. By eliciting a protective response against particular pathogens in the immune system, vaccines have saved innumerable lives and significantly alleviated the burden of infectious diseases across the globe. In 1974, a resolution by the World Health Organization (WHO) suggested implementing the "Expanded Program on Immunization" (EPI) (Kissi et al., 2022; Qazi and Usman, 2021) globally. However, the field of vaccination has grown considerably more complex with the rise of various vaccine types and innovative immunization strategies. Analyzing the entirety of the vaccine system presents a significant hurdle due to its intricate nature and interrelated components. Traditional analytical approaches frequently fall short of capturing the complex relationships and structural patterns within multivariate vaccination data. However, the process of implementing complex network analysis presents a hopeful opportunity for comprehending the fundamental dynamics of vaccination networks and their reactions to external stimuli.

Over the last two decades, the key advancement in complex system science has been the gradual improvement of the concept of complex networks and its methodology, which draws on mathematical graph theory. In a complex network, nodes refer to entities within a complex system, with edges representing statistical associations between distinct entities. The strength of these edges is measured using correlations between nodes. The construction of complex networks has garnered attention from numerous scholars both domestically and internationally and has found extensive application in diverse fields. Albert. R et al.'s research primarily integrates complex networks with statistical mechanics (Albert and Barabási, 2002; Barabási and Albert, 1999; Wang et al., 2019; Zhang et al., 2016). Besides its use in network pharmacology (Moyeenul et al., 2023; Zhang et al., 2023), complex networks find extensive application in the transmission of infectious diseases (Armbruster et al., 2022; Wang et al., 2014) within the medical field. Yang et al. constructed a dynamic network to study the spread of infectious diseases in relation to social structure, using computational sociology methods and interpersonal relationships (Yang et al., 2022). Additionally, the complex network was employed to analyze time series. Donner et al. put forth various innovative techniques to analyze time series' structural properties using complex systems (Donner et al., 2010; Plerou et al., 1999; Podobnik and Stanley, 2008; Zou et al., 2019). Moreover, the intricate network finds widespread application in finance, traffic, meteorology, and other domains (D'Arcangelis and Rotundo, 2016; Ding et al., 2019; Steinhaeuser et al., 2012).

In the field of public health, complex network models are mostly used to study infectious diseases and epidemiology. Researchers use these models to describe interpersonal contact networks and transmission pathways, revealing the mechanisms of disease transmission and the spread of risks. Although vaccination can act as an immunization measure, no research has been reported on the construction of vaccination networks. Kang et al. investigate the present vaccine viewpoint on social media. They achieve this by constructing and analyzing semantic networks of vaccine information from highly shared websites of Twitter users in the United States (Kang et al., 2017). In this study, we concentrate on observing the transformation of the vaccination network in the Nanan District of Chongqing, China, before and after the COVID-19 pandemic. The COVID-19 pandemic, triggered by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (Shi et al., 2021), has dramatically affected global healthcare systems and vaccination strategies. Examining how this unparalleled public health crisis has impacted the immunization network can generate invaluable perspectives into the adaptability and resilience of vaccination programs.

This paper examines recent changes in the vaccination system and the underlying reasons by constructing a topological network. To illustrate, a topology network was built for 23 vaccine types in the Nanan District of Chongqing between 2016 and 2022 based on the correlations of nodes. Secondly, the study examined alterations in the topological characteristics of the vaccination network pre- and post-COVID-19 pandemic at both macro and mesoscale levels. The results indicate that the correlation and activity of the vaccination network increased after the COVID-19 pandemic, particularly during spring and winter, whilst the community structure and average interaction weakened post-pandemic. Finally, this study examined the correlation levels of various nodes in the vaccination network encompassing immunization and non-immunization program vaccines across different time periods at the micro level. Fig. 1 shows the research framework for this article.

Methods

Data collection. The evaluation dataset was sourced from the Chongqing Immunization Planning Information Management System. Over 5 million vaccine doses were recorded as administered within Nanan District from January 2016 to May 2022. The data was classified based on vaccine type and year, including 23 forms of National Immunization Program (NIP) vaccinations and non-NIP vaccines (Hu et al., 2015).

Definition. NIP vaccines are defined as the free vaccines that residents should receive following government regulations. Guardians shall ensure that children of appropriate age receive scheduled immunization vaccines according to law. NIP vaccines provided by the Chongqing Municipal government include the hepatitis B vaccine (HepB), Bacillus Calmette-Guerin vaccine (BCG), diphtheria-pertussis- tetanus vaccine (DPT), diphtheria-tetanus vaccine(DT), oral poliovirus vaccine (OPV)/ inactivated poliomyelitis vaccine (IPV), measles-containing vaccine (MCV)/ measles-mumps-rubella vaccine (MMR), Japanese encephalitis vaccine (JEV), meningococcal polysaccharide vaccine type a(MPV-A), meningococcal polysaccharide vaccine type a and c(MPV-AC), hepatitis A vaccine (HepA).

Non-immunization program vaccines refer to other vaccines that are voluntarily administered by residents, including Haemophilus influenzae type b (Hib) and inactivated polio combined vaccine (Penta), Haemophilus influenzae type b combined vaccine (Quad), influenza vaccine (Flu), pneumonia vaccine (PCV), human papillomavirus vaccine (HPV), Varicella vaccine (VZV), Rotavirus vaccine(RVV), Rabies vaccine (Rab), Enterovirus Type 71 Vaccine (EV71), Mumps vaccine (Mum), COVID-19 vaccine (COVID-19) (Hartonen et al., 2023), etc.

Vaccines time series diagram. According to vaccination data from Nanan District in Chongqing, we utilized R software (version 4.2.2) to create time series graphs for various vaccines which would be shown in the Results. These graphs allowed us to observe trends and seasonal changes in vaccination rates.

Research methods for constructing vaccination network. A network consists of nodes connected by edges, where nodes
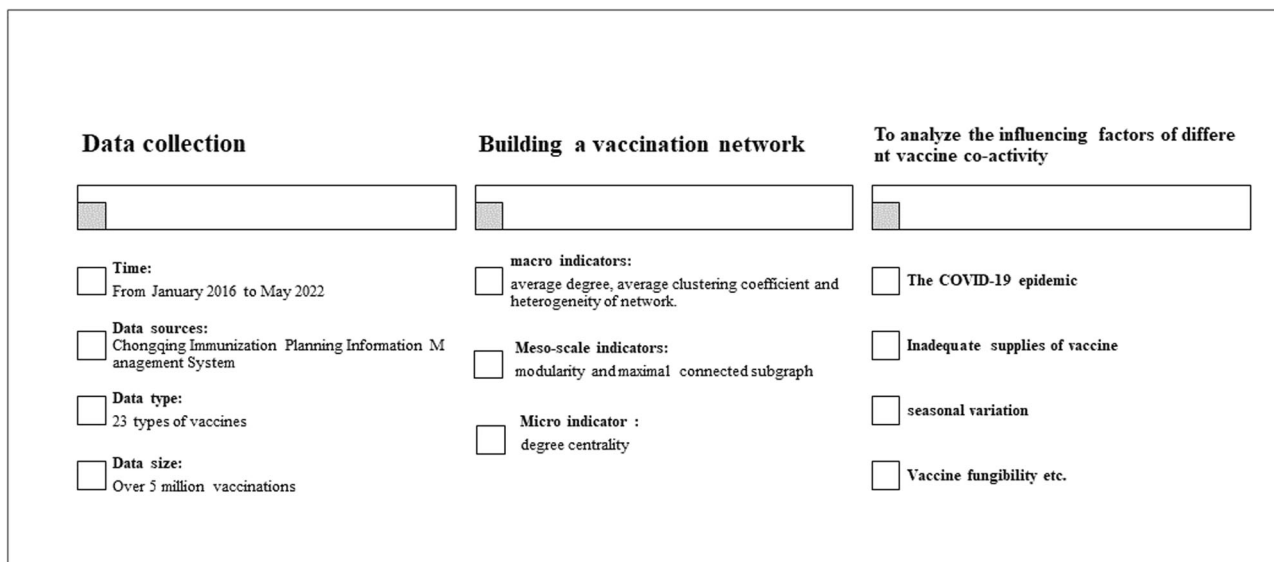
Fig. 1 The research frame of the article. This figure shows the research process and framework of this study.

usually represent either individuals or organizations in reality and edges represent the connections between them, and researchers commonly utilize an adjacency matrix to depict the connection relationship between vertices.

To construct a vaccination network, consider each vaccine as a node and a time window of every 30 days. The Pearson correlation coefficient quantifies the strength of the correlation between two vaccines. A larger coefficient indicates that an increase in the dose of one vaccine corresponds to an increase in the dose of the other vaccine, reflecting a correlation between diseases. Additionally, from a medical resource perspective, it reflects the competition or synergism effects for medical resources. The Pearson correlation coefficient (Deng et al., 2021; Donges et al., 2009) was used to calculate the correlation between the 23 vaccines. If the coefficient value exceeded the appropriate threshold, a strong correlation between two nodes was detected, thereby generating a link. This link allowed for the construction of an adjacency matrix, which in turn formed the basis of the vaccination network. Changes in the vaccination network were then tracked by continuously sliding the time window.

Data preprocessing. The vaccine's Pearson correlation coefficient is not computed if the average daily dose per vaccine falls below 10 doses within one window. Additionally, if the number of days in which the vaccine dose remains at 0 exceeds 15 days, it is not included in the calculation.

The data for vaccines is the daily number of vaccinations, which has been standardized. Besides, the data used in the article has no missing values.

Calculate the correlation coefficients of nodes. The Pearson correlation coefficient is utilized in statistics to evaluate the correlation between two variables X and Y. A more significant absolute value indicates a stronger relationship between these two variables.

In each time window of 30 days, calculate the Pearson correlation coefficient between the two vaccine nodes.

Constructing vaccination network. When the Pearson correlation coefficient falls to 0.8, it is an indication of the strong

correlation between sequences. In order to ensure the connectivity of the network, the system should have as many maximally connected subgraphs as possible. Therefore, after comparing with other thresholds, it was observed that a correlation coefficient threshold of 0.8 provided a more distinct topology of the network. Due to the conclusion not qualitatively changing, this paper elects a threshold of 0.8 for network edge construction. When the Pearson correlation coefficient exceeds 0.8, the corresponding series value is set to 1. If the correlation coefficient is less than 0.8, then the series value is set as 0. Using the updated matrix as the adjacency matrix of the network, the vaccination network is constructed accordingly. Next, progress through each day sequentially to create new time windows. Based on data from 2016 to 2022, a total of 2326 time windows were generated. To examine the traits and features of the network, the topological measures of the immunization network are evaluated using standard statistical indicators.

Then, create a visualization of the vaccination network using Gephi software (Heymann and Grand, 2013) as can be seen in Fig. 2.

Theory
The topological indicators of the network. In this study, the topological indicators of the network (Burcu and Vincent, 2013) are calculated and analyzed at macro, mesoscale, and micro levels. The macro indicators consist of average degree, average clustering coefficient, and network heterogeneity, while the mesoscale indicators comprise modularity and maximal connected subgraphs. The degree of centrality serves as the micro indicator. By examining macro indicators, we can analyze how various vaccine nodes are grouped in vaccination networks and the characteristic scale, enabling us to understand the overall topology of the network. Meanwhile, mesoscale indicators allow us to assess the strength of community division structures in vaccination networks. Additionally, micro indicators can determine the significance of each vaccine node in the network and the correlation that exists between them.

In every network, calculate and analyze these indicators.

Average degree (Tang et al., 2006) is a common attribute of the network. The degree of a node in an undirected network is the
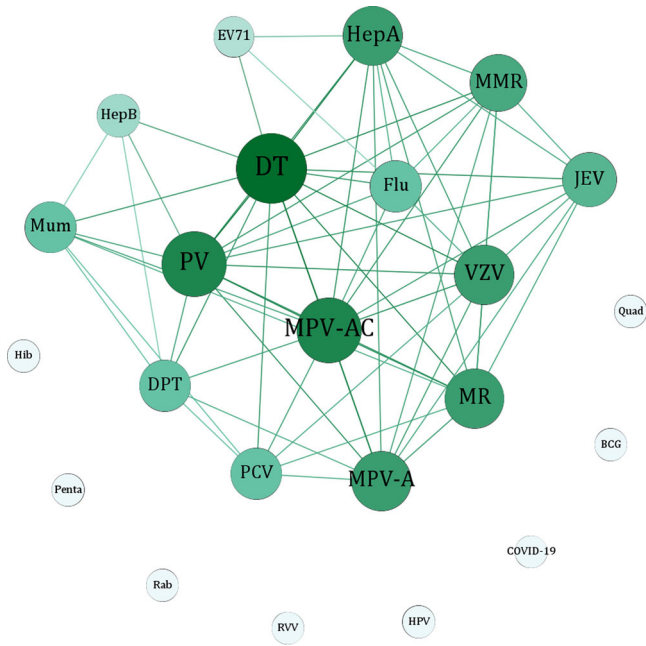
Fig. 2 Visualization of the vaccination network. This is a visualization of one of the sliding vaccination networks created using Gephi software.

number of edges connected to it. Average degree $\langle k \rangle$ is simply the average degree of per node in the network, and we have

$$\langle k \rangle = \frac{1}{n} \sum_{i=1}^{n} k_i. \qquad (1)$$

where k_i is the degree of node i. It is a rough measure of the stability of the network. In the context of vaccinations, an increase in the average degree of a vaccination network indicates a stronger degree of aggregation and increased network activity, resulting in greater stability.

The clustering coefficient (Saramäki et al., 2007) is an important indicator in social networks, which is a coefficient used to describe the degree to which vertices in the network are clustered together. The clustering coefficient of the network is based on a local clustering coefficient for each node

$$C_i = \frac{M_i}{k_i (k_i - 1)}, \qquad (2)$$

where M_i indicates the number of edges between adjacent nodes of node i, and $k_i (k_i - 1)$ indicates the number of possible edges between adjacent nodes of node i. The average clustering coefficient for the whole graph is the average of the local values C_i, and we have

$$C = \frac{1}{n} \sum_{i=1}^{n} C_i, \qquad (3)$$

where n is the number of nodes in the network. In the vaccination network, the larger the average clustering coefficient of the network is, the stronger the degree of linkage of vaccine nodes is, and the denser the structure of the vaccination network is.

Network heterogeneity (Xiang et al., 2022) means that the connection status (degree) of each node has a serious uneven distribution. The degree of most nodes is small, while the degree of a few nodes is large. In this paper, it is defined as

$$T = \frac{\langle k^2 \rangle}{\langle k \rangle^2}, \qquad (4)$$

where $\langle k^2 \rangle$ is the average of the squared degrees of the network, $\langle k \rangle$ is the average degree of the network. In the vaccination

network, the greater the network heterogeneity, the more uneven the degree distribution of vaccine nodes is, and the more significant the difference of vaccine nodes is.

Modularity (Newman, 2006) is a measure of the quality of the division of network modules (also known as node sets or communities). If the modularity degree is high, the connections within the node-set are tight. Modularity is defined as

$$Q = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \gamma \frac{k_i k_j}{2m} \right) \delta \left(c_i, c_j \right), \qquad (5)$$

where m is the number of edges, A is the adjacency matrix of network, k_i is the degree of node i, γ is the resolution parameter(simply use $\gamma = 1$), and $\delta(c_i, c_j)$ is 1 if i and j are in the same community, else 0. In the vaccination network, the larger the modularity is, the stronger the community structure of the vaccination network is, the more consistent the detected community with the characteristics of tight inside and loose outside is, and the better the grouping quality is.

The maximal connected subgraph (Guo et al., 2016) represents the connectivity of a network graph. It means any two vertices in it can be connected by edges and cannot be extended by adding more nodes or edges. In this paper, the index of measuring the maximal connected subgraph is defined as

$$S = \frac{n_s}{n}, \qquad (6)$$

where n_s is the number of nodes in the maximally connected subgraph, and n is the total number of nodes in the network. In the vaccination network, as S increases, the connectivity component also increases, resulting in stronger network connectivity.

Degree centrality (Wen et al., 2023) is a metric used to assess the significance and impact of nodes within a network. Technical abbreviations will be explained when first used. The average degree can be distorted by nodes with the highest degree, making degree centrality (Zhang and Luo, 2017) a better measure when evaluating a node's centrality based on its degree. Degree centrality defines the fraction of nodes a given node i is connected to. To ascertain the significance of each vaccine node, it is crucial to understand that in the vaccination network, the correlation between vaccines is stronger with a higher degree of centrality of vaccine nodes. Therefore, vaccines with a stronger degree of centrality are more critical. Every three months, nodes are ranked based on their calculated degree of centrality in order to assess their importance (Cadini et al., 2009).

Results

Basic information on vaccination. Nanan District covers an area of 262.43 square kilometers, with jurisdiction over 8 subdistricts and 7 towns. It has a permanent resident population of 1,197,600, with an urbanization rate of 97.8%. The immunization coverage rate among school-age children has remained at a high level, reaching 98.23 percent in 2022. A total of 5,271,374 vaccination data were collected from January 2016 to May 2022. There were 23 kinds of vaccines, among which 3,071,963 doses of COVID-19 vaccine were given, accounting for 58.28 percent of the total. The vaccination data for each year are shown in Table 1.

Macroscopic topological property of vaccination network. The network topological indicators of 2326 sliding windows are drawn and analyzed using the Networkx library of Python software.

As can be seen from Fig. 3A, C, the average degree of vaccination network and the average clustering coefficient of the network are generally higher in spring and winter. As can be seen from the boxplot of Fig. 3B, D, both the mean and quantile of $\langle k \rangle$

Table 1 The vaccination data of each year.

Year of inoculation	COVID-19 vaccine doses	Other vaccines doses	Accumulated vaccination amount
From January to December 2016	0	210,262	210,262
From January to December 2017	0	299,898	299,898
From January to December 2018	0	331,015	331,015
From January to December 2019	0	382,261	382,261
From January to December 2020	2294	312,273	314,567
From January to December 2021	2,594,056	477,882	3,071,938
From January to May 2022	475,613	185,820	661,433
Accumulated vaccination amount	3,071,963	2,199,411	5,271,374
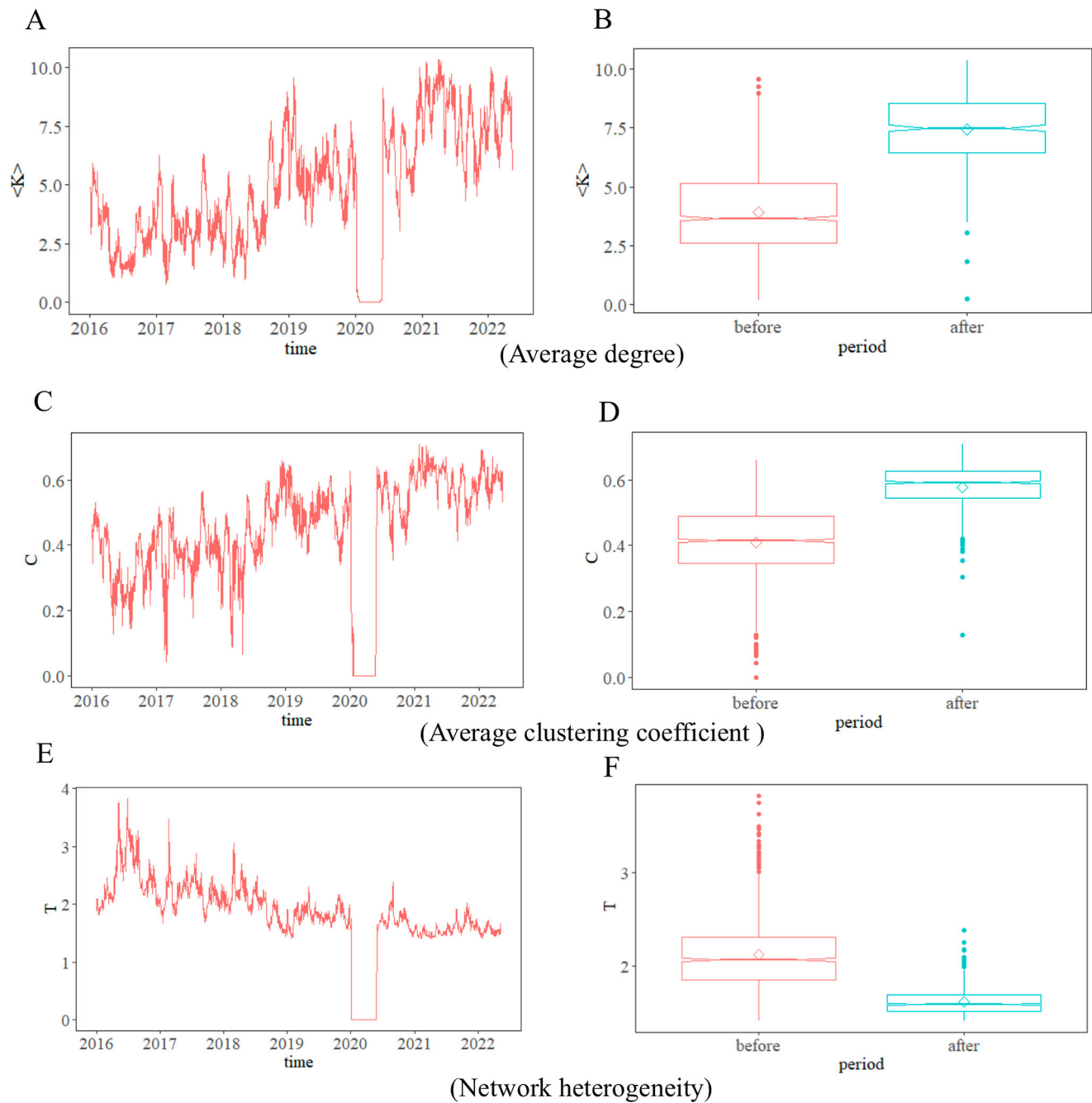
Fig. 3 Macroscopic topological property changes of vaccination network. A The line chart shows the variation in the average degree in the vaccination network. **B** The boxplot shows the comparison of the average degree in the vaccination network before and after the COVID-19 outbreak. **C** The line chart shows the variation of the average clustering coefficient in the vaccination network. **D** The boxplot shows the comparison of the average clustering coefficient in the vaccination network before and after the COVID-19 outbreak. **E** The line chart shows the variation of network heterogeneity in the vaccination network. **F** The boxplot shows the comparison of network heterogeneity in the vaccination network before and after the COVID-19 outbreak.
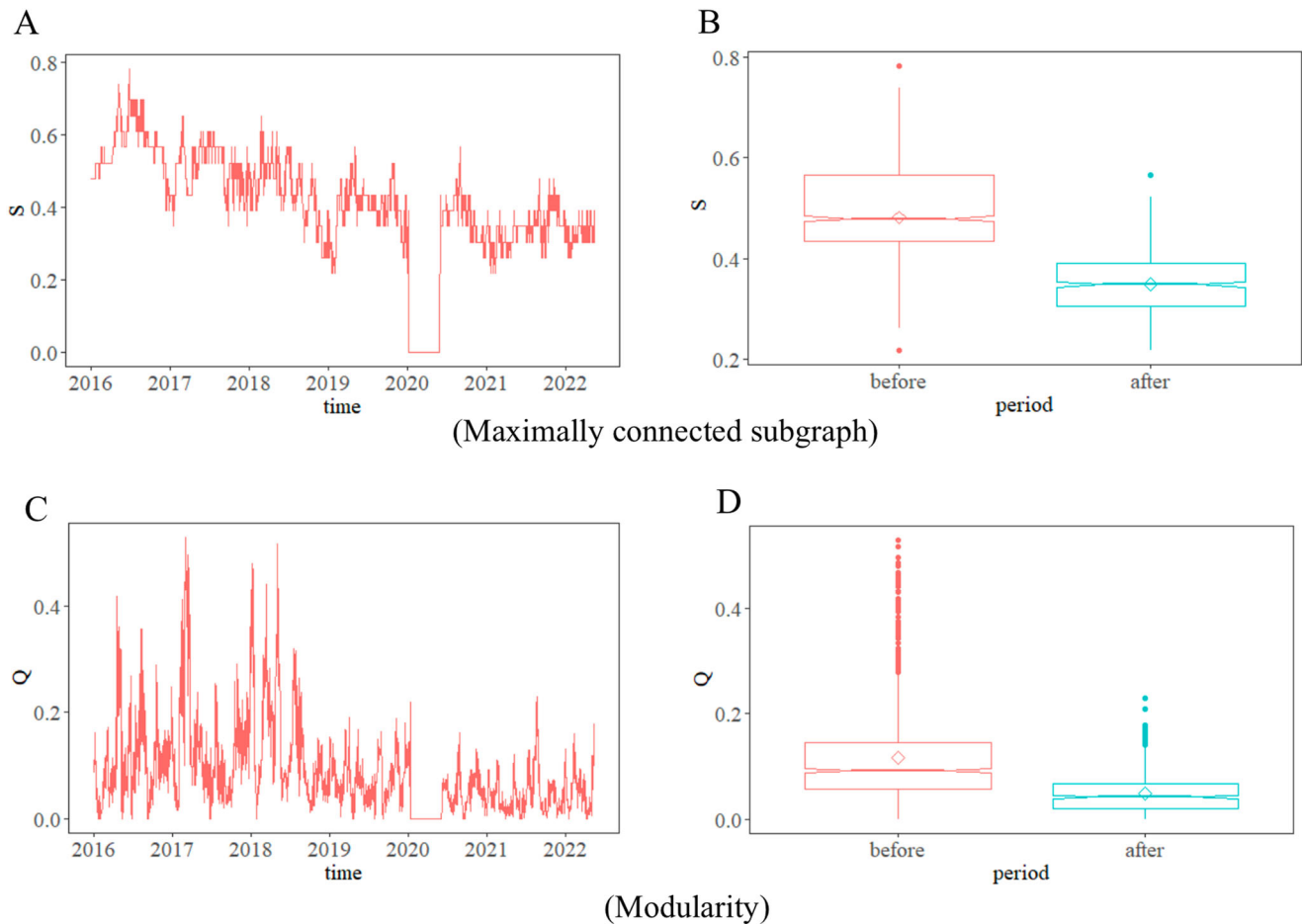
Fig. 4 Mesoscale topological property changes of vaccination network. A The line chart shows the changes in the maximally connected subgraph in the vaccination network. **B** The boxplot shows the comparison of the maximally connected subgraph in the vaccination network before and after the COVID-19 outbreak. **C** The line chart shows the changes in the modularity of the vaccination network. **D** The boxplot shows the comparison of the modularity in the vaccination network before and after the COVID-19 outbreak.

and C increase significantly after the epidemic, indicating that the average degree and average clustering coefficient of the vaccination network increased after the epidemic.

The average degree and clustering coefficient values are elevated during spring and winter, suggesting that the vaccination network is closely linked and increasingly active. Post-epidemic, the values of average degree and clustering coefficient demonstrate an increase in trend. On one hand, the expansion of vaccine varieties leads to an increase in nodes, which in turn reinforce the connections within the network. On the other hand, the interrelation of the entire vaccination network is becoming increasingly intimate. This suggests an increase in vaccination activities resulting from seasonal illnesses. The COVID-19 pandemic has raised public awareness of vaccination, and health infrastructure has likely improved in certain regions, leading to greater accessibility to vaccination networks.

As can be seen from the Fig. 3E, F, the network heterogeneity decreases after the epidemic, indicating that the degree distribution of vaccine nodes is uneven before the epidemic, and there are some vaccine nodes with high degrees. However, following the epidemic, there has been a reduction in network heterogeneity, which indicates that vaccine nodes' degree is becoming average and small. This proposes that the average interactivity of the vaccination network has diminished after the outbreak. In light of the COVID-19 outbreak, governments and healthcare professionals have implemented far-reaching measures to endorse

vaccination and guarantee a fairer distribution of vaccination opportunities. This approach renders the network less heterogeneous, as a more extensive population receives immunization. Reduced network heterogeneity is commonly viewed as advantageous as it suggests greater accessibility of vaccination to the public and increased societal acceptance of vaccination, resulting in higher vaccination coverage and a reduction in the spread of outbreaks.

Mesoscale topological property of vaccination network. As can be seen from the boxplot of Fig. 4B, D, the mean and quantile of the values of maximally connected subgraph S and modularity Q decrease after the epidemic, indicating that the strength of the community structure of the vaccination network is weakened after the epidemic, and the internal co-activity between vaccines is weakened due to the epidemic. This implies that greater accessibility to vaccination and the availability of diverse vaccines have led to higher immunization rates and decreased prevalence of particular vaccine types within populations. Authorities and governments may have implemented policies and programs to promote the use of various vaccines. This could entail the implementation of diverse vaccine types in various regions or at different periods, to guarantee sufficient vaccine stocks. Such policies might have impacted the interrelationship among vaccines in the community.
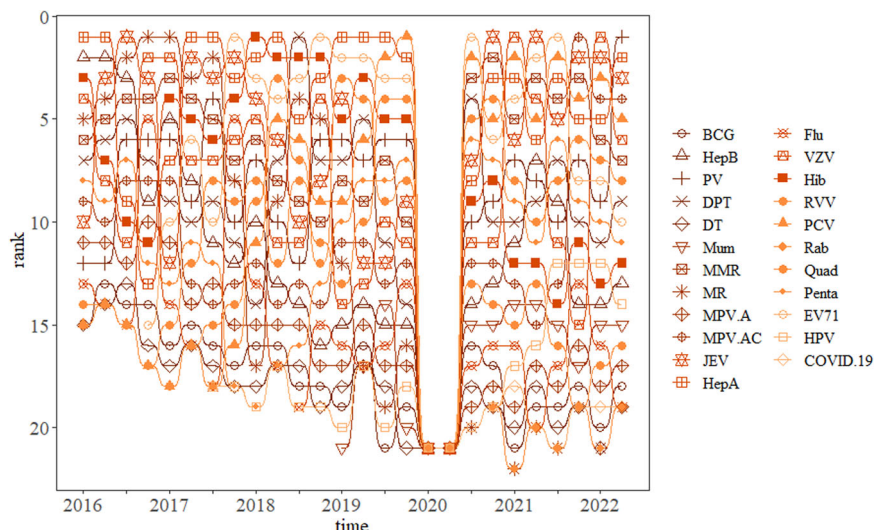
Fig. 5 Ranking changes in node-degree centrality of vaccines. This figure shows the changes in the node-degree centrality ranking of 23 vaccine nodes in the vaccination network from 2016 to 2022.

Micro topological property of vaccination network. As shown in Fig. 5, the node with the highest average ranking of node-degree centrality is the hepatitis A vaccine (HepA). The top five nodes are HepA, EV71 vaccine, JEV vaccine, MMR vaccine, and Hib vaccine. Among them, the node centrality ranking of HepA vaccine is basically high, indicating that the hepatitis A vaccine has the strongest correlation with other vaccines. This implies that governments or health authorities could have implemented a well-coordinated vaccination approach, encouraging or scheduling the administration of various vaccines simultaneously at specific times or events. Such a synergistic strategy has the potential to improve vaccination efficacy whilst guaranteeing that individuals receive immune protection from multiple vaccines. Thus, the pronounced correlation between the hepatitis A vaccine and other vaccines may be indicative of an alignment in health policies.

Upon dissection and examination of the node-degree centrality ranking chart for the vaccination network, it has been discovered that there are fluctuations in the ranking of various types of vaccines during different periods and seasons. This implies that the correlation between different vaccines alters at distinct time points. Consequently, we proceed to examine the correlation of diverse vaccine types.

a. Immunization program vaccines
Fig. 6 shows the time series of doses of immunization program vaccines from 2016 to 2022. Based on the curve shown in Fig. 7, no discernible pattern has been identified. Immunization program vaccines are typically administered on a fixed schedule for each child, making them less vulnerable to outbreaks.

b. Flu
As shown in Fig. 8A, the ranking of node centrality of influenza vaccine is higher in spring and winter, indicating a higher correlation between spring and winter. The ranking of node centrality of influenza vaccine basically reaches a peak in winter, indicating the highest correlation in winter.

Influenza typically peaks during the winter, making flu vaccination essential during spring and winter. Additionally, seasonal diseases that are more prone to spreading during specific periods may also necessitate vaccination.

Consequently, the correlation between vaccine uptake and seasonality could indicate the development of seasonal vaccination strategies by public health authorities to guarantee optimal protection during influenza outbreaks. During flu season, health departments may recommend additional vaccinations to enhance immune protection in individuals who receive the flu vaccine. This approach, known as the cascade effect, encourages people to consider getting other vaccines to boost their immune system's response, reducing the likelihood of contracting multiple infectious diseases simultaneously. During flu season, the demand for flu vaccines rises sharply, requiring adjustment of the vaccine supply chain to guarantee adequate vaccine distribution. This may lead to supply chain modifications for other seasonal vaccines as well to meet demand. Thus, a strong correlation implies the necessity of supply chain management.

c. VZV
As shown in Fig. 8B, the node-degree centrality ranking of the Varicella vaccine is higher in spring and winter, indicating that the Varicella vaccine has a strong correlation in spring and winter. The Varicella virus is a seasonal outbreak, with a higher incidence rate during the spring and winter seasons. It can be compared to the flu vaccine, where there is a strong association with the spring and winter seasons.

d. PCV
As shown in Fig. 8C, the degree centrality ranking of the pneumonia vaccine shows an upward trend, and the degree ranking increases significantly from the end of 2019, indicating that the pneumonia vaccine is increasingly related. After the outbreak of COVID-19 in 2020, degree centrality has ranked at the highest level of stability, indicating an extremely strong correlation with the pneumonia vaccine. It is essential for preventing respiratory illnesses, and therefore its relevance has increased significantly since the outbreak. The global outbreak of COVID-19 has caused widespread public health concerns. Pneumonia vaccines are regularly administered to prevent various pneumonia-related illnesses, which can exacerbate public health challenges during such outbreaks. Therefore, healthcare professionals should take action to enhance the
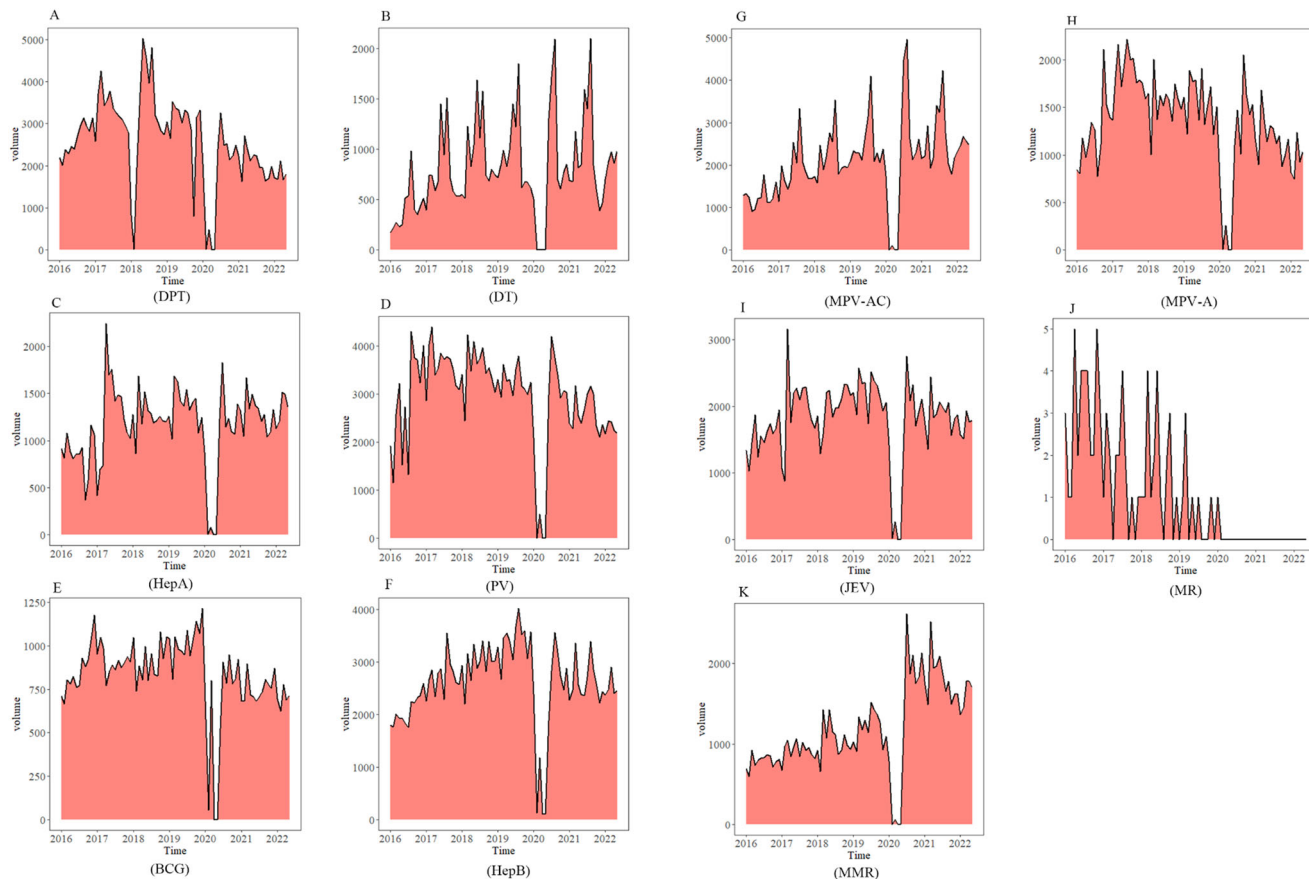
Fig. 6 Time series diagram of vaccination doses for immunization programs. A–K The time series of doses of 11 immunization program vaccines from 2016 to 2022.
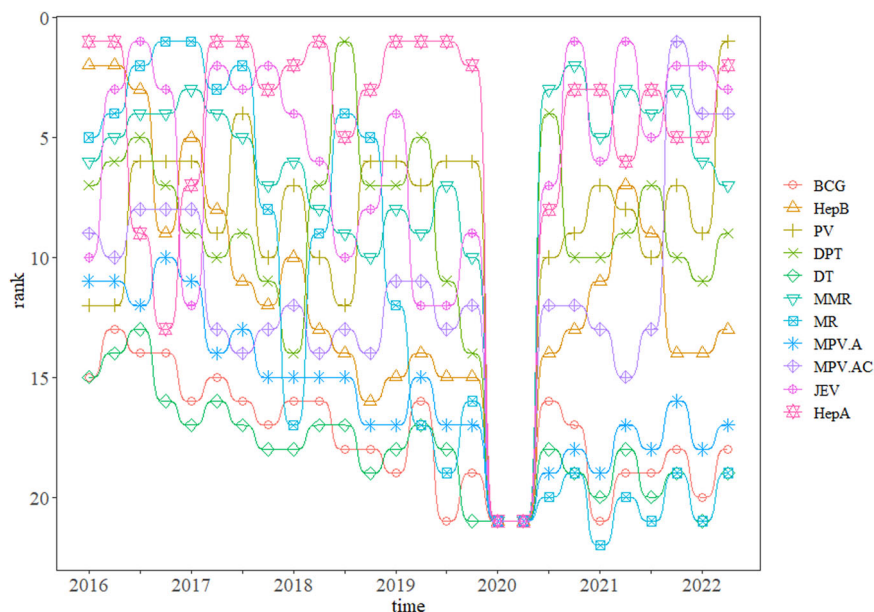

Fig. 7 Ranking changes of node-degree centrality of immunization program vaccines. This figure shows the change in the degree centrality ranking of 11 immunization programme vaccine nodes in the vaccination network from 2016 to 2022.

promotion and vaccination of pneumonia vaccines. Encouraging the administration of such vaccines alongside others would improve individuals' immune protection.

e. HPV

As illustrated in Fig. 8D, the degree centrality ranking of HPV was comparatively low prior to 2020, but saw a significant increase thereafter, suggesting significant enhancement in HPV correlation after 2020. The nine-valent HPV vaccine began to gain popularity in outpatient clinics around 2020. Fewer people had received the HPV vaccine in China before 2020, leading to a noteworthy increase in HPV vaccine correlation after 2020.
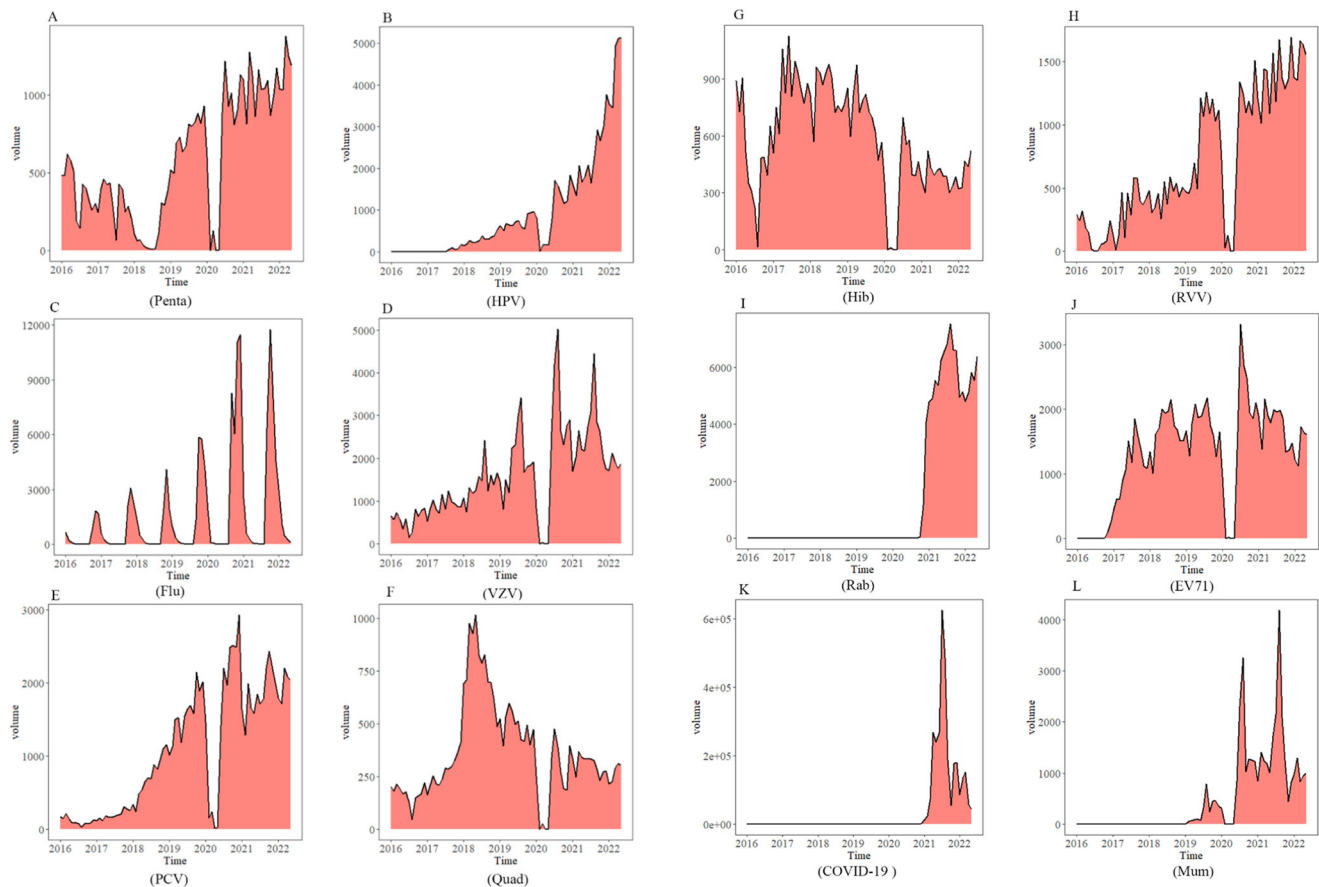
Fig. 8 Time series diagram of vaccination doses for non-immunization programs. A–L The time series of doses of 12 non-immunization program vaccines from 2016 to 2022.

f. Quad and Penta Vaccine
As depicted in Fig. 8E, the node-degree centrality ranking of Quad vaccine and Penta vaccine is staggered, indicating an alternative correlation. Moreover, the ranking of the Penta vaccine is lower when the ranking of the Quad vaccine is higher. The quad and penta vaccines are frequently administered to prevent several related infections, differing slightly in their composition and purpose. The public may opt for either vaccine based on medical counsel, personal health circumstances, and vaccine availability. The public may opt for either vaccine based on medical counsel, personal health circumstances, and vaccine availability. Therefore, individual requirements and medical recommendations determine vaccine preferences. The accessibility and availability of vaccines can impact individuals' decisions to get vaccinated. The quad vaccine may be more prevalent or accessible in certain regions or time periods compared to others, influencing individuals' choices. Such disparities in vaccine availability can lead to individuals having to choose between the available vaccines.

g. COVID-19 Vaccine

As demonstrated in Fig. 8F, the COVID-19 vaccine has a consistently low degree centrality ranking, suggesting a weak correlation with other vaccines. This highlights its independent nature within the vaccination system, rendering it less susceptible to external factors. During an outbreak and spread, health authorities and governments are likely to prioritize the administration of COVID-19 vaccinations to contain the spread of the

epidemic as soon as possible. This may result in the timing and location of the COVID-19 vaccine becoming distinct from that of other vaccines, thereby reducing their correlation (Figs. 8 and 9).

Discussion
The paper investigates changes in the vaccination network before and after the COVID-19 outbreak by constructing a network and studying it from macro, micro, and mesoscale perspectives. Analysis of vaccination data from the Nanan District of Chongqing yields valuable insights into the dynamics and characteristics of the vaccination network. These findings hold significant implications for comprehending the effects of the COVID-19 crisis, seasonal fluctuations, and the correlation patterns between various vaccine types.

One of the main discoveries in our investigation is the enhancement in correlation and activity within the vaccination network subsequent to the COVID-19 pandemic. This finding is consistent with the public's heightened awareness and emphasis on vaccination in response to the pandemic. Within this context, the COVID-19 vaccine played a significant role in stimulating the observed increase in correlation and activity. The prioritization and widespread administration of COVID-19 vaccines is likely to have resulted in more individuals engaging with the healthcare system and a general increase in vaccination rates. Notably, our analysis has also uncovered a declining trend in the community structure and average interaction within the vaccination network in the post-pandemic era. There may be several factors that contribute to this finding. It is possible that the emphasis on COVID-19 vaccinations caused a temporary shift of resources
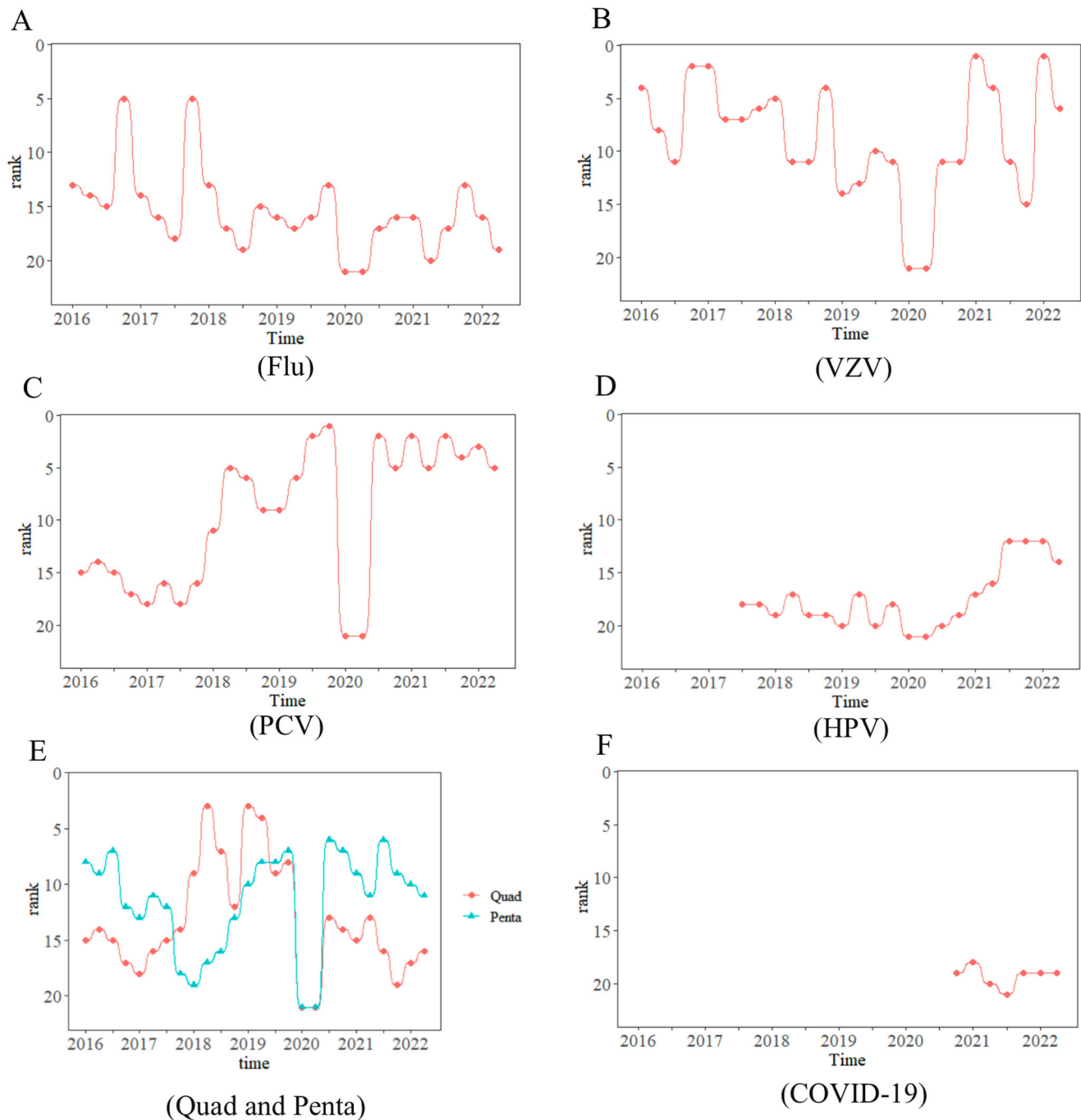
Fig. 9 Changes in node-degree centrality ranking of part of non-immunized programming vaccines. A The chart shows the ranking change of node-degree centrality of flu vaccine. **B** The chart shows the ranking change of node-degree centrality of VZV. **C** The chart shows the ranking change of node-degree centrality of PCV. **D** The chart shows the ranking change of node-degree centrality of HPV. **E** The chart shows the ranking changes of node-degree centrality of Quad and Penta vaccines. **F** The chart shows the ranking change of node-degree centrality of COVID-19 vaccine.

and attention from other routine vaccinations, leading to decreased interaction and community cohesion within the vaccination network. Furthermore, alterations in public health priorities and vaccination strategies during and after the pandemic may have impacted the network's overall dynamics.

The hepatitis A vaccine (HepA) has been identified as the node with the highest average ranking of node-degree centrality, indicating its crucial role within the vaccination network. This finding highlights HepA's significance in the local immunization program. Furthermore, the fluctuating rankings of various vaccine types in terms of node-degree centrality imply differing levels

of correlation and interconnectedness among the vaccines at different time points. An understanding of these dynamic interconnections can enable vaccination strategies to be better informed, along with resource allocation and targeted interventions for specific vaccine types. The stability and consistency noted in the vaccines included in the NIP emphasize the significance of adhering to fixed vaccination schedules. The NIP vaccines comply with a standardized immunization cycle for each child, offering a dependable framework for vaccination planning. This stability reduces the likelihood of outbreaks and ensures comprehensive coverage across the vaccination network.

The innovation point of this study is to build a topological network to study vaccination issues in public health. Studying the nature of the topological network reflects the changes in the vaccination system before and after the epidemic, in various seasons, and under the influence of policies, and explains the changes in the network in combination with the practical factors of public health. By constructing Vaccination networks, disparities in vaccine uptake among populations can be identified and analyzed. This enables targeted vaccine promotion and outreach efforts, ultimately leading to improved vaccine coverage, increased population immunity, and effective control and prevention of infectious disease outbreaks and transmission. Vaccination networks assist researchers in evaluating the effectiveness of different vaccine administration strategies and optimizing vaccination plans. Analyzing the network topology facilitates the identification of optimal vaccine administration strategies, thereby enhancing vaccination efficiency and the protection of target populations. Constructing Vaccination networks helps researchers forecast the development trends and transmission pathways of epidemics, enabling risk assessment. Utilizing network models, different vaccine administration scenarios can be simulated to assess their impact on epidemic transmission, providing scientific evidence for formulating prevention and control strategies.

This investigation employs mathematical methods to analyze public health concerns, aiding in the more precise prognostication of disease prevalence and optimal allocation of resources, including vaccines, for healthcare entities, and in maximizing benefits under restricted resources, allowing healthcare providers to offer more medical services. The outcomes of this inquiry may assist health officials in formulating more effective policies and strategies to safeguard public health.

Limitations. This study is limited in several ways. Firstly, it has not explored and explained some vaccines at the micro level whose topological characteristics have stayed unchanged.

Secondly, the vaccination data in the Nanan District of Chongqing has been modeled and analyzed, which is inadequate to portray the vaccination network in all regions. Extending research into vaccination across a broader geographic area could yield significant benefits. Firstly, varying regions may exhibit disparate epidemiological characteristics, including infectious disease transmission rates, infection prevalence, and the prevalence of variants. These disparities will impact vaccination needs and strategies. Secondly, disparities may exist in the distribution of healthcare infrastructure and resources across geographical regions. Certain regions may possess superior medical facilities and vaccine administration sites, thus facilitating the delivery of vaccination services. Oppositely, other regions may encounter challenges related to supply chain limitations and insufficient resources. Moreover, socio-cultural factors and attitudes in various geographical locations may affect the reception of vaccines. As a result, some regions may exhibit a higher rate of vaccination uptake, while others may experience vaccine hesitancy or refusal. Therefore, vaccination research necessitates the consideration of these factors, warranting the adoption of diverse communication and education strategies.

Thirdly, the findings are specific to the Chinese context and may not directly apply to other countries or regions. We tried to expand the study to other regions, but no publicly available data was available. Therefore, caution should be exercised when generalizing these results. In the future, more in-depth analysis and research can be conducted through more in-depth data analysis.

Conclusion
In conclusion, our study offers significant insights into the dynamics of the vaccination network in the Nanan District of Chongqing. The enhanced correlation and activity following the pandemic, alongside the weakened community structure and average interaction, underscore the intricate interplay of factors influencing vaccination patterns. The findings underscore the need to adapt vaccination strategies to address evolving dynamics and promote consistent coverage. Future studies can expand on these discoveries to guide focused intervention strategies, improve immunization programs, and advance public health outcomes within the vicinity. Public health officials and policymakers can enhance their vaccination strategies in specific regions by utilizing the regularity of vaccinations. Initially, it is important to establish a fitting vaccination schedule that is aligned with the habits and requirements of the target vaccination population. For instance, factoring in seasonal and holiday elements should aid in determining the optimal timing for vaccination. Secondly, it is crucial to ensure an adequate supply of vaccines in line with vaccination schedules. Finally, it is necessary to promote and encourage vaccination, as well as raise public awareness of its importance.

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Author contributions

JL, JF, and WW designed the study. JF, LZ, XW, and CL collected the data. JL, JF, and WW performed most of the data analysis. JL, JF, and WW coordinated and supervised the study. JL, JF, and WW drafted the manuscript. All authors reviewed the manuscript and approved it for submission.

Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval was not required as the study did not involve human participants.

Informed consent

Informed consent was not required as the study did not involve human participants.

Additional information

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