# Co-evolution of COVID-19 Research and China's Policies

**Cheng Xi**
Soochow University https://orcid.org/0000-0001-9014-2560
**Tang Li**
Fudan University https://orcid.org/0000-0003-4971-6192
**Zhou Maotian**
Emory University https://orcid.org/0000-0002-5274-8083
**Wang Guoyan** ( gywang@suda.edu.cn )
Soochow University https://orcid.org/0000-0002-3175-6025

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# Co-evolution of COVID-19 Research and China's Policies

**Abstract:** The dynamics of research are a prism that reflects interactions between science, the societal environment, and government policies. Against the backdrop of the ongoing global COVID-19 pandemic, this study explored the changes in, and development of, COVID-19 research in the period from December 30, 2019 to April 27, 2020. The study observes a salient change in research content: an earlier focus on "all patients", "common symptoms", and "nucleic acid test" was gradually replaced by a focus on "children", "pregnant patients", "severe symptoms", and a combination of "nucleic acid test" and "antibody assay". Some topics such as "vaccine R&D", "knowledge, attitude, and practice" (KAP), and "mental health" were persistent throughout the recent history of China's COVID-19 research. This study also reveals a correlation between the evolution of COVID-19 policies and the dynamic development of COVID-19 research. In the early stage of the outbreak in China, the formulation of COVID-19 policies followed a rapidly-progressing co-evolutionary model (CEM). The results of this study apply more broadly to the formulation of policies in public health emergencies, especially in the early stages.

**Keywords:** COVID-19, China, Scientific research, Policy, Co-evolutionary model

## 1. Introduction

COVID-19 has been a focus of global concern since the beginning of 2020, and research literature, social media, and other information resources related to COVID-19 are being generated at high speeds and in unprecedentedly large quantities (Hechenbleikner et al. 2020). According to *Science*, the number of publications on COVID-19 has been doubling every 20 days since January; this is the biggest explosion of scientific literature ever recorded (Brainard 2020). As of June 14, 2020, the amount of literature on COVID-19 collected in the PubMed database had reached 22,366 publications. In the face of an unknown virus, scientific research has the power, alongside medical treatment and health management, to guide us through unprecedented times.[1] This fact partially explains the explosion of papers during the COVID-19 pandemic.

Scholars from China have published the largest number of papers on COVID-19 worldwide (Rafiei Nasab and Rahim 2020). Considering that the pandemic initially broke out in China, and the fact that China was the first to effectively control the local COVID-19 epidemic[2], this study selected China as a case for study. The developmental trends of China's COVID-19 research

[1] https://www.forbes.com/sites/startswithabang/2020/04/07/the-3-ways-science-will-get-us-through-the-covid-19-pandemic/#39ee6ca52fc3

were analyzed from the perspective of bibliometrics. The priorities and goals of China's COVID-19 prevention and control policies in different stages of the epidemic are here identified.

As scientific research is a process of problem-solving and resolving disputes (Heffernan and Teufel 2018; Fortunato et al. 2018), publications on COVID-19 indirectly reflect whether a scientific consensus has been reached, or whether a solution has been developed for a particular problem. Such connections can be revealed when one studies the length of time that particular topics remain popular. Policies play a vital role in providing the physical facilities and knowledge base on which scientific and technological institutions depend (Pratten and Deakin 2000), and policy-making also requires the participation of science (Watson 2005; Youtie et al. 2017). Therefore, research on dynamic trends in research helps us to better understand the interactivity between science and policy-making.

Previous research on the evolution of policy response to public events has had a largely theoretical focus (Choi et al. 2005; Edmondson et al. 2019). Moreover, the rate of policy evolution with regard to COVID-19 far outpaces the progress of policymaking with regard to environmental pollution (Wan et al. 2020) and EU policymaking with regard to climate change (Humphreys 2009). Here, by means of real-time assessment, investigations of a practical dimension were carried out through exploration of the dynamics of relevant COVID-19 research in China. This study focused on the period from December 30, 2019 [3] (the initial announcement of the pandemic) to April 27, 2020. By calculating the variations in the co-occurrence of items over a range of time intervals, it was found that there are more items with long-term popularity than those with short-term popularity in China's COVID-19 research literature. In the late stage of the epidemic in China, the trend of research on "all patients", "common symptoms", and "nucleic acid test" began to decline. In contrast, research on "children or pregnant patients", "severe symptoms", and combined use of the "nucleic acid test" and "antibody assay" began to rise. Vaccine R&D, KAP, and mental health are long-term "hot" issues in China's COVID-19 research. The formulation of relevant COVID-19 policies in China is constantly evolving, and this is partially in response to these dynamic variations in COVID-19 research. In the early stage of the outbreak in China, the formulation of COVID-19 policies followed a rapidly progressing CEM. This model is applicable to policy-making in public health emergencies in other contexts, especially in the early stages.

## 2. Methodology

### 2.1 Data collection

The research data for this study was derived from PubMed. The alternate names of COVID-19 provided by the Dimension database[4] were used as search terms.[5] The types of literature to be

[3] http://www.chinadaily.com.cn/a/202004/06/WS5e8b2f5aa31012821728496b_2.html

[4] https://covid-19.dimensions.ai/

[5] Search syntax: (("2019-nCoV"[All Fields] OR "COVID-19"[All Fields] OR "SARS-CoV-2"[All Fields] OR "hcov"[All Fields] OR "NCOVID-19"[All Fields] OR "severe acute respiratory syndrome coronavirus 2"[All Fields]) AND ("CHINA"[Affiliation]))

searched were limited to Article and Review. As of April 27, 2020, the PubMed database had collected a total of 1,427 papers on COVID-19 published by scholars from China. The scheme used in this study adopted an expanding overlapping aggregation / overlapping time series approach (Cerqueira et al. 2017; Hotta et al. 1992; Jeon and McCurdy 2017.) A total of 10 statistically valid time intervals were used, following the examples of Petropoulos, Makridakis, and Roosa (Petropoulos and Makridakis 2020; Roosa et al. 2020). Specifically, the time intervals were from December 30, 2019 to January 28, 2020, from December 30, 2019 to February 7, 2020, from December 30, 2019 to February 17, 2020, etc., cumulatively increasing in 10 day increments until April 27, 2020. The specific intervals and corresponding dates are detailed in Part 1 of the Supplementary Material. This strategy of collecting data in overlapping time series can reduce the influence of randomness on the variability of data in short time periods and thus can present more stable trends than is possible with the use of continuous time series (Jeon and McCurdy 2017; Cerqueira et al. 2019). Simultaneously, to avoid any bias introduced by the selection of the duration of the time interval, a robustness test (see details in Part 2 of the Supplementary Material) was conducted. It was found that the variation significance of co-occurrence keywords calculated under the 10-day interval scheme and under the 20-day interval scheme were highly correlated, with a correlation (R) value of 0.916. This correlation suggests that the variation significance of co-occurrence keywords can be effectively demonstrated using different time interval schemes. In particular, the ten-day interval scheme can not only reveal more significant variations in the number of COVID-19 papers, but also reasonably avoids the random fluctuations to which an excessively short interval would be susceptible.

### 2.2 Data processing

All selected literature was imported into VOSviewer in MEDLINE format for co-occurrence analysis. When setting the analysis conditions, the minimum number of occurrences of a keyword was set as 2, meaning that the keyword appeared in at least two documents. The data on the total link strength of co-occurrence items in different time intervals were extracted, to calculate the differences in co-occurrence items. It not only records the occurrence frequency of a given item but also reflects the link strengths of other items appearing at the same time as the given item (Van Eck and Waltman 2013). According to studies by Guo (2019) et al., total link strength can be used to effectively identify research trends. Given that VOSviewer is not able to recognize synonyms, synonym items were manually merged in this study (see the list of merged synonym items in Part 3 of the Supplementary Material).

The data on the total link strengths of corresponding items varied significantly, because of the significant differences in the numbers of papers published during different intervals of different duration. According to the results exported from VOSviewer, the maximum total link strength in the first interval was 78, while that in the last interval was 5,273. To make the subsequent analysis more consistent, it was necessary to first normalize the total link strengths by transforming their values into percentages[6]. The number of articles (9) and co-occurring items

[6] Percentage of the total link strength of a given co-occurrence item equals the total link strength of the given co-occurrence item divided by the sum of the total link strengths of all co-occurrence items.

(26) in the first interval were significantly fewer relative to other intervals, resulting in high percentage values for each item. On that account, the data of the first interval were rejected in subsequent analysis. This left a total of nine valid time intervals.

### 2.3 Identification of items with significant variations

Given that the number of co-occurring items varied in different intervals[7], data imputation was conducted to determine the missing percentages of the total link strengths of co-occurrence items to facilitate subsequent analysis. Because the missing data fell into the category of Missing Not at Random (MNAR), this study adopted minimum value imputation as its method (Hunt, 2017). Specifically, the minimum percentages of the total link strength of co-occurrence items in the nine intervals were extracted separately. Then, data was randomly selected from the range constituted by the nine minimum percentages for imputation. After imputation, a one-sample t-test was conducted on the percentage of the total link strength of each co-occurrence item in one interval relative to all prior intervals. This was done according to the following formula:

$$t = \bar{X} - \mu_0 / SE$$

where $\bar{X}$ denotes the average percentage of the total link strength of the co-occurrence item in all prior intervals. $\mu_0$ denotes the percentage of the total link strength of the co-occurrence item in the current interval, and SE denotes the standard error of the percentages of the total link strength of the co-occurrence item in all prior intervals.

According to the rules of the one-sample t-test[8], significance analysis could not be conducted on the data of the second and third intervals, so ultimately seven groups of t values were obtained. Next, Students' left-tailed t-distribution test was conducted on the t values to calculate the significance of the data variations of co-occurrence items across different intervals. To avoid any differences in the significance of data variations caused by random imputation, this study performed ten random imputation iterations on the entire dataset. The final imputation and t-test results adopted the average results of ten random imputation iterations. According to t-test results, the seven intervals (starting with the fourth interval) respectively had 38, 63, 61, 57, 51, 59, and 62 co-occurrence items (188 in total after deducting repetitions), which showed significant variations in at least one interval.

### 2.4 Classification of items

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[7] The numbers of co-occurrence items in each of the nine intervals were 73, 104, 153, 235, 319, 382, 490, 571, and 656, respectively.

[8] A one-sample t-test compares target data and test data. The first step is to see if the data for a particular item in a particular interval differ from the data for that same item in the previous interval. If so, the data in that interval are adopted as target data, while the data in the previous interval are adopted as test data. Data from at least two previous intervals are required for comparison with the target data. For this reason, no t-test was performed on the second or third intervals. (Recall that the first interval was already discarded for other reasons.) After deleting these two intervals, we ultimately obtained seven groups of t values.

The interrelationships of the 188 co-occurrence items which showed significant variations were explored by classifying them through hierarchical clustering. In light of the significant differences among different items in their percentages of total link strength, Z-score Transformation was first performed on the data for each item across the nine intervals. After that, Scikit-learn[9] was used to analyze the transformed data to produce a dendrogram (Pedregosa et al. 2011). The dissimilarities among co-occurrence items were calculated according to average linkage and Euclidean distance metric parameters. According to the exported dendrogram (Part 4 of the Supplementary Material), the 188 items were classified into seven major clusters based on their variation trends in research "heat." Figure 1 below shows the variations in research heat of all items in each cluster across different intervals, as measured by Z-score. A high amplitude in Figure 1 represents a steady increase in research focus rather than an instance of constant high research focus. These amplitude variations are referred to as "heat variations" in the remainder of this paper.

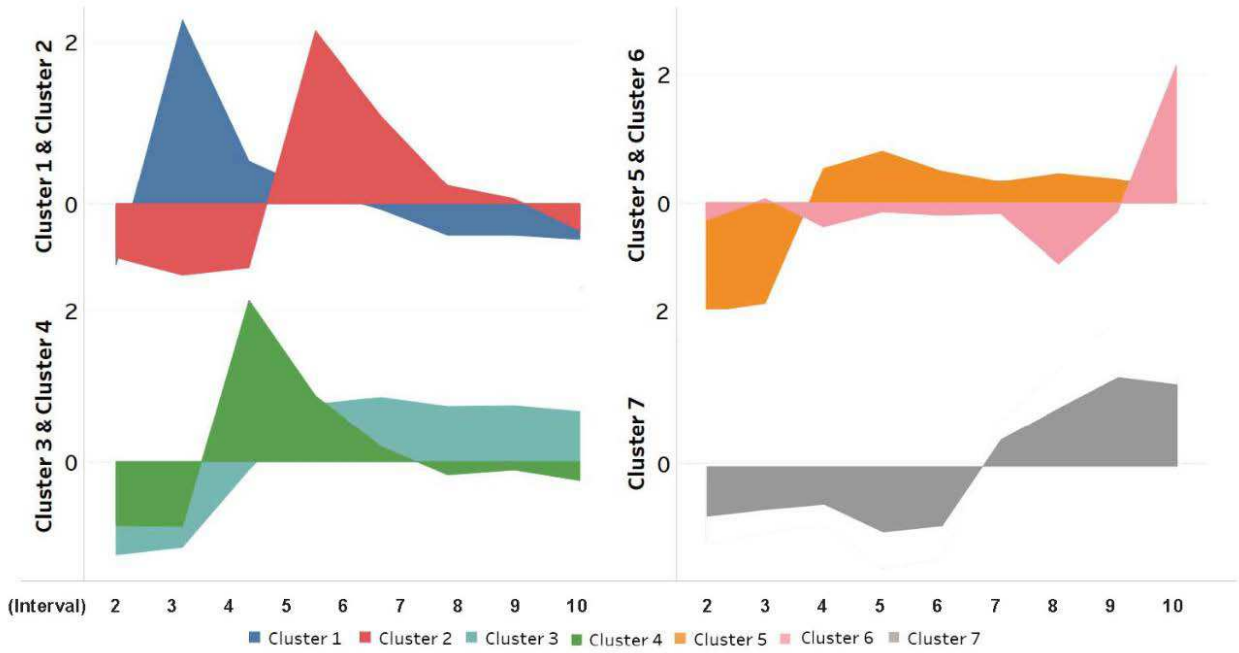


**Figure 1:** Heat variation trends of different clusters across different intervals

## 3. Data Analysis

In Figure 1, the periods of rising heat for the items in Clusters 1, 2, and 4 lasted for only one 10-day interval[10], so they are referred to as items with short-term heat. By contrast, the periods of rising heat for the items in Clusters 3, 5, and 7 lasted for longer than one interval, so they are

[9] Scikit-learn is a Python-based machine learning library.

[10] The heat of the ten items in the sixth group rose in the last interval. Considering the difficulty in judging whether their heat trends are long-term or short-term, we have rejected this group of data. As a result, the total number of co-occurrence items included in this study was decreased to 178.

referred to as items with long-term heat. Specifically, there were a total of 75 items with short-term heat (42.13%) and 103 items with long-term heat (57.87%).

Co-occurrence items were then categorized according to the eight topic categories[11] of COVID-19 literature released by the Johns Hopkins Bloomberg School of Public Health. About 24% of the items with short-term heat fell under the category of "Epidemiology", and 12% under "Pharmaceutical Interventions". The items under the category of "Epidemiology" mainly concerned the natural history, transmission rate, and incidence rate of the virus. Items under the category of "Pharmaceutical Interventions" mainly concerned existing drugs that are already used for other diseases, such as chloroquine and traditional Chinese medicine (TCM). Notably, about 17% of the items with short-term heat were difficult to categorize. These were mostly related to topical issues such as "anatomy", "Beijing", and "Hong Kong". Among items with long-term heat, 26% fell under the category of "Clinical Presentation & Prognostic Risk Factors", 16% under "Non-pharmaceutical Interventions", and 7% under "Vaccines". The items with long-term heat under the category of "Clinical Presentation & Prognostic Risk Factors" mainly concerned symptoms in severe patients, radiology, and symptoms in children and pregnant women. Items under the category of "Non-pharmaceutical Interventions" mainly involved contact tracing, surveys and questionnaires, isolation, and KAP. About 8% of items with long-term heat were related to mental health. These items were listed as a separate category because mental health constitutes a separate aspect of COVID-19 treatment, and different mental health measures can be classified under either category of "Pharmaceutical Interventions" or "Non-pharmaceutical Interventions".

### 3.1 Analysis of trend variations

Items that showed significant variations were grouped based on available classification, and five representative groups were selected to analyze their heat trend variations as follows.

#### 3.1.1 Patients: a shift from adolescents to children and pregnant women

According to the data, the focus on child-related items such as "child", "child, preschool", "infant", and "infant, newborn" began to increase after the third interval, reached its peak between the fifth and eighth intervals (Figure 2) and declined after that. Attention towards the item "adolescent" began to drop abruptly after the fifth interval. Relative to adults, children did not receive much attention in the early stage (Wei et al. 2020). However, child patients present a special set of potential problems, such as a longer incubation period (Wei et al. 2020), and the inability of some child patients to describe the route of infection, and these presented difficulties to later prevention and screening (Su et al. 2020). Familial infection was found to be the primary path of child infection (Su et al. 2020; Hong et al. 2020), and this may partially explain the rising research focus on "family clusters" and "family health" in the late stage.

Pregnant women also received close attention in the late stage of the pandemic. Comparable to the rising trends for "infant" and "infant, newborn", the research focus on "pregnancy" and

[11] https://ncrc.jhsph.edu/topics/.

"pregnant women" also increased after the second and sixth intervals. This focus either remained steady or continued to rise in the late stage of the pandemic. Pregnant women are susceptible to respiratory pathogens (Liu et al. 2020). However, no consensus was reached on the effects of COVID-19 on pregnant women (Qiao 2020), such as the existence of vertical transmission (Hong et al. 2020) or the impact on fetal development (Chen et al. 2020).


**Figure 2:** Heat variation trends of items related to children and pregnant women across different intervals

### 3.1.2 Symptom characteristics: a shift from common symptoms to severe symptoms

The focus on the most severe illness-related items rose in the fourth interval and rose even more in the eighth interval (Figure 3.) The heat of common symptoms or clinical indicators such as "fatigue, WBC count, cytokines, and diarrhea" according to *Diagnosis and Treatment Protocol of COVID-19 (DTPC Trial Version 7)*, declined after the sixth interval. The same document listed "dyspnea, cytokine storms, IL-6, and D-dimer" as manifestations of severe symptoms or clinical indicators of severe disease. *DTPC Trial Version 7* mentions that critical patients usually experience dyspnea one week after onset of the disease, in which "plasma" exchange or filtration was listed as a way of treating severe patients. Severe COVID-19 patients have relatively high mortality compared to general patients (Tang et al. 2020), and the clinical indicators of severe patients mentioned above are also related to mortality. The focus on the items "mortality" and "hospital mortality" began to rise after the sixth interval, and rose significantly after the ninth interval.

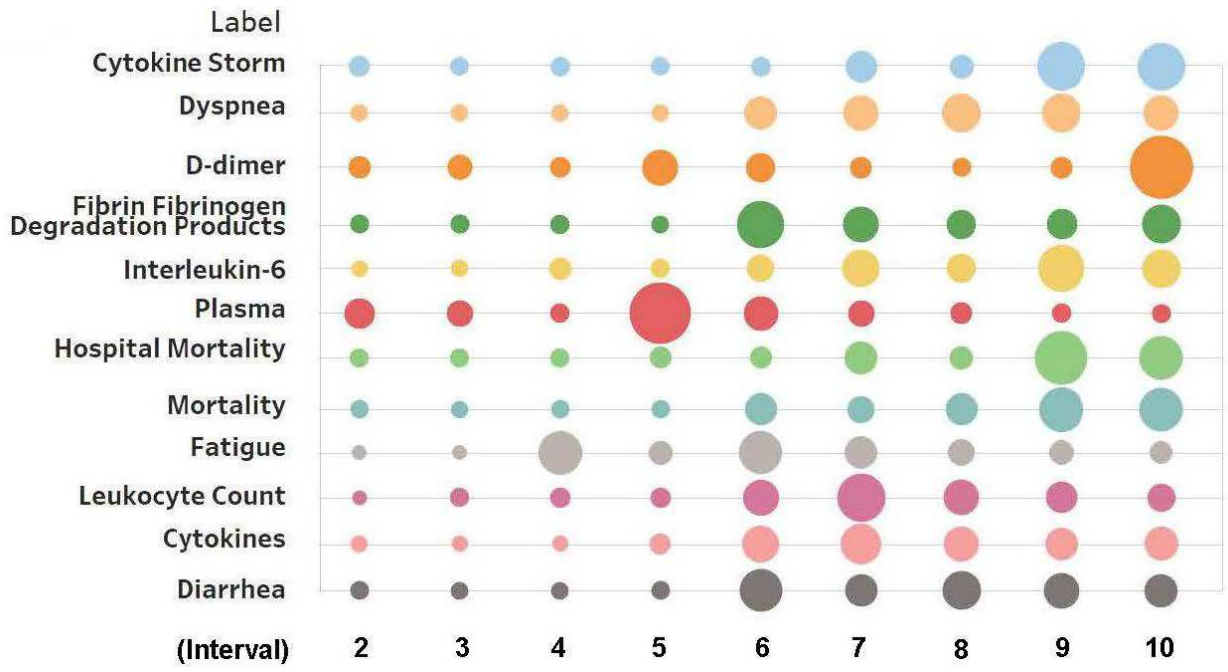


**Figure 3:** Heat variation trends of items related to symptoms across different intervals

### 3.1.3 Virus testing: a shift from nucleic acid tests to a combination of nucleic acid tests and antibody assays

PCR/RT-PCR testing, considered to be the "gold standard," was commonly used when there were many suspected and confirmed cases in the early stage of the COVID-19 outbreak (Tahamtan and Ardebili 2020). In the late stage of the epidemic, when the numbers of suspected and confirmed cases in China declined, antibody assays helped to assure a safe reopening of the economy. As a result, items related to virus testing presented a shift from "nucleic acid test" to a combination of "nucleic acid test" and "antibody assay". The focus on "seroepidemiologic studies" and the "neutralization tests," both of which are antibody assay-related items, increased rapidly after the seventh interval and maintained that momentum. While the focus on "nucleic acid test" began to decrease after the fifth interval, the focus on nucleic acid test-related items such as "PR-PCR" and "sensitivity and specificity" went up dramatically after the seventh and eighth intervals (Figure 4).

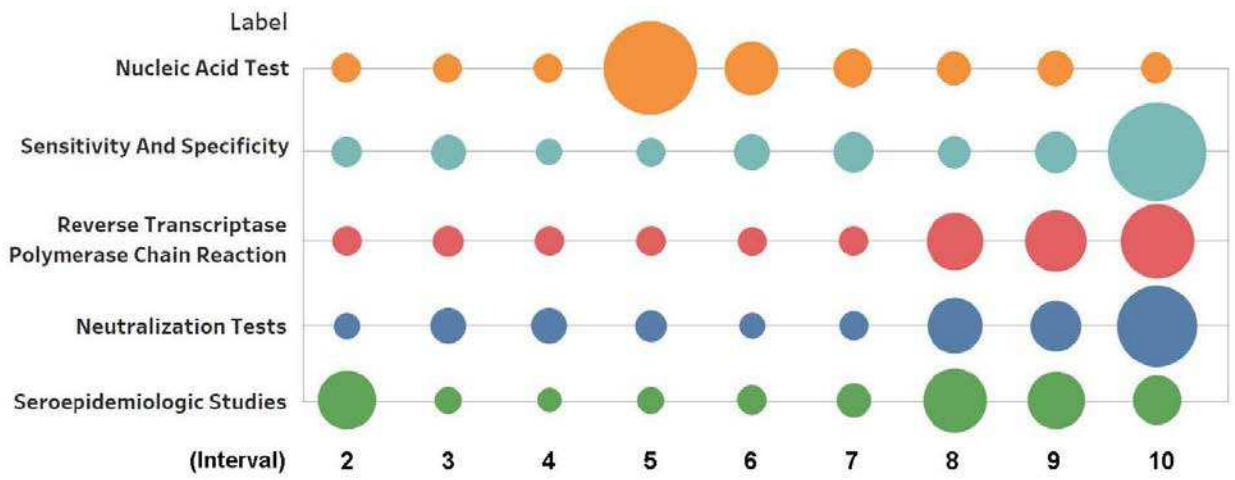


**Figure 4:** Heat variation trends of items related to virus testing across different intervals

### 3.1.4 Decreased focus on drug research and continuously increased focus on vaccine R&D

The research focus on most drug-related items began to decline in the late stage of the pandemic. The focusing of research on "preclinical drug evolution" and the existing drugs "chloroquine", "TCM", "interferons", and "cytochrome P-450 CYP3A inhibitors" began to decline after the fourth, fifth and sixth intervals (Figure 5). The focus on all drug research-related items other than "protein domains" and "molecular docking simulation" declined in the late stage. In particular, "monoclonal antibodies" saw a substantial decline. The variation trends for pharmaceutical intervention-related items suggested that, with the rise of recoveries and the accumulation of experience and consensus, drug research was no longer a top priority.

However, vaccine R&D was still underway, with increased use of the keywords "vaccination" and "vaccine". The items "protein domains", "protein multimerization", and "neutralization tests" expressed detailed information for vaccine R&D (Yuan et al. 2020; Ou et al. 2020), and the focus on these three items remained little changed at the late stage of the pandemic. In addition, some items also reflected the evolution of vaccine R&D through successive stages. The research focus on "Vero cells", "mice" (as a "biological model",) and "*Chlorocebus aethiops*" (a species of monkey that serves as a model organism for virus research) began to rise rapidly after the ninth interval, indicating that China's vaccine R&D had entered the clinical trial[12] and animal experiment stages (Nie et al. 2020; Xia et al. 2020).

[12] http://www.chictr.org.cn/showprojen.aspx?proj=53003

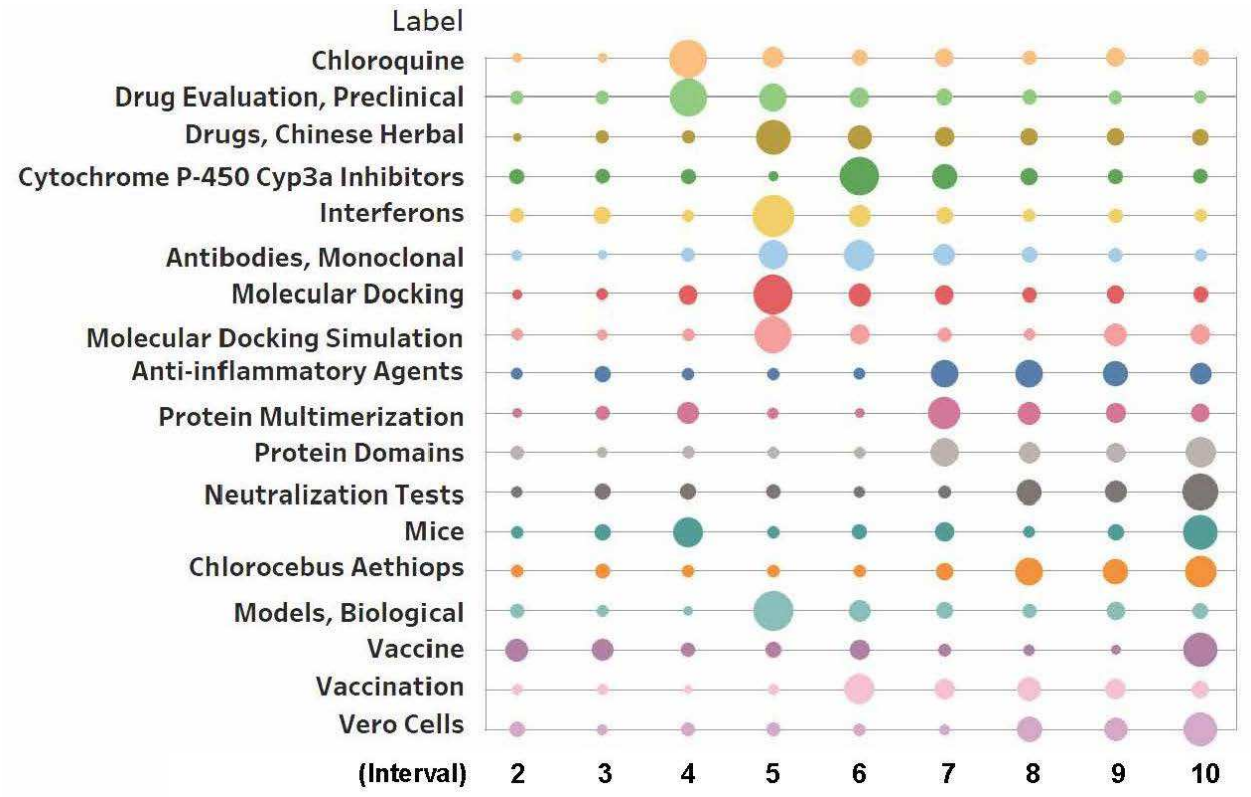


**Figure 5:** Heat variation trends of items related to candidate therapies and vaccines across different intervals

### 3.1.5 Long-term attention to knowledge, attitude, and practice (KAP) and mental health

KAP surveys test what is known, believed, and done by a group- in this case with regard to biomedical concepts (ul Haq et al. 2013). KAP survey results can offer some reference for adjusting prevention and control plans. China launched KAP surveys at the end of January and began to acquire results in February and March; the focus on related items rose continuously after the fourth, fifth, and seventh intervals. China also began to deploy mental health surveys in January in order to determine the impact of COVID-19 on public mental health (Y. Zhang and Ma 2020). As shown in Figure 6, increases in the heat of different research topics related to mental health appeared successively over time, so that overall, mental health maintained a long-term research focus. China's mental health research paid close attention to medical staff and people at the epicenter (Liu et al. 2020) in the early stage of the pandemic, and the attention shifted to the public at large in the middle and late stages (Tian et al. 2020).

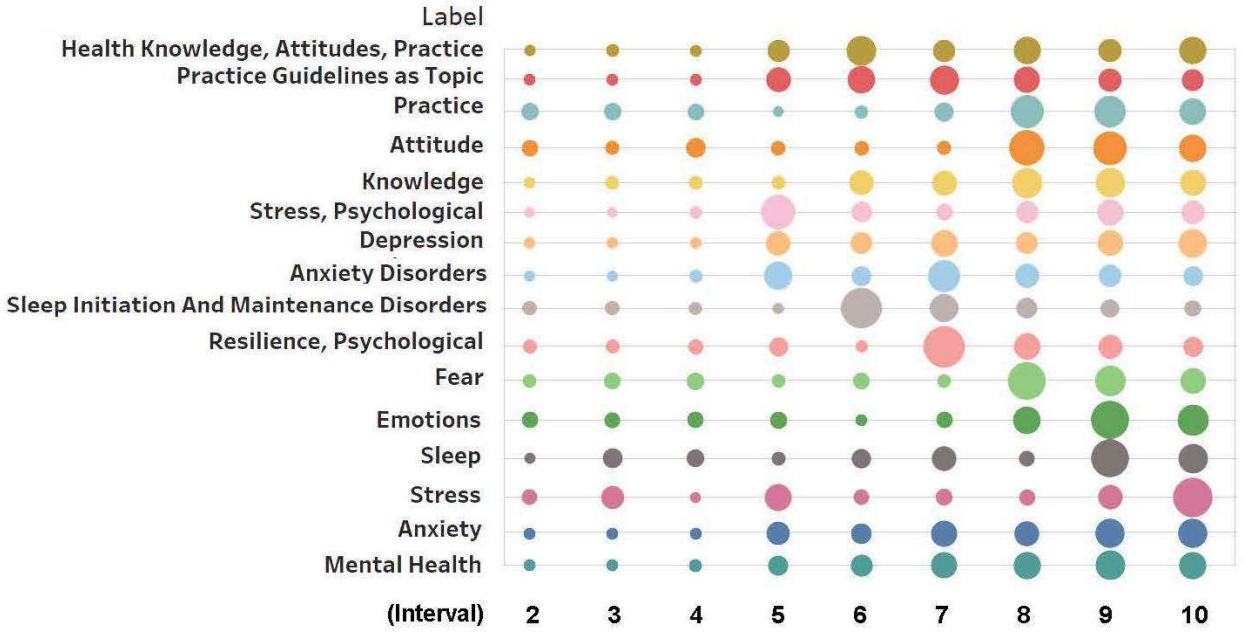


**Figure 6:** Heat variation trends of items related to cognition, psychology, and mental health across different intervals

### 3.2 Analysis of policy-making

This study compared the onset of the period of maximum heat in each cluster and the issuance date of the corresponding national policy/guidance program for each of the five trend changes (Table 1. See the list of policies in Part 5 of the Supplementary Material.) By calculating the differences between the two, an average interval of 11.2 d was found between the issuance of a policy and the maximum heat period of research on related topics. Meanwhile, the increase in interest for various clusters all followed the release dates of relevant policies and guidelines, which likely suggests that policies exert some effect on the variations in interest in the corresponding research topics. Thus, the policies and guidelines formulated by China to combat COVID-19 may have a guiding influence on the variations in research trends investigated in this study.

**Table 1:** Stages of rising heat for various clusters in China's COVID-19 research and release dates of relevant policies/guidelines

| Cluster | Release dates of relevant policies or guidelines (**a**) | Stages of rising heat for clusters of research topics (**b**) | | Interval between the first date of **a** and that of **b** |
|---|---|---|---|---|
| | | Time span | Average growth rate | |
| Mental health | 1.27 – 4.7 | 2.7 – 4.17 | 29.64% | 11d |
| Children | 1.28 - 3.14 | 2.17 – 4.7 | 67.01% | 20d |
| Pregnant women | 2.2 - 3.4 | 2.7 – 3.28 | 59.90% | 5d |
| Severe patients | 2.21 - 4.1 | 2.27 – 3.18 | 62.03% | 6d |
| Antibody test | 3.4 - 4.19 | 3.28 – 4.17 | 42.12% | 14d |

**Note:** At the time of writing, there is no information available involving COVID-19 policies specific to vaccines and KAP.

The progress of scientific research is also of vital significance for policy-making (Gortmaker et al. 2011; Youtie et al. 2017) and promotes the adaptive adjustment of policies (Wise et al. 2014). In the first two months after announcing the pandemic situation, the Chinese government adjusted its *Diagnosis and Treatment Protocol* seven times and revised its *Protocol for Prevention and Control* six times. The data indicate that the increased focus on some items preceded the release time of relevant policies or guidelines (Table 2), and some of the studies examined here explicitly suggested that their research results be used to guide policy. For example, Gao (2020) proposed in papers published on February 4 and February 19, respectively, that chloroquine is an effective treatment for COVID-19, and he suggested that chloroquine be included in the Diagnosis and Treatment Protocol.

The *Diagnosis and Treatment Protocol of COVID-19 (Trial Editions 6 and 7)*, released on February 19 and March 4, respectively, both included chloroquine as a recommended drug. Later, with the further enrichment of clinical trial data on chloroquine, the *Notice on Adjusting the Usage and Dosage of Chloroquine Phosphate in Treating COVID-19 on a Trial Basis*, published on February 28, 2020, further adjusted the usage and dosage recommendations for chloroquine. In addition, "masks", "universities", "asymptomatic diseases", "asymptomatic infection", and "plasma" also showed similar time differences between the stage of rising heat of an item and the release of relevant policies or guidelines (see Table 2). Thus, the research foci identified in this study affect the formulation of COVID-19 policies and guidelines in China. The Chinese government also introduced overseas research results into its policies and guidelines at the early stage. For example, the *Guidelines on the Survey and Management of Close Contacts of COVID-*

*19 Cases* defined the time limit of close contacts as 4 d before onset; this was based on a paper on onset spacing by a Japanese researcher (Nishiura et al. 2020).

**Table 2:** Stages of rising heat for different items in China's COVID-19 research and release dates of relevant policies and guidelines

| **Item** | **Stage of rising heat** | **Relevant policies or guidelines in early stage** | | **Relevant policies or guidelines in late stage** | |
|---|---|---|---|---|---|
| | | Name | Release date | Name | Release date |
| Chloroquine | 2.17 - 2.27 | *Diagnosis and Treatment Protocol of COVID-19 (Trial Version 6)* | 2.19 | *Notice on Adjusting the Usage and Dosage of Chloroquine Phosphate in Treating COVID-19 on a Trial Basis* | 2.28 |
| Mask | 2.17 - 3.18 | *Notice on Issuing the Technical Guidelines on the Selection and Use of Masks used for Prevention and Control of COVID-19 in Different Populations* | 2.5 | *Notice on Issuing the Guidelines on the Scientific Wearing of Masks* | 3.18 |
| University | 3.18 - 3.28 | *Notice on Conducting Scientific and Precise Prevention and Control of COVID-19 according to Law* | 2.25 | *Notice on Issuing the Technical Guidelines on Prevention and Control of COVID-19 in Institutions of Higher Learning* | 4.14 |
| Asymptomatic disease | 2.17 - 3.8<br>3.28 - 4.7 | *Protocol for Prevention and Control of COVID-19 (Trial Version 3)* | 1.25 | *Code for Management of Asymptomatic Carriers of SARS-CoV-2* | 4.6 |
| Asymptomatic infection | 2.27 - 3.8 | | | | |
| Isolation relief | 2.27 - 3.8 | *Diagnosis and Treatment Protocol of COVID-19 (Trial Version 6)* | 2.19 | *Diagnosis and Treatment Protocol of COVID-19 (Trial Version 7)* | 3.4 |
| Plasma | 2.27 - 3.8 | *Diagnosis and Treatment Protocol of COVID-19 (Trial Version 6)* | 2.19 | *Notice on Issuing the Scheme of Clinical Treatment Using the Convalescent Plasma of COVID-19 Survivors (Trial Version 2)*[13] | 3.4 |

[13] By June 1, 2020, the *Notice on Issuing the Protocol of Clinical Treatment Using the Convalescent Plasma of COVID-19 Survivors (Trial Version 1*) was no longer available on the official website of China's National Health Commission.

## 4.Conclusions and Discussion

### 4.1 Trend variation characteristics of China's COVID-19 research

Considering that scientific research is a process of solving problems and resolving disputes, the following conclusions can be drawn from this study. First, a series of new issues emerged in the late stage of the COVID-19 pandemic with regard to children, severe symptoms, and antibody assays. Second, vaccines and mental health have remained under-researched in China's fight against COVID-19, and the sensitivity and specificity of nucleic acid tests still need to be improved. Third, there are still disputes about the characteristics of SARS-CoV-2 infection in pregnant women, such as whether vertical transmission is possible. Finally, with the continuous accumulation of experience in treating general patients, consensus has been reached on common symptoms and on some drugs.

In their review of the existing global COVID-19 literature, Haghani et al. (2020) discovered that most studies have focused on drug safety, vaccine safety, the safety of pregnant women, and safety issues related to mental health. This study supports these results, suggesting that interest in these issues is shared by countries across the globe. However, different countries are known to face different challenges with regard to COVID-19, such as the problem of imported cases in Europe and China over different periods of time. The EU emphasized imported cases in late January while China did so after March.

### 4.2 Application of the CEM to the formulation of COVID-19 policies

There are continuous interactions between science and policy-making. In a study by Stine (2009), the effects of policies on scientific research are referred to as Policy for Science. The effects of science on policies are referred to as Science for Policy. The effects of policies on scientific research have been examined in many studies. These include the ways in which policies provide application-oriented research directions for science (De Jong et al. 2015), how they affect the pace of variation of technological systems (Edmondson et al. 2019), and how they accelerate the utilization of discoveries (Morrison and de Saille 2019). The formulation of policies requires the involvement of scientific research, especially during scientific emergencies (Hegger et al. 2020). These relationships between science and policy underscore the fact that scientific knowledge should be effectively reflected in policies (Gluckman 2016).

Policy-making and scientific research are both gradual processes. Scientific research is the practice of resolving scientific disputes (Dunlop and Veneu 2019) and aims to approach the truth (Anderson et al. 2009). Given that policies are usually a step behind technological development, it is necessary for them to be constantly updated (McLaren and Markusson 2020) or to be given adaptive adjustments in response to emerging issues (Wise et al. 2014). While policy-makers rely on the participation of other parties concerned with the dynamic adjustment of policies, scientists within the same socio-technological circles need to maintain continuous interactions with policies (Turnheim et al. 2015; Edmondson et al. 2019). Policies are also an important tool for social public management (Gortmaker et al. 2011). In the face of a public health emergency, policies need to coordinate efforts to combat COVID-19, and this includes scientific research. The process of gradual changes in policy and research reflects their mutual interaction. In the

fight against COVID-19, scientific research and policy formulation serve the same goal, and this fact underlies their interactions.

The interactions between COVID-19 policies and guidelines on the one hand, and scientific research on the other, in the early stage of the outbreak in China reflect the co-evolutionary model (CEM) of policy-making. The CEM is a nonlinear model, one of four models used to understand the formulation of science policy (Zwanenburg and Millstone 2005; Wan et al. 2020). Under this model, scientific research and policy formulation interact with each other in social, political, and cultural contexts that affect the final form of the policies (Zwanenburg and Millstone 2005; Wan et al. 2020). Interactions between scientists and policymakers can also be regulated by boundary actors (White et al. 2010). The CEM is regarded as the best model for effectively capturing the interactions between science and policy-making (Gallardo et al. 2018). As seen in Table 1, there is an overlap between the increases in focus on the five clusters and the release dates of relevant policies and guidelines. In Table 2, the focus on some items falls before, and for other items falls after, the release dates of relevant policies and guidelines. This indirectly proves the CEM's relevance to the formulation of COVID-19 policies in the early stage of the pandemic in China.

In the past, China tended to adopt another of the four linear models, the decisionist model, in formulating science and technology policies. Chen and Naughton (2016) summarized the formulation process of technological industrialization policies in China as follows: the initial policy fermentation stage is dominated by politicians, and experts or think tanks are invited to play certain roles in the late fermentation stage and the formulation stage. The role played by the CEM in the formulation of COVID-19 policies and guidelines suggests that this model is applicable to public health emergencies. According to Edmondson (2019), the interactions between science and policies in the CEM are also affected by external factors such as catastrophic events. As discussed above, in the early stage of the pandemic, China quickly released COVID-19 papers, policies, and guidelines to respond to the changing pandemic situation. Therefore, the CEM progresses rapidly in public heath emergencies, especially in the early stage. This is different from its progress in the formulation of climate change policies, where it has proven difficult to reach a consensus between scientists and government officials even after much discussion (Watson 2005; Humphreys 2009).

### 4.3 Limitations and prospects

This study has limitations with regard to sample selection and research cycle delineation. Some COVID-19 policies and guidelines adopted in the early stage of the outbreak in China were no longer available when writing this paper, and this may introduce inaccuracies into our conclusions. The timescale of this study was about 4 months; future studies may find it profitable to use a longer timescale. Ten days was adopted as the base time interval to investigate variations in research trends, but there may be other, better division schemes. It is important to deepen our understanding of how the CEM plays out in policy formulation during public health emergencies. In addition, this study found that the research trends for some items, usually of short-term significance, were affected by topical events. Science has been described as a process of social construction (Zimring 2019). We have discussed the research interest in the

item “Beijing”, and similar variations can be observed in the interest in “anatomy” and “forensic pathology”. On February 16, 2020, surgery was performed on the first COVID-19 patients in China, after which the interest in “anatomy” and “forensic pathology” immediately began to rise. Thus, topical issues affect scientific research in certain ways, and the specific effects can be explored in future studies.

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# Figures

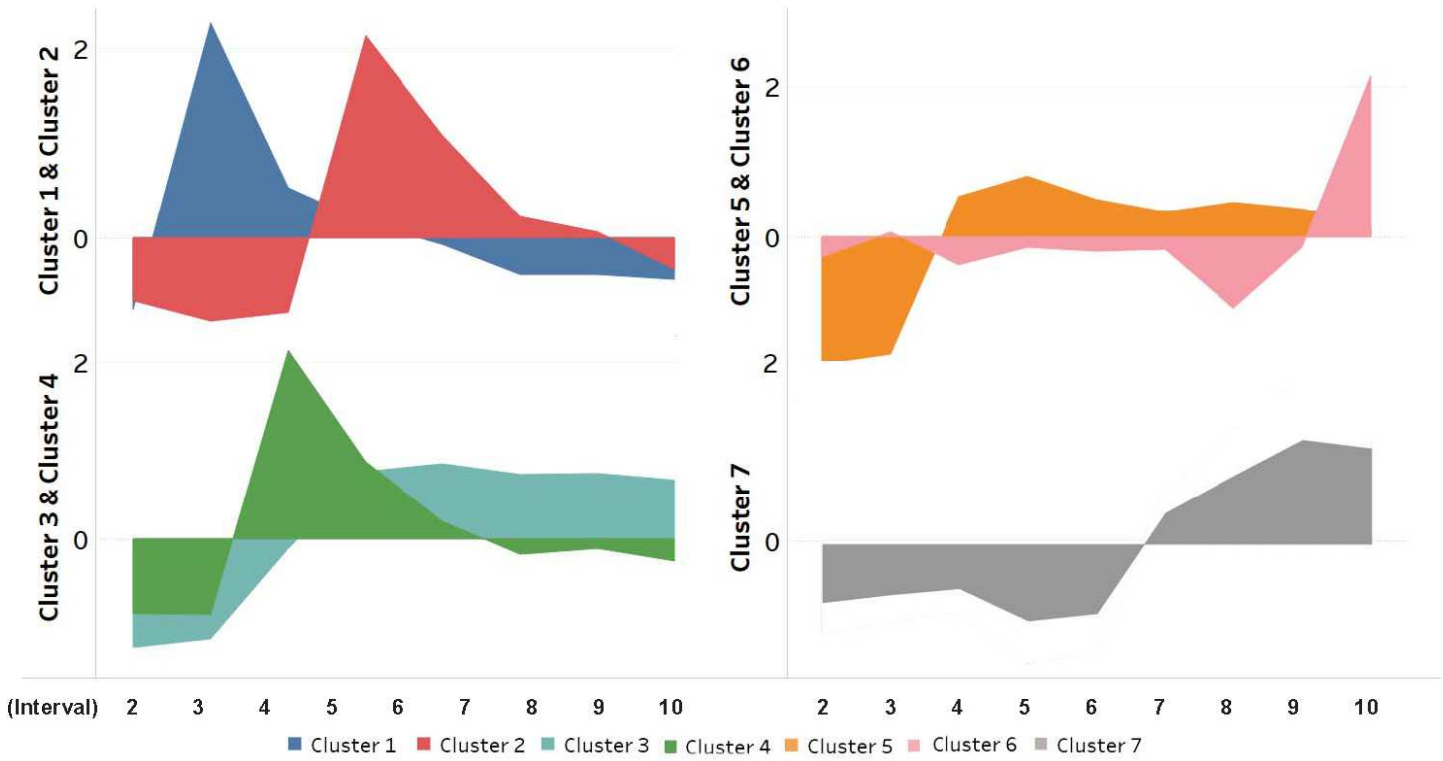



**Figure 1**

Heat variation trends of different clusters across different intervals

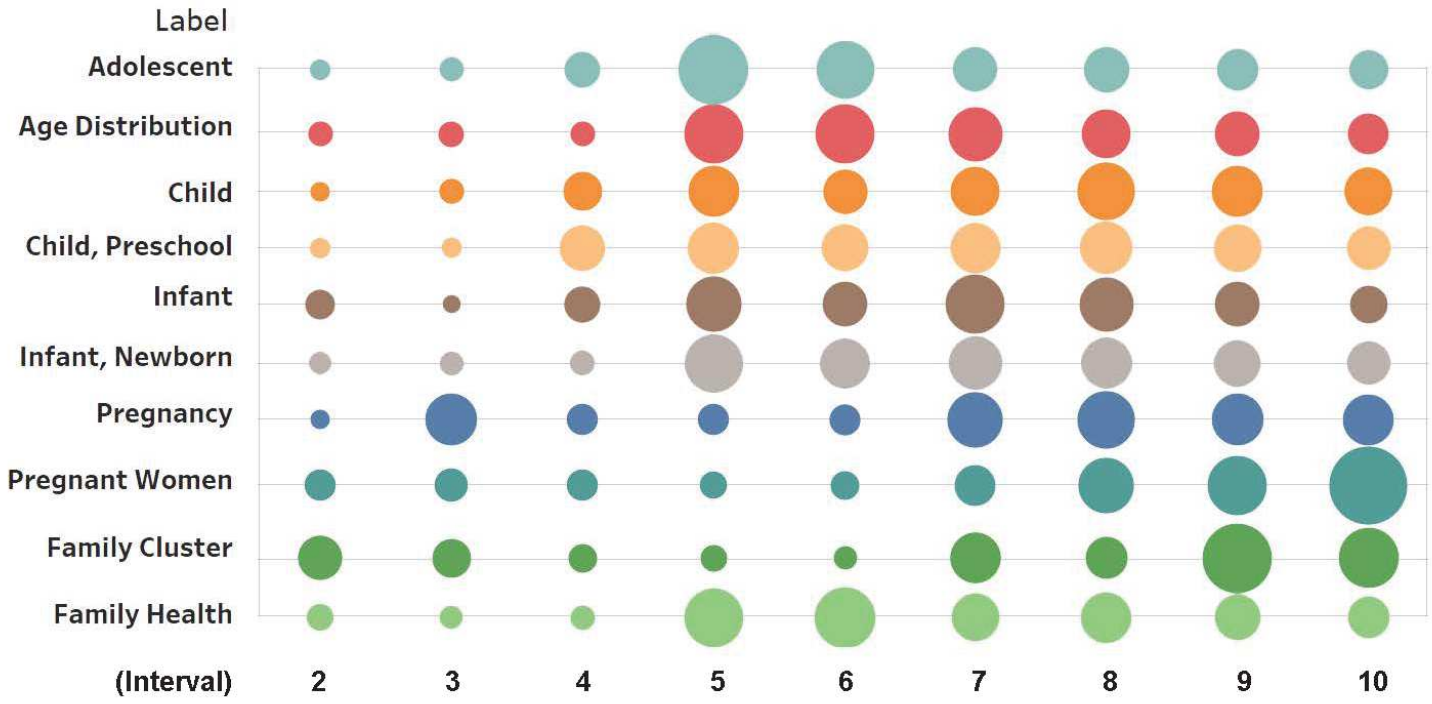



**Figure 2**

Heat variation trends of items related to children and pregnant women across different intervals

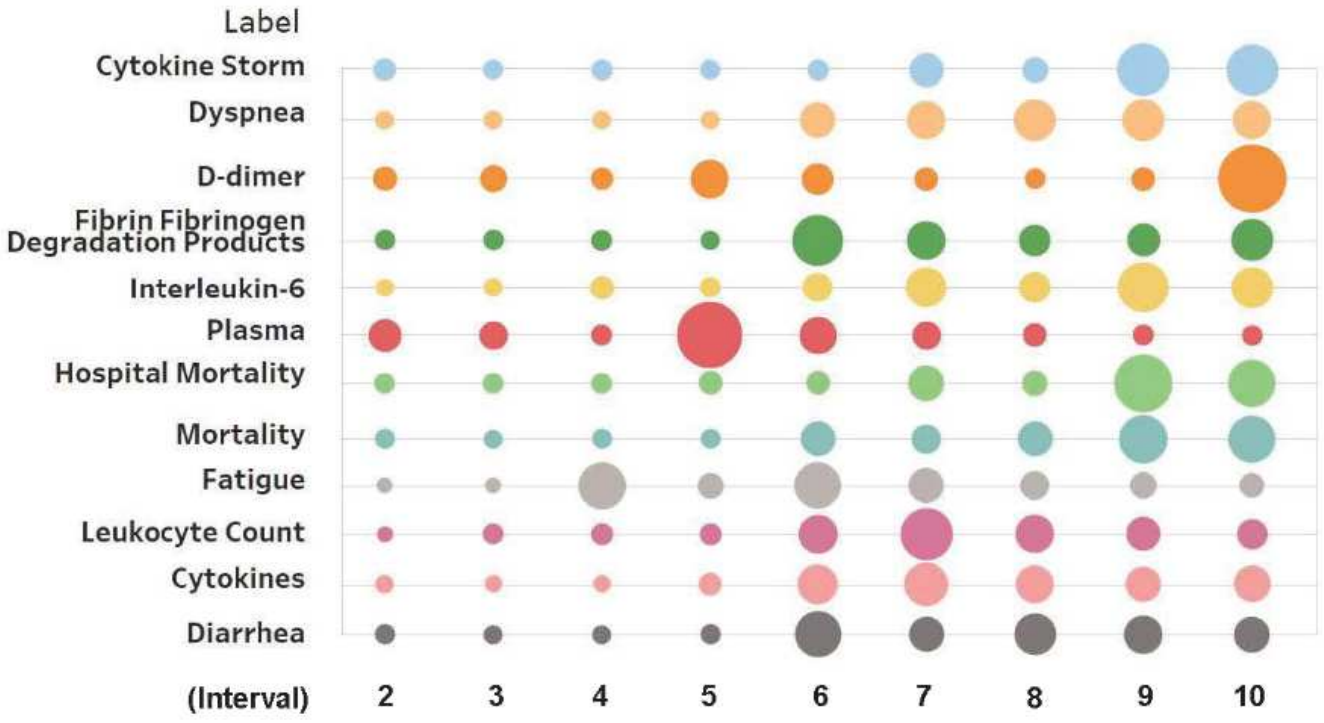



**Figure 3**

Heat variation trends of items related to symptoms across different intervals

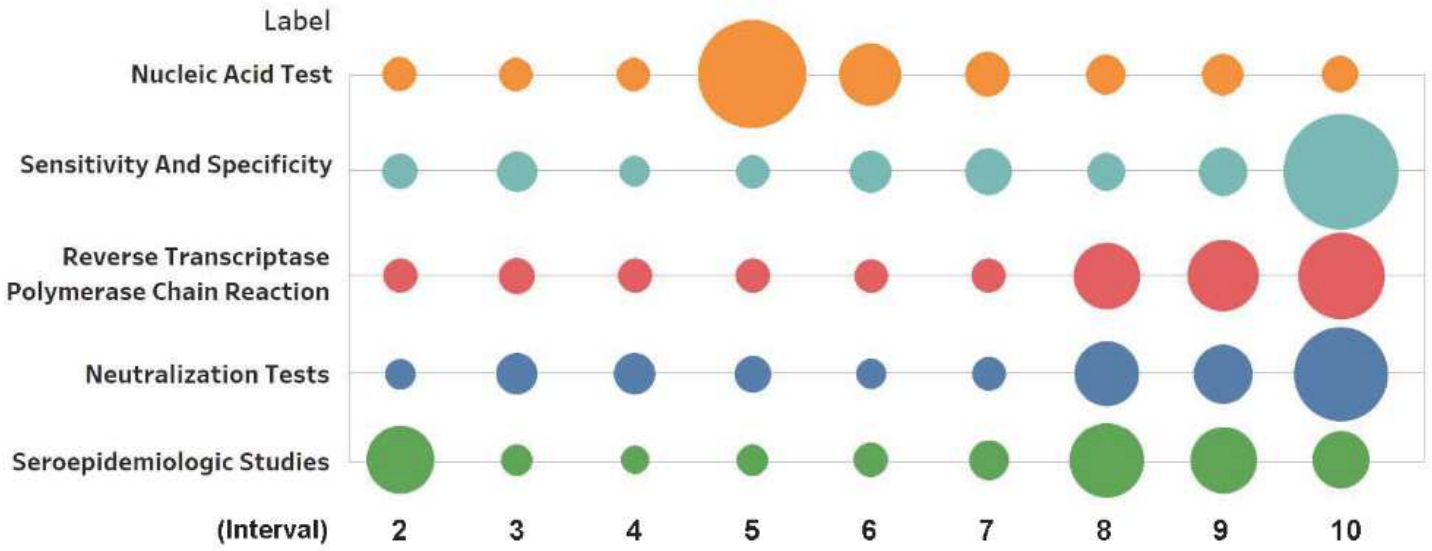
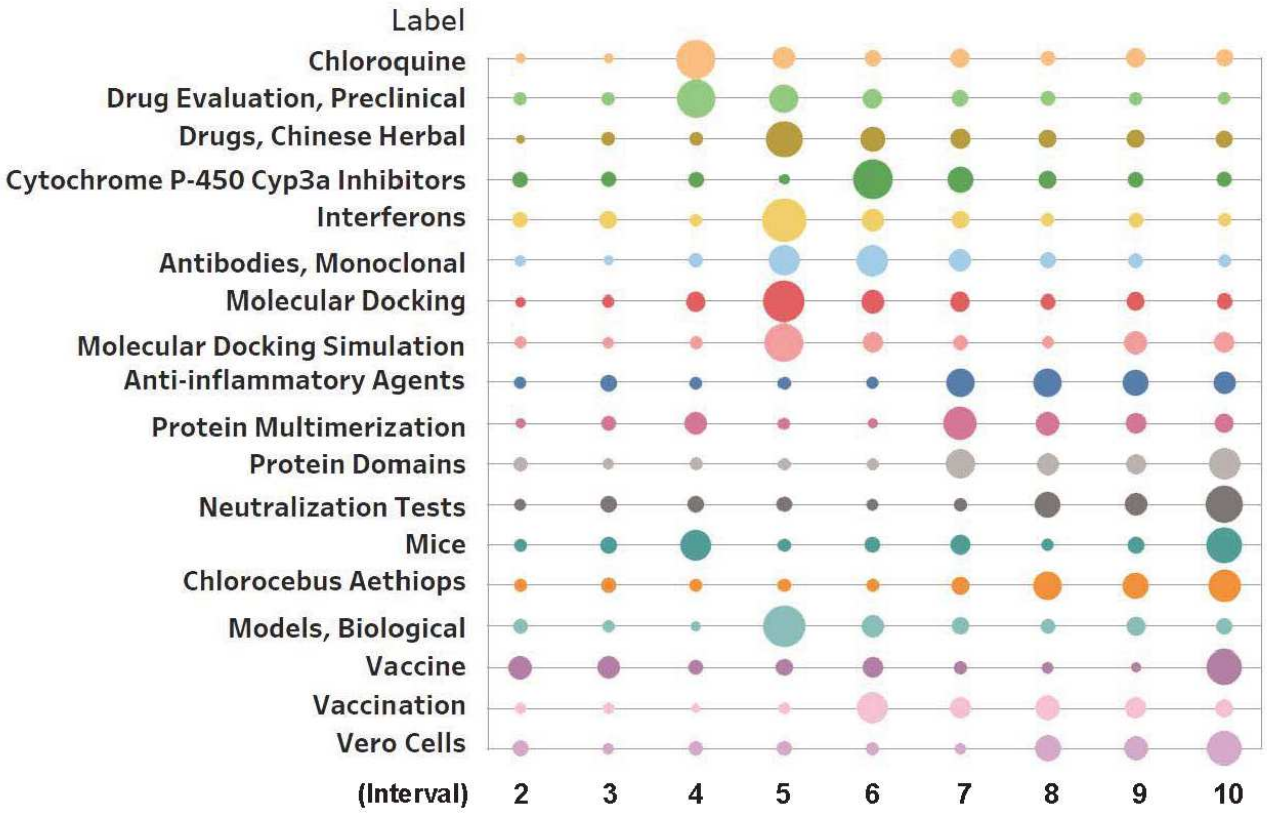



**Figure 4**

Heat variation trends of items related to virus testing across different intervals




## Figure 5

Heat variation trends of items related to candidate therapies and vaccines across different intervals

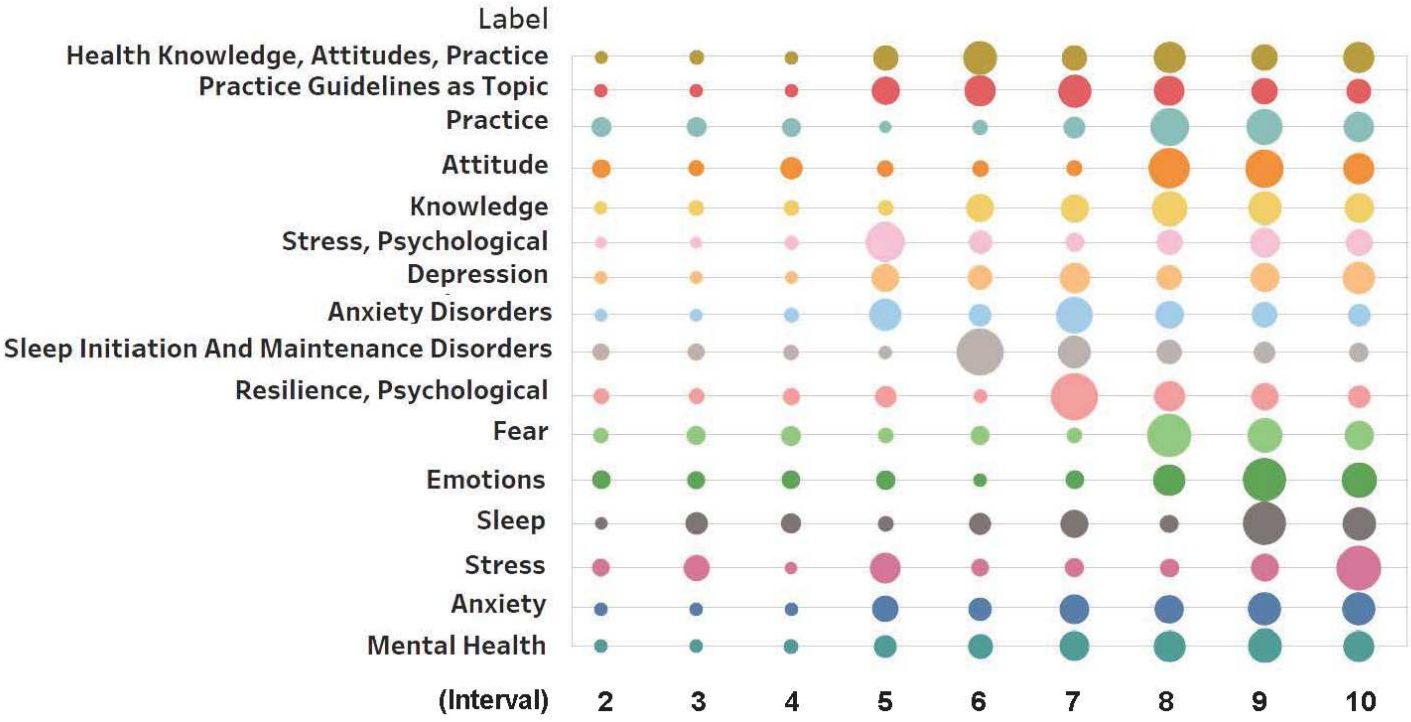



**Figure 6**

Heat variation trends of items related to cognition, psychology, and mental health across different intervals

# Supplementary Files

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- 01SupplementaryMaterials.pdf