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A Review Study on the Use of Dynamic Complex Networks in Combating the COVID-19 Pandemic

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ABSTRACT

The COVID-19 pandemic has profoundly affected multiple facets of society, including social interactions, financial activities, international relations, economic stability, and education. The unprecedented scale of the pandemic and the rapid transmission of the virus have necessitated multidisciplinary collaborations, bringing together researchers from diverse fields such as medicine, epidemiology, and computer science to develop predictive models and preventive strategies. Within this interdisciplinary landscape, the study of dynamic complex networks and artificial intelligence (AI) has emerged as a critical tool complementing traditional medical approaches. In the realm of computer science, network theory offers a powerful framework for modeling and simulating the spread of infectious diseases, providing valuable insights into transmission dynamics and intervention strategies. Additionally, AI-driven technological tools have been instrumental in facilitating COVID-19 control measures, including contact tracing, real-time monitoring of infected individuals, and predictive analytics for outbreak management. Many countries have leveraged network science methodologies to track viral spread and assess the broader societal impacts of the pandemic. This study systematically reviews and categorizes key research contributions in the field of dynamic complex networks applied to COVID-19. By analyzing these works, the study highlights major trends, methodological advancements, and challenges in the application of network science and AI. The findings provide a foundation for future research directions, emphasizing the potential of computational methods in enhancing pandemic preparedness and response strategies.

1. INTRODUCTION

The SARS-CoV-2 virus was first identified in late 2019 in a local market in Wuhan, China. The Chinese government quickly implemented a complete quarantine of the city, creating the impression that the disease was under control. However, the virus gradually spread to all countries worldwide. The official announcement of the virus's arrival in Iran was made on March 1, 2020 [1]. As a result of the pandemic, the medical community and healthcare professionals mobilized to combat the virus. However, many aspects of the virus, including its impact on the economy, social behavior, and psychological issues, can also be studied from other scientific perspectives. In

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this context, computer science has become increasingly important due to its ability to provide modeling and simulation tools. Computer science can be used to study the impact of virus spread on society, the effects of policies, the current status of at-risk and infected individuals, compliance with COVID-19 regulations, and related issues. One of the most useful applications of computer science is the use of dynamic complex network concepts and their implementation through computational tools. These tools can be employed for data collection, modeling, simulations, or tracking individuals in the community. This research begins with several important questions: Are quarantine measures for controlling pandemics a relic of the Middle Ages? How can super-spreaders be identified? How should mass vaccination be conducted and in what order? What behaviors within networks lead to epidemic waves? How can new epidemic waves be prevented? How many people are typically affected by a new wave of infection? The study of complex networks in the context of COVID-19 provides valuable insights into societal conditions, the effectiveness of control measures, and the status of the community during the pandemic, helping to address these questions. In this paper, we first explore the significance of dynamic complex networks in controlling the COVID-19 pandemic, then review papers that identify transmission factors and contact tracing techniques, and finally examine papers modeling disease spread in the community.

2. RESEARCH METHODOLOGY

Engineers and computer science students play a crucial role in analyzing the COVID-19 virus. Their primary mission is to study the behavior of the virus in networks, the behavior of individuals within networks, the impact of the pandemic on social and economic networks, the effectiveness of policies adopted to combat the virus, and the associated costs. Engineers use various tools for simulation and modeling. The research on the use of dynamic complex networks for analyzing COVID-19 can be categorized into three main groups: articles focusing on the importance of dynamic complex networks, articles utilizing dynamic networks for modeling transmission factors, and articles using dynamic networks for modeling policies and disease spread.

3. THE IMPORTANCE OF USING DYNAMIC COMPLEX NETWORKS

The primary significance of dynamic complex networks lies in their application to modeling and simulations. For example, Edwin Montz et al. proposed an approach to identify COVID-19 spreaders by analyzing the relationship between cultural, social, and economic characteristics with transmission rates and mortality across different countries. They used a five-layer multiplex network model to analyze and categorize countries based on criteria such as social economy, population, GDP, health, and air connectivity [2]. In another study, Manzo emphasized that dynamic complex networks can answer crucial questions about epidemic spread and concluded that these networks have not been adequately utilized for disease prevention and control. Networks are effective for modeling complex issues from multiple perspectives. In the case of COVID-19, where understanding the side effects of policies on the community is crucial, dynamic complex networks offer valuable insights [3].

4. IDENTIFYING TRANSMISSION FACTORS USING DYNAMIC COMPLEX NETWORKS

Another application of dynamic complex networks is identifying factors contributing to virus spread within networks. Sociologists and researchers have many questions regarding whether transmission factors are uniform across different communities. For example, do restrictions on movement in Iran and Finland have the same impact? Addressing such questions requires a detailed understanding of the factors driving virus transmission.

5. CONTACT TRACING

Dynamic complex networks are also used for contact tracing of infected individuals. Contact tracing breaks the chain of virus transmission by identifying and notifying individuals who have been in contact with an infected person. Traditional contact tracing involves manually notifying close contacts, which is often incomplete and inefficient. Digital contact tracing, using smart devices such as smartphones and wearable technology, has been implemented in several countries, including Nordic countries [4]. This approach includes three main categories [5]:

- Outbreak Response Tools: These tools involve developing appropriate programs and infrastructure for creating and analyzing a dynamic complex network in the project's backend. The program must ensure accurate data storage and retrieval.

- Proximity Tracking Tools: These tools use technologies like Bluetooth or GPS to measure the proximity of individuals in the community. If individuals come within a certain distance, the system notifies a server, and a connection is established in the dynamic network. Notifications are then sent to potentially exposed individuals.

- Symptom Tracking Tools: These tools focus on continuous monitoring of individuals' health. If alerts are issued by smart devices, individuals are advised to visit health centers for further evaluation, especially if quarantine conditions are not being met.

An example of a contact tracing application is the COVIDSafe app [6].

6. MODELING USING DYNAMIC COMPLEX NETWORKS

One of the reasons dynamic complex networks have become popular in studying the COVID-19 epidemic is their ability to provide highly accurate modeling and simulations compared to other methods. Key discussions about analyzing COVID-19 in networks involve modeling and executing simulations. For instance, studies on the impact of policies, transmission dynamics, and social behavior within networks have been conducted. Network models are computer programs designed to understand issues by simulating various scenarios to explore different dimensions of the problem. Due to the importance of this topic, the main task for computer scientists is modeling and simulation.

7. MODELING POLICIES

The SI unit system is the only acceptable system for formulating problems. In special conditions where formulation in other systems is necessary, their SI equivalents should also be mentioned. Ensure that units for values in tables or axis titles in figures are not forgotten.

This section examines the policies implemented to combat the epidemic and their effects. A key advantage of modeling with dynamic complex networks is that the resulting models are more accurate and do not require highly precise initial data to achieve the best model for the issue at hand. Small and Kavanagh, members of IEEE, demonstrated that precise knowledge of transmission parameters is not necessary for creating an informative disease spread model. They presented an accurate model of network topology under various external control methods. Their model uses a contact graph to represent community interactions, with the graph structure chosen to match community control criteria. Their model differentiates disease spread through three types of networks: scale-free networks, random graphs, and small-world lattices. The model showed good agreement between simulation data and observed data from the 2020 COVID-19 pandemic. Their results suggest that to minimize disease spread, quarantine along with monitoring and limiting strategies like social distancing are essential. If restrictive measures are less than 80% of complete quarantine and physical isolation, the spread of the disease will be catastrophic [7]. These findings align with observations of explosive disease spread in regions such as Iran, India, and Brazil. Consequently, in areas with weaker health systems, without decisive government intervention for severe measures like quarantine and travel restrictions, disease spread becomes severe and uncontrollable.

The next topic is evaluating the effectiveness of non-pharmaceutical interventions implemented to control the COVID-19 pandemic. This approach has been employed in various countries, including Greece. Greece constructed a network of patients, hospital resources, and treatment facilities. It then applied parameters such as resource availability to a weighted graph representing people's connections with these centers. By creating a graph based on people's interactions with healthcare facilities, considering epidemic prevalence, and analyzing areas with higher disease spread and the availability and transferability of resources, a comprehensive model was developed to predict more accurate policy outcomes. This approach resulted in significantly lower disease statistics compared to the global average. The success was attributed to using a precise model for monitoring the population and evaluating the impact of social policies. A significant challenge faced by researchers was obtaining accurate data. Consequently, researchers incorporated time-series data on infection rates and mortality into complex networks, employing methods described in [8]. This allowed them to manage associations and implement policies to address each association. This study elucidates Greece's highly successful performance in managing the first wave of the pandemic [9].

Another question that arises is whether network science can prevent the spread of disease. Where did the outbreak originate? Researchers Zanin and Papo attempted to describe the epidemic on a macro-scale. They constructed and analyzed networks using functional networks and tools such as Cytoscape. They evaluated network topological features using metrics like link density, maximum out-degree of a node, assortativity, and transitivity. The objective was to determine the extent of disease propagation within the network and how policies such as road or air travel restrictions could prevent widespread virus transmission. They analyzed data from Portugal, Spain, the UK, and Italy, identifying local transmission patterns. Their results, summarized in Table 1, indicate that countries like the UK and Portugal, which effectively implemented policies to reduce network transitivity and assortativity, made significant progress in controlling the disease.

Table 1. Topological Metrics for Four Different Networks

Standard	Portugal	Spain	Italy	England
Density	0.095	0.155	0.199	0.0972
Assortativity	-1.0	-0.0419	-0.0459	-0.645
Transitivity	0	0.399	0.434	0.033

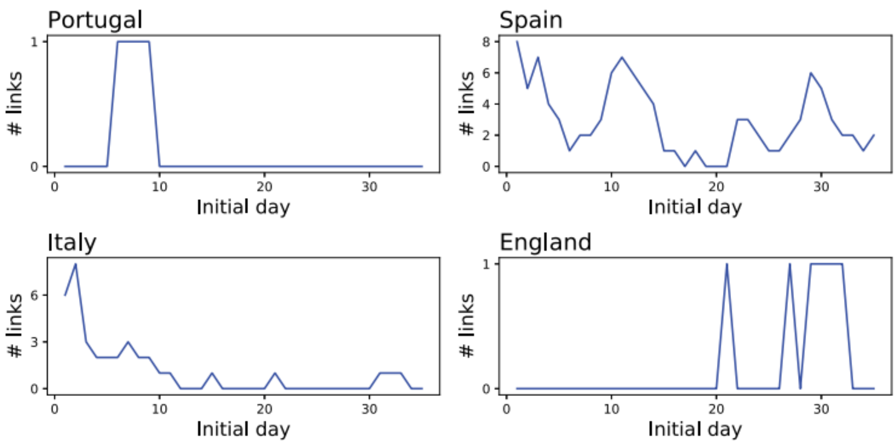

Fig.1. Performance of Various European Governments in Controlling Disease

Figure 1 illustrates how effectively different governments managed disease fluctuations. For instance, Portugal performed exceptionally well, while Italy gradually controlled fluctuations. However, Spain's situation remained complex. One reason for these fluctuations is the level of clustering coefficient in the region; higher clustering coefficients are associated with greater fluctuations [18].

A related question is the effectiveness of restrictions such as quarantine. German researchers led by Frank Schlosser demonstrated that COVID-19 quarantine caused structural changes in mobility networks. After the pandemic outbreak, many countries implemented restrictions to reduce disease transmission. Studies showed a significant reduction in mobility across different countries. However, it remained unclear whether these reductions caused deeper structural changes in mobility networks or how such changes might affect dynamic processes within networks. Schlosser et al. used mobile phone movement data to show that mobility in Germany not only significantly decreased but that severe quarantine measures led to fundamental and long-lasting changes in the mobility network. Their findings indicated a significant reduction in long-distance travel post-pandemic. A crucial result was that removing and pruning long-distance routes led to more localized and clustered networks, mitigating the "small-world" effect. Additionally, structural changes had a substantial impact on flattening the epidemic curve and delaying its spread to more distant geographical areas.

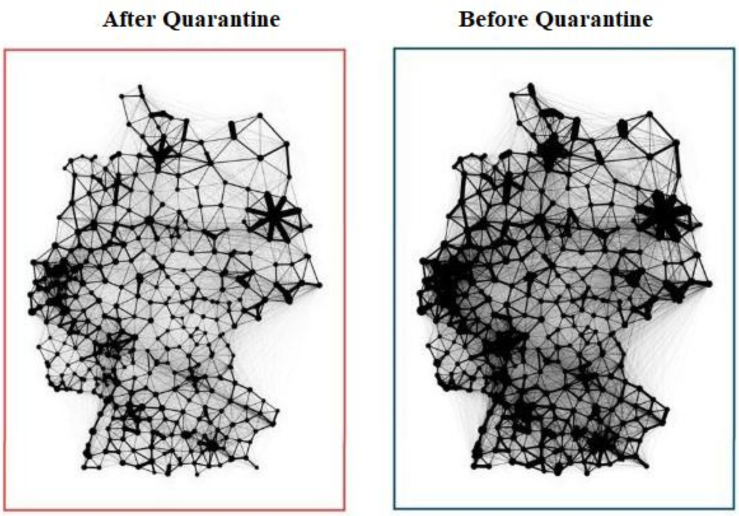

Fig. 2. Network Structure Before and After Quarantine

As shown in Figure 2, the network structure in Germany post-restrictions became more clustered, with numerous small local networks formed. Schlosser et al. implemented the SIR model to assess how widespread quarantine-induced changes in mobility affect epidemic spread. They adjusted the model to account for changes in overall mobility, which the original model did not capture. Analysis of the SIR model showed that quarantine measures had varying effects on epidemic spread, notably reducing overall disease occurrence and delaying peaks to later times. Quarantine measures "flatten the curve" [11].

Block et al. investigated the effectiveness of three social distancing strategies for combating the COVID-19 epidemic. In the first strategy, individuals select their communication partners based on personal characteristics, meaning they prefer to interact with others who share similar traits, such as living in the same neighborhood. The second strategy allows individuals to interact only with those whose partners also have connections with these individuals. A common feature of communication networks is triadic closure, where a person’s communication partners tend to connect with each other. For the third strategy, each individual must specify with whom they wish to interact regularly and must limit their interactions to these individuals over time. Modeling results demonstrated that, compared to no intervention or simple, non-strategic social distancing, all three strategies significantly reduced the virus’s transmission rate. Among these, the third strategy, where interactions are confined to family members and regular contacts, proved to be the most effective.

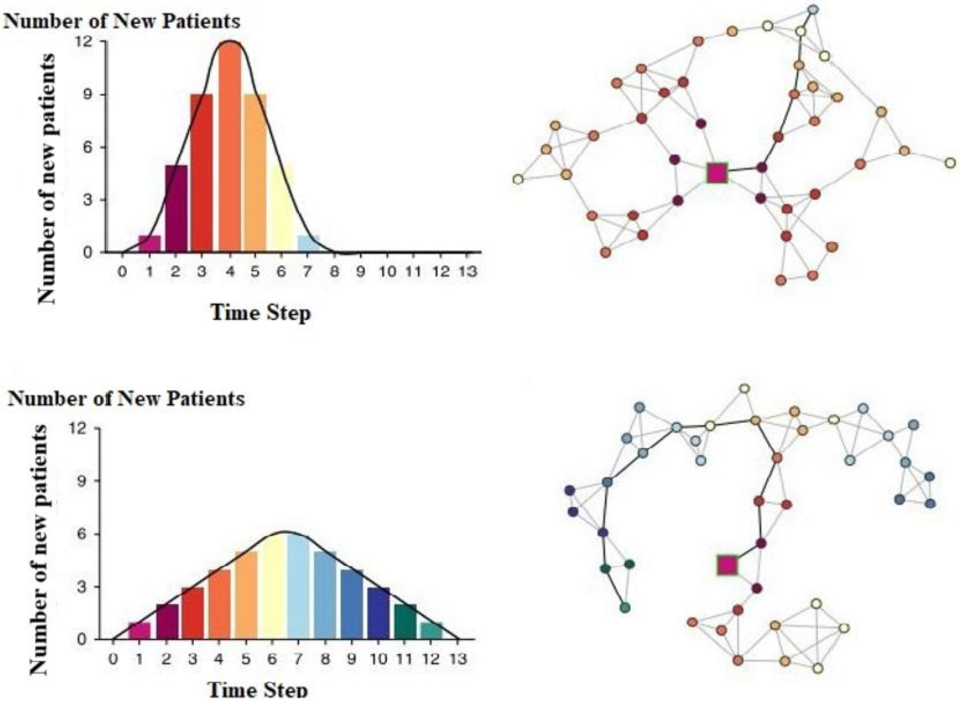

Fig. 3. Networks with Different Path Lengths

Figure 3 illustrates two networks with differing path lengths, where contamination in each network begins with a node infected with the COVID-19 virus, represented by a purple square. At each stage, the disease spreads from the infected node to adjacent nodes. Comparing these figures reveals that in networks with longer paths between nodes, disease transmission occurs at a slower rate, resulting in a "flatter" curve [12].

Following a rapid decline in COVID-19 cases in the United States from January to March 2021, and despite the extensive rollout of vaccination programs, infection rates increased in several states. This rise was attributed to the emergence of a more transmissible variant of the coronavirus and the relaxation of preventive measures, such as those related to school reopenings, businesses, and gatherings. The COVID-19 Modeling Teams in the United States utilized a six-model approach to provide long-term forecasts of COVID-19 incidence, hospitalizations, and mortality. They implemented four different scenarios combining varying vaccination coverage rates and adherence to non-pharmaceutical interventions (such as quarantine and social distancing) over a six-month period. The modeling was influenced by factors including the population's immunity level, the emergence or non-emergence of viral variants, the effectiveness of existing non-pharmaceutical interventions, and the level of vaccination coverage. The researchers' results indicated that among these four scenarios, reducing non-pharmaceutical interventions, such as social distancing and other restrictive measures, would undermine the vaccination gains in the coming months. If this reduction coincides with the emergence of new viral variants, it could lead to increased infection rates and subsequently higher hospitalizations and mortality. Additionally, high vaccination rates and adherence to preventive measures, such as social distancing, are essential for controlling the COVID-19 pandemic and preventing surges in hospitalizations and deaths [13].

Mr. Matteo Chinazzi et al. examined the effects of travel bans imposed in Wuhan and international travel restrictions. They utilized the Global Epidemic and Mobility model (GLEAM), a stochastic, agent-based, and spatial epidemic model. GLEAM employs a network-based approach that considers the world as a collection of subsets centered around major transportation hubs, such as airports. These subsets are connected through individuals who commute daily between these transportation centers. The model developed by these researchers encompassed over 3,200 subsets across approximately 200 countries and territories. Their approach involved modeling COVID-19 transmission within each subset using a compartmental representation of the disease, wherein individuals can be classified into one of the following states: susceptible, latent, infected, and removed. Susceptible individuals are those who can become infected through contact with infected individuals and subsequently move to the latent state (those who are infected but not yet capable of transmitting the infection). Latent individuals' transition to the infected state at a rate inversely proportional to the latency period, and infected individuals move to the removed state at a rate proportional to the duration of the illness. The sum of the mean latency and infectious periods defines the generation time. Removed individuals are those who can no longer transmit the disease (e.g., individuals in quarantine, hospitalized, recovered, or deceased). The model considered a range of possible epidemic scenarios based on varying numbers of newly infected individuals, the timing of disease introduction into each subset, and the number of travelers carrying the disease. This enabled the estimation of importation cases into different regions worldwide from China. The innovative model showed that following the imposition of travel restrictions in Wuhan on January 23, the five cities with the highest international importation rates were Shanghai, Beijing, Shenzhen, Guangzhou, and Kunming. The modeling results indicated that the travel quarantine from Wuhan delayed the overall epidemic progress in China by only three to five days but had a significant international impact. Furthermore, the research demonstrated that sustained 90% reductions in travel to and from China had a moderate effect on the epidemic trend, unless accompanied by a 50% or greater increase in restrictions within the destination community [10].

8. EPIDEMIC MODELING

The central question is whether a precise model of disease spread can be developed to provide the most accurate responses regarding disease transmission. This inquiry seeks to understand the nature of the virus. A correct understanding of the virus's nature is crucial for subsequent investigations, including policy-making and studying the effects of quarantine. Generally, the study of these characteristics is divided into two main categories: the first involves studying virus characteristics and developing suitable models using complex networks, while the second utilizes deep networks for modeling. Although deep networks are not directly related to the topic, they are highly effective for understanding dynamic network-based models.

9. MODELS BASED ON COMPLEX NETWORKS

As is well known, the principal model for virus spread in networks is the SIR model. Researchers typically modify this model based on the prevailing conditions and the network under study. Mr. Alexandru Topîrceanu et al. proposed a new agent-based model named SICARS, which allows for the evaluation of the impact of both centralized and decentralized isolation strategies on the spread of COVID-19 in heterogeneous complex networks. Understanding the definitions of centralized and decentralized strategies, as well as their combinations, is essential. An example of a centralized strategy is the Lockdown or quarantine imposed by the government. Decentralized strategies include voluntary and automatic isolation, where individuals who become aware of their illness spontaneously cut off their social connections, while automatic isolation involves healthy neighbors separating individuals from infected ones. The combined strategy merges centralized and decentralized isolation policies. Compared to other models, SICARS incorporates an additional state where an infected individual actively cuts off their connections with others. This feature distinguishes SICARS from the SEIR model, which is the most well-known model in the field of epidemic modeling. With this provision, the SICARS model is capable of evaluating decentralized strategies.

Utilizing this model, researchers demonstrated that moderate to strict quarantine measures could extend the duration of the epidemic by approximately 40% with a combined approach and up to 80% with a centralized approach compared to a scenario with no restrictive measures. Although longer quarantine periods may have complex economic consequences, the unparalleled benefits of isolation strategies, such as significantly reduced fatalities, are noteworthy. The research findings indicate that while decentralized isolation strategies are beneficial, they are insufficient on their own. Decentralized methods cannot promptly mitigate the impact of major disease spreaders—i.e., nodes with high degrees. Thus, centralized isolation strategies appear crucial due to their significantly higher efficiency compared to decentralized approaches. Given the findings, the combined strategy is deemed the most effective, though even this strategy loses its effectiveness if not implemented timely [14].

Italian researchers led by Leonardo Stella investigated the role of asymptomatic individuals in the COVID-19 epidemic through dynamic complex networks. They proposed a model derived from the well-known SEIR model, called SAIR. Instead of using the term "Recover," commonly found in most models, they used "Remove" to avoid distinguishing between those who recover and those who die. The advantage of this model is its ability to differentiate between symptomatic and asymptomatic COVID-19 cases. In this model, interactions with asymptomatic and symptomatic individuals are recorded separately, allowing for the study of the impact of asymptomatic carriers. This research conveys an important message: the number of asymptomatic cases is significantly underestimated in official data, and neglecting their role can destabilize the system and lead to further waves of disease spread [15].

10. NEURAL NETWORK-BASED MODELS

Mr. Mikhail Vychurchk et al. proposed a neural network model for predicting the spread of COVID-19. They employed a classical deep learning approach using the NAdam training model. The training data were sourced from official and open databases, such as the CSSE dataset from Johns Hopkins University. This dataset is freely available for academic purposes and includes continuously updated time-series data, comprising fully verified samples for various countries and some large global regions. Their model provided predictions for countries and various global regions, encompassing a wide range of COVID-19 spread values. The results of their proposed model demonstrated high accuracy, reaching over 99% in some instances [16].

Mr. Nicholas Soures and his team developed a hybrid machine learning model named SIRNet for predicting the spread of the COVID-19 pandemic. Their work was interdisciplinary, integrating epidemiological modeling, physical sciences, and machine learning. By combining established metrics and well-known disease dynamics, they created an approach that is both data-driven and scientifically grounded. Their studies confirm the impact of reduced mobility on limiting epidemic spread and provide tools for forecasting the effects of various mobility scenarios [17].

11. SUGGESTIONS FOR FUTURE WORK

Several aspects reviewed in the articles could serve as topics for future research:

- Modeling Spread Using Dynamic Complex Networks: Greece's work on virus spread modeling using dynamic complex networks is noteworthy [9]. Unfortunately, such efforts have not yet been undertaken in Iran, partly due to the Iranian Ministry of Health's reluctance to publicly disclose detailed virus spread data over time, which affects the completeness of initial data for Iran. If such data were accessible, the primary challenge would be converting time-series infection data into complex networks. The next challenge would be ensuring the accuracy of this conversion. The resulting complex network must be precise.

- Examining the Impact of the Epidemic on Economic Sectors: An example of work related to Iran's economy is the impact of the COVID-19 pandemic on the Iranian stock market [19]. This model could be applied to other sectors. Causes of inflation, economic recession, and market downturns in various sectors—such as real estate—could be examined using complex networks.

- Impact of Virus Mitigation Policies: Many restrictions are aimed at preventing disease spread by super-spreaders. For instance, nighttime curfews are among the cheapest and simplest policies to impose restrictions on them. However, by modeling the community and conducting further analysis, better policies to limit super-spreaders could be identified. For example, imposing restrictions on public places with poor hygiene practices, such as tea houses, might effectively curb disease spread more than nighttime curfews.

12. CONCLUSION

This paper aimed to explore the significance and diverse applications of dynamic complex networks in combating the COVID-19 pandemic across various aspects. These aspects were categorized into two general areas: evaluating the effectiveness of implemented policies and modeling disease spread. For example, contact tracing has received considerable attention in developed countries. Another critical area in policy feedback studies is assessing the effectiveness of government-imposed restrictions. It may be possible to replace existing restrictions with more effective alternatives. In the disease spread modeling section, we examined models based on complex networks and neural networks. We believe that a correct understanding of the microscopic properties and spread of the disease leads to an accurate comprehension of its macroscopic characteristics and effective modeling of the issue. In conclusion, the authors believe that dynamic complex networks provide a suitable framework for studying epidemics such as COVID-19, necessitating precise modeling, appropriate initial data collection, and public dissemination for researchers to initiate investigations.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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