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Does the internet help governments contain the COVID-19 pandemic? Multi-country evidence from online human behaviour

Qi Zhang^{a,b}, Chee Wei Phang^c, Cheng Zhang^{b,*}

^a Party School of the Chengdu Committee of the Chinese Communist Party, Chengdu 610110, China

^b School of Management, Fudan University, Shanghai 200433, China

^c Business School, University of Nottingham Ningbo, Ningbo 315100, China

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ABSTRACT

The effectiveness of social distancing and other public health interventions for containing the COVID-19 pandemic has been demonstrated. However, whether and how Internet use behaviours can lead to enhanced self-protection and reduced transmission when considered in conjunction with behavioural interventions remains unclear. This study investigated the strength of effective Internet behaviours and its interaction with global public health interventions for controlling the COVID-19 pandemic. We conducted an econometric analysis of multisource infection and policy information, Internet behaviour, and meteorological information from worldwide in a 3-month period. People's Internet behaviours may contribute crucially to pandemic containment. Furthermore, they may help enhance the effects of public health interventions, particularly behavioural interventions. We discussed plausible mechanisms through which Internet behaviours reduce epidemic spread independently or in tandem with behavioural interventions. Further investigation into the heterogeneity of the interventions demonstrates Internet behaviour's significance in heightening the effects of difficult-to-implement, primitive crisis orientation, and specific objectives of interventions. Governments should recognise the importance of the Internet and leverage it in managing social crises. Our findings serve as a reference for the formulation of global public health policy. Specifically, the insights provided herein can facilitate the implementation of strategies for containing ongoing secondary outbreaks of COVID-19 or outbreaks of other emergent infectious diseases.

1. Introduction

COVID-19 is both a public health crisis and an information crisis. Considerable efforts are required to model and predict the threat of the spreading virus and its development pattern, especially in the absence of efficient solutions. Moreover, unreliable and low-quality information with potentially dangerous impacts might capture more attention from the public, contributing to mass hysteria and panic, noncompliance with precautionary measures, and unnecessary hoarding of medications (Banerjee & Meena, 2021). Thus, many issues of direct relevance to the information science field remain unresolved (Xie, Zang, & Ponzoa, 2020). One such concern is the role of the Internet in interventions. When the public faces uncertainties arising from the pandemic spread, access to up-to-date information on the latest developments and precautionary measures is necessary for easing anxiety and facilitating self-protection. When the pandemic spread is rampant, informed individuals

adopt measures to protect themselves more readily than uninformed individuals (Chen, Min, Zhang, Wang, & Evans, 2020). In this regard, the Internet may serve as an effective channel through which instant access to information is provided.

For its convenience and ubiquity, the Internet may exert negative effects on public awareness during a pandemic through a mechanism called an *infodemic*. This phenomenon is defined as an overabundance of information that makes it difficult for people to find trustworthy sources and reliable guidance when they need it (Islam et al., 2020; Islam et al., 2020). Spreading false or misleading information may prevent the timely and effective adoption of appropriate behaviours and public health recommendations or measures (Waszak, Kasprzycka-Waszak, & Kubanek, 2018). Moreover, relatively often, the propagation of such information reinforces multiple and conflicting mental models of virus conspiracies (Bunker, 2020). Although the role of Internet use in this context has been acknowledged and discussed from both academic

* Corresponding author.

E-mail addresses: zhangqi18@fudan.edu.cn (Q. Zhang), CheeWei.Phang@nottingham.edu.cn (C.W. Phang), zhangche@fudan.edu.cn (C. Zhang).

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(Alamsyah & Zhu, 2021; Al-Surimi, Khalifa, Bahkali, EL-Metwally, & Househ, 2017; Bunker, 2020; Galaz, 2009; Sharma, Yadav, Yadav, & Ferdinand, 2017) and practitioner perspectives,^{1,2} empirical evidence of its complex roles as a contributor to pandemic spread is lacking. Some studies have found a positive association between the onset of pandemic spread and Internet use behaviours (Chiou & Tucker, 2020; Effenberger et al., 2020; Kummitha, 2020). However, whether and how Internet use can strengthen or reduce self-protection and lower transmission risk, when considered in conjunction with behavioural interventions, remains unclear. Herein, effective Internet use refers to counterinfodemic Internet use. Conversely, ineffective Internet use subscribes to the existence of an infodemic.

Although studies have confirmed the effectiveness of various government interventions during COVID-19 outbreaks (Kraemer et al., 2020; Tian et al., 2020), few have examined the combined effects of such interventions and Internet use. The central research question of this study is: How does public Internet use operate alongside intervention policies to slow pandemic spread? We postulated that the mechanism governing the Internet use–intervention policy association can be explained from the social learning theory perspective, which views human behaviour in terms of continual interactions between cognitive, behavioural, and environmental influences (Bandura & Walters, 1977). Behaviour is learned and updated through interaction with and observation of others. We predicted that Internet use would exert the opposite effects on pandemic spread.

We employed an econometric model with a quasi-experimental design as a basic setup to assess the association between the effects of intervention policies and the joint effects of Internet use across countries. Specifically, we assembled a unique data set containing information on Internet usage from M-lab,³ a worldwide network diagnostics website, Internet search data from Google Trends,⁴ and behavioural intervention policy data, as well as data on daily confirmed cases on 100 countries. The primary dependent variable in the base model was the ratio of the number of newly confirmed cases to the total number of confirmed cases in the previous day (*Confirmrate*). We used a time-varying variable, *Sum_Intensity*, to represent the number of interventions each country implements on each day. On the basis of these variables, we constructed a panel model under the interrupted time series framework (Cavusoglu, Phan, Cavusoglu, & Airoidi, 2016), which enabled the analysis of how Internet use may operate alongside intervention policies in slowing pandemic spread. Furthermore, we explored various types of interventions and exploited the heterogeneous joint effects of Internet use. Our quantitative results revealed that effective Internet use significantly reduced pandemic spread, whereas ineffective Internet use exerted a negligible effect. Focusing on offline policies and online information diffusion over a specific period, our analysis highlighted the potential interactions between online and offline behaviours during a crisis. Regarding the heterogeneity of interventions, effective Internet use significantly strengthened the effects of difficult-to-implement, primary crisis orientation and interventions with specific objectives.

The contributions of this study can be categorised as follows. First, we identified the mechanisms of Internet use in tackling the COVID-19 global health crisis. The extent to which a society feels threatened by uncertain attempts to retrieve information also affects the response of that society to the COVID-19 pandemic. Second, we employed social learning theory in a cross-country context, observing that Internet use moderates policy effects consistently across countries. Third, the

findings enrich the stream of research on public health crisis management in extending the context to Internet use in general.

2. Literature review

2.1. Internet use and health crisis management

Relatively few studies have directly examined Internet use in health crisis management. Notably, Pierewan and Tampubolon (2014) reported that individual Internet use was not associated with well-being but was during periods of crisis. Social media, applications that enable people to share information through the Internet, constitute an indispensable part of Internet use (Denecke & Atique, 2016). The role of social media in health crises and emergencies has garnered intense interest (Alexander, 2014; Chen et al., 2020; Elbanna, Bunker, Levine, & Sleigh, 2019; Oh, Agrawal, & Rao, 2013). As Alexander (2014) summarised, social media fulfils three functions: listening, monitoring, and integration into emergency planning. Studies have confirmed that social media provides easy access to health-related information, empowering the public to evaluate relevant risks and manage global health concerns (Alexander, 2014; Soroya, Farooq, Mahmood, Isoaho, & Zara, 2021; Yu, Li, Yu, He, & Zhou, 2021). For example, Twitter has been used to disseminate information on the number of casualties and the amount of damage sustained during Zika crisis, as well as educational content. (Glowacki, Lazard, Wilcox, Mackert, & Bernhardt, 2016). In response to global public health crises, social media users typically produce and share health-related information available through local and international sources (Abbas, Wang, Su, & Ziapour, 2021). Healthcare professionals and governments can leverage social media to contain and manage the adverse consequences of public health crises (Ho, Chee, & Ho, 2020). These studies have focused on how social media has been used by emergency managers and government agencies (Lindsay, 2011) to facilitate effective communication. Specifically, examining the types of interpersonal communication during health crises serves as a reference for organising information exchange on the basis of social media (Gong & Ye, 2021).

The role of social media in the ongoing COVID-19 pandemic has mostly been observed at the individual level (e.g. Farooq, Laato, & Islam, 2020; Kim & Hawkins, 2020; Oh, Lee, & Han, 2020). A global view of its role at the national level is lacking. Moreover, the contributions of websites, online search, and other Internet-based channels through which information is accessed should be investigated. Considering its continual growth, including innovative developments such as contact tracing applications, the Internet plays an increasingly relevant role in disaster management. Kavanaugh et al. (2012) presented recommendations for governments to improve their services and enhance communication with the public. There is an increasing demand for a thorough understanding of the role and type of the general Internet use.

The potential of the Internet to convey accurate health-related information and advice has not yet been fully realised. Recent publications in the health crisis management literature have examined information from social media but have ignored their joint effects with offline interventions (Abbas et al., 2021; Alexander, 2014; Soroya et al., 2021; Yu et al., 2021). Integrating online and offline data is critical for determining the interdependence between policy and online information, which in turn facilitates the development of effective targeted interventions during crises (Feng & Kirkley, 2021). Moreover, integrating online behaviours with offline data can provide more practical insights into predicting and controlling crisis situations (Feng & Kirkley, 2021). Therefore, the first specific research question of this study is as follows: How can online information complement offline interventions during a health crisis?

2.2. Social learning and the infodemic

Social learning theory can be referenced to explain how Internet use

¹ <https://cio.economicstimes.indiatimes.com/news/next-gen-technologies/covid-19-8-ways-in-which-technology-helps-pandemic-management/75139759>

² <https://www.weforum.org/agenda/2015/06/4-ways-technology-can-help-fight-future-epidemics/>

³ <https://www.measurementlab.net/>

⁴ <https://trends.google.com/trends/>

may contribute to pandemic development. According to [Bandura and Walters \(1977\)](#), human behaviour is learned through interaction with and observation of others in a social context. The human learning process is promoted progressively. First, something in the environment captures a person's attention. The person remembers what was noticed and acts under the influence of that element. The environment eventually provides a consequence, either reward or punishment, which changes the probability that the action will be repeated. Research on social learning theory has been gradually extended to global contexts, but relevant studies remain scarce. For example, [Liu and San \(2006\)](#) explored international digital divides from the social learning perspective, observing that a country with more favourable social learning can reduce heterogeneity among its population and facilitate technological diffusion. [Haas \(2000\)](#) identified institutional properties that facilitate or inhibit social learning in the management of global environmental risks by international institutions.

Under social learning theory, people who actively or passively receive relevant information regarding a crisis through the Internet tend to realise the urgency and importance of intervention policies. A deeper understanding of the motivation behind and efficacy of an intervention leads to greater compliance. During the ongoing COVID-19 pandemic, the Internet, or information technology communication in general, has enabled people to work and study from home, enhancing social connectedness and providing greatly needed entertainment ([Sun et al., 2020](#)). Moreover, researchers have argued that the Internet 'helps prevent the spread [of the pandemic], educates, warns, and empowers those on the ground to be aware of the situation, and noticeably lessen the impact.'¹ In particular, the Internet provides people with instant access to pandemic-related information. Individuals who are able to complete tasks at work or in their daily lives through digital communication (rather than relying heavily on physical contact) may experience relatively little difficulty in adapting to interventions such as quarantine and social distancing. Notably, Internet-related practices suggest that governments can increase public awareness by disseminating pandemic-related information through social media and websites ([Chen et al., 2020](#); [Farooq et al., 2020](#)).

Regarding ineffective Internet use, the negative side of the Internet involves noise and false information. Specifically, when an emergency or crisis occurs, human communication activity is largely characterised by the production of informational noise and even misleading or false information ([Rapp & Salovich, 2018](#)). Therefore, the government and public are fighting against not only a pandemic but also an infodemic—the rapid and far-reaching spread of questionable information. Infodemic effects proliferate when credible information sources fail to capture the attention and trust of some sectors of the public. These effects then generate large amounts of unreliable and low-quality information with potentially dangerous impacts on society's capacity to respond adaptively to the crisis ([Waszak et al., 2018](#)). In the absence of the rapid adoption of pandemic containment regulations and behaviours, ineffective Internet use can contribute to mass hysteria and panic, noncompliance with precautionary measures, and unnecessary hoarding of medications. As social learning theory indicates, individuals who consume information under ineffective Internet use might follow and comply with the false instructions to treat the virus. For example, false or misleading news may lead to refusal to adhere to precautionary measures among the general population. People might unthinkingly overestimate the risk of disease spread as well as underestimate the possibility of timely intervention ([Bonneux & Van Damme, 2006](#)). During crises, the primitive part of the brain usually becomes more prominent, prompting individuals to engage in behaviours necessary for survival⁵. However, rumour-led behaviours are often risky and can even be life threatening. Furthermore, they can exacerbate pandemic

situations. Studies have centred on ineffective Internet use; effective Internet use has yet to be examined ([Bunker, 2020](#); [Islam, Sarkar, et al., 2020](#); [Islam, Sharp, et al., 2020](#); [Zarocostas, 2020](#)). Herein, we presented the importance of effective Internet use (as a measure of information quality) in curbing pandemic spread at the national level. Therefore, we investigated the following research question: How do the infodemic and counterinfodemic phenomena affect pandemic spread?

2.3. Interaction between internet use and intervention policy

(1) Intervention Policy and Pandemic Spread

Numerous studies have confirmed that government interventions during pandemic outbreaks are critical to the protection of public health (e.g. [Li et al., 2020](#); [Munster, Koopmans, van Doremalen, van Riel, & de Wit, 2020](#); [Paules, Marston, & Fauci, 2020](#); [Tian et al., 2020](#); [Wu, Leung and Leung, 2020](#)). During such crises, containment policies such as travel restrictions, quarantine, and social distancing are implemented to minimise potential contact between the infected and the uninfected. Governments have also introduced various nonpharmaceutical measures that have been largely overlooked in the literature, including the provision of financial support to medical equipment manufacturers and pharmaceutical companies; price gouging reductions; and providing psychological counselling services to the public ([Ragonnet-Cronin et al., 2021](#)). These measures may restore economic and social order, thus enhancing social support and the ability of the healthcare system to control the outbreak. They may also raise public morale.

Thus far, most investigations evaluating intervention policies against COVID-19, particularly empirical studies (e.g. [Hsiang et al., 2020](#)), have been limited to a few countries. Understanding of such interventions on a global scale is warranted. For example, [Wu et al. \(2021\)](#) explored three distinct COVID-19 response strategies adopted by eight countries, concluding that aggressive containment was the optimal approach to limiting the loss of lives and livelihoods. [Duhon, Bragazzi, and Kong \(2021\)](#) employed multiple regression to reveal correlated predictors of COVID-19 spread, observing a strong association between climatic variables and the initial growth rate of COVID-19. [Chernozhukov, Kasahara, and Schrimpf \(2021\)](#) empirically examined the impacts of a behavioural policy impact in the United States. Pandemic research from cross-country perspectives is pivotal. Moreover, the heterogeneity among intervention policies merits comprehensive analysis. Three undervalued characteristics, namely difficulty of implementation, policy objectives, and primary or secondary crisis orientations, are discussed in the following section.

(2) Joint Effects of Internet Use and Intervention Policy

Internet use may affect epidemic spread independently or in tandem with behavioural interventions through several plausible mechanisms. First, as social learning theory suggests, public participation can initiate the learning process, which translates uncoordinated actions into collective actions. [Bandura and Walters \(1977\)](#) emphasised the importance of acquiring new knowledge and skills by paying attention, retaining the information absorbed, reproducing the observed behaviour, and being motivated to continue the newly learned behaviour. Through this process, individuals may acquire information regarding policy changes at the national level in a social context ([Stagl, 2006](#)). This is essential for understanding public interventions and concerns during the crisis and for simultaneously minimising public panic, fear, and anxiety. Researchers have noted that the Internet can help improve the capacity of government agencies to process crisis-related information and provide public services ([Chatfield & Reddick, 2017](#); [Graham, Avery, & Park, 2015](#)). This line of reasoning also applies to accurate online information from credible sources.

Second, Internet use may facilitate a learning process such as that described by social learning theory. For example, individuals might

⁵ <https://www.businessinsider.com.au/why-people-are-panic-bulk-buying-during-the-coronavirus-pandemic-2020-3/amp>

acknowledge, follow, and learn from the cautious behaviours of fellow Internet users, such as those who express their concerns about going outside and who limit such ventures during pandemic times (Cai, Chen, & Fang, 2009). Thus, the effectiveness of government interventions can be enhanced. Furthermore, greater Internet use during pandemic times leaves less time and opportunity for interpersonal contact offline, thus reducing transmission risk. The search for relevant information from the Internet enables the public to learn more about the situation of an epidemic or pandemic and to become more aware of its severity and self-protection measures. With the understanding of the rationales for interventions such as social distancing, the public may also be more likely to comply with relevant requirements. In addition, due to the dissemination of information through the Internet, the larger the proportion of the population that gains access to pandemic-related information, the higher the likelihood that the remainder of the population will also become aware of interventions and related information is. Repetitive exposure to information regarding intervention policy familiarises individuals with relevant policy guidelines, promoting sustained compliance with the intervention (Barabas & Jerit, 2009).

Overall, because the Internet has become the most essential channel through which the public accesses information, awareness and engagement are crucial to pandemic containment. The effects of effective Internet use on pandemic containment merits investigation.

(3) Heterogeneous Effects of Internet Use on Various Intervention Policies

During a pandemic, governments implement various policies to contain the spread of disease. Such policies may be classified in distinct categories. McDonnell and Elmore (1987) designed a framework to delineate four categories of policies: mandates, inducements, capacity-building, and system-changing. They attempted to find a fit between problem and policy as well as basic conditions enabling successful policy implementation. Schneider and Ingram (1990) identified five categories of policies according to relevant behaviour restrictions: authority, incentives, capacity-building, symbolic and hortatory, and learning. Herein, we focused on variations in governments' response to the COVID-19 pandemic as well as on the conditions or boundaries of successful policy implementation. We assumed that each policy would possess unique features, among which the Internet gene might play an incremental effect. We addressed the following three characteristics relevant to the implementation of intervention policies.

a. Primary and secondary crisis orientation

The primary crisis caused by pandemics is the threat to people's health and lives. Social and economic crises (i.e. secondary crises) also occur. Home quarantine and workplace closure lead to the stagnation of economic activities, and travel restrictions and testing requirements might generate discontent from certain social groups. Therefore, we can categorise policies with the goal of government management: whether policies seek to resolve the crisis itself (i.e. the primary crisis) or the resumption of regular economic activities (i.e. the secondary crisis).

As mentioned, individuals rely heavily on the Internet for information access. Public awareness of the threat and impact of the pandemic, promoted through effective Internet use, is integral to their compliance with primary crisis-oriented containment policies. Regarding secondary crisis-oriented measures, given that only a small proportion of businesses can undergo virtualisation, the effect of Internet use may not be substantial.

b. Different Policy Targets

Howlett, Ramesh, and Perl (2009) divided policies into informational, economic, authoritative, and voluntary tools. On the basis of this framework, we followed Hale, Petherick, Phillips, and Webster (2020) in

classifying intervention policies into five categories: social distancing measures (SDE; e.g. public event cancellations and public transportation closures), financial measures (FIN; e.g. fiscal measures, monetary measures, emergency investment in healthcare, and investment in vaccines), closure measures (CLO; e.g. school and workplace closures), individual movement restriction (MOV; e.g. contact tracing and restrictions on domestic and international travel), and public information campaigns (INF).

Internet use might promote compliance with certain types of intervention policies. When the public is required to stay at home, information on suitable protective measures can be accessed through effective Internet use, thus reinforcing adherence to intervention policies and facilitating effective containment. However, fiscal measures are not linked to personal compliance.

c. Difficulty of implementation

The resources required and difficulty level of policy implementation may vary. The costs of achieving successful implementation are even higher for those involving large-scale group restrictions. Easy-to-implement policies, such as public information campaigns, fiscal measures, monetary measures, emergency investments in healthcare, and investments in vaccines, have a relatively limited scope and involve less public cooperation. Policies that are more challenging to implement, such as school and workplace closures, restrictions on domestic and international travel, contact tracing, public event cancellations, and public transportation closures, often necessitate public compliance. Furthermore, the logistics and coordination often involve substantial efforts.

The Internet can reduce the difficulty of implementing such challenging interventions. Through the social learning process, the public becomes aware of the pandemic situation and adheres to government measures accordingly. Thus, pandemic containment can be improved.

3. Materials and methods

3.1. Variables

COVID-19 situation in every country was measured over time from 22nd January, when the WHO officially reported the epidemic,⁶ to 20th April. To investigate the effect of public intervention, we considered the rate of newly confirmed cases (*Confirmrate*) as our primary dependent variable. *Confirmrate* was derived as the ratio of newly confirmed cases to the total confirmed cases in the last period. The cumulative number of COVID-19 was collected from a database maintained by Johns Hopkins University.

After a comprehensive search of potential factors influencing the pandemic trend, we also controlled for country-level fixed effects, concerning economics (Stojkoski, Utkovski, Jolakoski, Tevdovski, & Kocarev, 2020)- (including GDP per capita, GDP increase, income class), demographic and social (Maaravi, Levy, Gur, Confino, & Segal, 2021; Stojkoski et al., 2020)- (percentage of the population using mobile, individualism culture, unemployment and population density), governmental (Moon, 2020; Zhang, 2021)- (including government transparency, government responsiveness to change and CPIA economic management cluster average from World Bank), hygiene (Lakshmi Priyadarsini & Suresh, 2020; Stojkoski et al., 2020)- (including newborn death rate, Global Health Security detection index) and mobility (Balcan et al., 2009; Fang, Wang, & Yang, 2020; Kraemer et al., 2020)-related factors (including inbound and outbound traveler numbers), which were collected from United

⁶ We excluded China in this analysis since China conducted a nationwide public intervention on the first day, i.e. 22nd January, of the epidemic. This makes it a special case, and it is difficult to estimate the effect of the intervention amidst the development of the epidemic.

Table 1
Descriptive Information of the Variables.

Category	Variables	Definition	Mean	S.D.	Min.	Max.
Pandemic-related	1. Confirmrate (CR)	Ratio of newly confirmed cases to the total confirmed cases in the last period	0.19	0.47	-0.02	10
	2. Effective internet Use (EIU)	Effective internet information intensity	0.03	1.07	-1.41	7.76
	3. Effective Internet Search (EIS)	Effective internet search intensity	0.01	0.61	-2.17	1.97
	4. Sum_Intensity	The sum of the intervention policies	10.45	6.03	0	24
	5. Treat	If the country declared the emergency response on each day (yes = 1, no = 0)	0.64	0.48	0	1
Demographic	6. PCT_mobile	Percentage of using mobile among the population	26.57	40.35	0	99
	7. culture-individualism	The hofstede score on the dimension of individualism	42.84	21.64	6	91
	8. Unemployment	Unemployment rate	6.3	5.69	0	26.96
Economic	9. Population density	Population/Area	274.96	1062.31	0	7815.21
	10. GDP increase	Gross Domestic Product Increase	2.72	2.16	-2.48	7.95
	11. Income	Income from low to high, ranking from 1-4	3.1	0.96	0	4
Weather	12. GDP per capita	Gross Domestic Product per population	20,011.96	20,585.92	0	96,792.6
	13. Temperature	Temperatures of the day	60.9	17.04	2.6	93.5
Mobility	14. Precipitation	Precipitation of the day	0	0.06	0	1.99
	15. departure	Departures of non-resident tourists/visitors	9432.58	17,192.78	0	92,564
Hygiene	16. arrival	Arrivals of non-resident tourists/visitors	12,757.6	20,355.22	0	89,322
	17. deathrate_newborn	Infant mortality rate	8.72	9.21	0	33.5
Government	18. health_index	Global Health Security detection index (GHS)	47.43	13.59	20.9	71.1
	19. gov_respo_chang	Government's responsiveness to change, from The Global Competitiveness Index Dataset	3.83	0.85	1.43	6.11
	20. gov_trans	Government Transparency, from The Global Competitiveness Index Dataset	0.33	0.93	0	4.5
Policy Heterogeneity	21. gov_management	CPIA economic management cluster average, from World Bank Data	0.58	1.2	0	4
	22. SDE	The number of Social distancing-type policies	1.99	1.50	0	4
	23. MOV	The number of movement restriction-type policies	4.36	2.20	0	7
	24. CLO	The number of closure-type policies	2.34	1.74	0	4
	25. FIN	The number of financial-type policies	0.62	0.56	0	2
	26. INFO	The number of information campaign-type policies	0.86	0.35	0	1
	27. EASY	The number of easy-to-implement policies	1.53	0.75	0	5
	28. HARD	The number of difficult-to-implement policies	9.85	5.27	0	18
	29. PRIM	The number of primary crisis-orientation policies	7.87	5.12	0	14
	30. SECD	The number of secondary crisis-orientation policies	2.58	1.92	0	10

Nations databases and World Bank Open Data. In this step, 63 countries are included in the dataset with all such information.

As the literature suggests that weather may affect human's physical behaviours (Hsiang, Burke, & Miguel, 2013; Scheffran, Brzoska, Kominek, Link, & Schilling, 2012) and epidemic development (Sajadi et al., 2020; Wang, Tang, Feng, & Lv, 2020), we collected countries' daily meteorological information, including temperature and precipitation (the two features have been repeatedly proved to affect the pandemic spread in Kubota, Shiono, Kusumoto, & Fujinuma, 2020 and Menebo, 2020). The data is retrieved from an online global weather website Wunderground.com.⁷ Overall, 58 countries with complete information are included in the dataset for analysis.

We utilized the network traffic and speed data as a proxy of Internet use intensity, which was provided by an opensource network diagnostic websites m-lab.⁸ In this study, we extracted daily Internet use intensity in the dataset using 546.8 million speed test measurements recorded from 144.6 million IPs over the past three-month period. Since the dataset provides network traffic throughput during the test period rather than the total information load, we calculated the effective data index on day t by

$$EffectiveInternetUse = \frac{1}{n} \sum_{i=1}^n Throughput_i * Fixedbroadbandsubscriptionsper * Population * Infodemic_index$$

where n is the sample size of a country. For explicitness, network throughput refers to how much data can be transferred from source to destination within a given timeframe. *Throughput* is computed for every server-to-client test as the ratio of the data transmitted during the test and the duration of the test. *Fixedbroadbandsubscriptionsper* measures the fixed broadband technology adopted by the population, expressed as the number of subscriptions per 100 inhabitants. To proxy for total Internet data, we rectified the measure with broadband capacity among all population. Additionally, *Infodemic_index*⁹ calculates the likelihood that a user endorses or engages with online messages pointing to potentially misleading sources. This index quantifies if and how users interact with circulating information. A high value of *Infodemic_index* means that a large number of users are interacting and retransmitting the potential mis-informative content, which reduces the information effectiveness. Table 1 and Table 2 provide a descriptive summary of the variables and correlation in this study.

Furthermore, we also consider a two-stage analysis to control for potential endogeneity between Internet information and policy interventions. For instance, countries with intervention strategies implemented may publish the information online, regarding the effectiveness

⁷ <https://www.wunderground.com/>

⁸ <https://www.measurementlab.net/>

⁹ <https://covid19obs.fbk.eu/#/>.

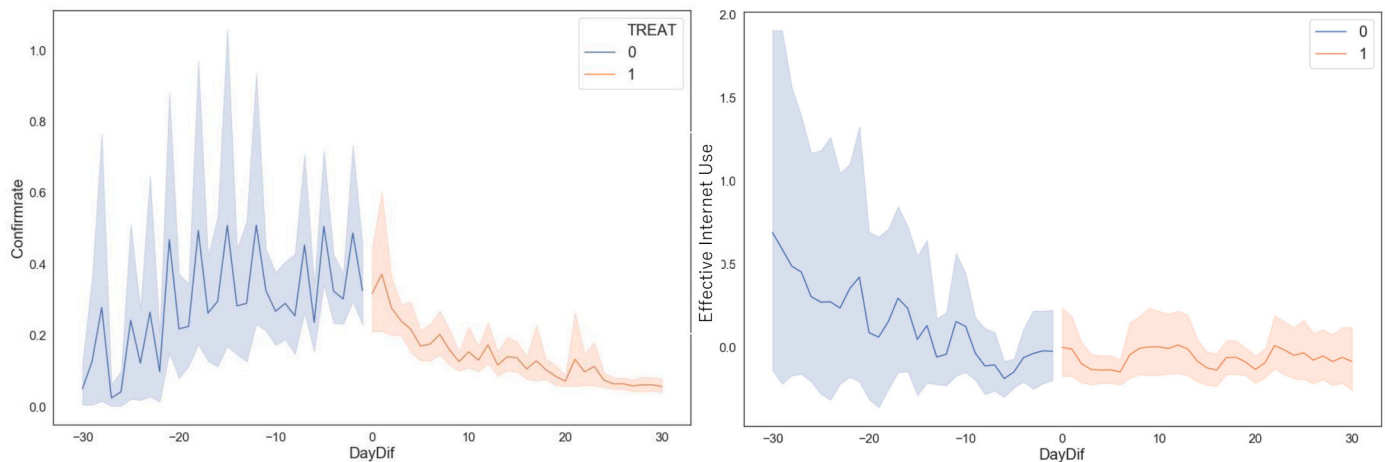


Fig. 1. Temporal variation of confirm rate and Internet usage 30 days before and after the countries implemented behavioural intervention policies. The horizontal axis shows the time intervals relative to the day of the intervention declaration. The vertical axis, from left to right, indicates extent of daily confirm rate and effective Internet Use, respectively, with 95% confidence intervals.

a comparison group. The main reason attributed to such strength is its control over the effects of regression to the mean (Campbell and Stanley, 2015; Linden, 2013). When the treatment group's outcomes can also be contrasted with those of one or more comparison groups, the internal validity is further enhanced by allowing the researcher to potentially control for confounding omitted variables (Linden, 2015). Moreover, it also possesses strong external validity, in that the unit of measure is at the population level or when the results can be generalized to other units, treatments or settings (Cook, Campbell, & Shadish, 2002; Linden, Adams, & Roberts, 2004). In this study, we follow Beck, Katz, and Tucker (1998) and Gottlieb, Townsend, and Xu (2016) to include the polynomial-time effects without sacrificing the degrees of freedom.

4. Results

4.1. Effects of internet use and intervention policies

We started by analyzing the effects of the behavioural intervention policies, since they are likely to show the most immediate effects on the epidemic spread. We used a time-varying treatment indicator *Treat*, with value 1 representing the dates after which the country declared the implementation of a behavioural intervention as an independent variable.¹⁰ Consistent with the recent research (Kraemer et al., 2020; Tian et al., 2020), the *Treat* variable holds negative significance in all models, showing strong power to contain the pandemic development. Since this analysis is not the core of this study, details are demonstrated in Appendix A1.

We then assess if the two-sided Internet use takes consistent effects during the pandemic. Column 1 in Table 3 reports that Internet Use, in general, can ease the pandemic spread ($Coef. = -0.0342, P\text{-value} < 0.1$). A deeper look at effective Internet Use reveals that it could significantly relieve the pressure of up surging virus spread ($Coef. = -0.00938, P\text{-value} < 0.1$), and it could reinforce the policy effects ($Coef. = -0.00746, P\text{-value} < 0.05$). However, the ineffective Internet Use demonstrates no statistically significant relationship with the pandemic ($Coef. = -0.00246, P\text{-value} > 0.1$). This finding is in accordance with our argument that effective Internet use could facilitate social learning and promote acceptance of plausible measures.

Furthermore, we investigate if the effective Internet use interact with

the intervention policies in influencing the spread of the COVID-19. The joint effects of Internet Use in general with the interventions are significant to reduce the spread ($Coef. = -0.0309, P\text{-value} < 0.01$). Column 4 in Table 3 reveals that the effective Internet information intensity decreases the confirm rate conjointly with public intervention ($Coef. = -0.00746, P\text{-value} < 0.05$). This implies that with the implementation of an intervention policy, the citizens' intense effective information can further mitigate the spread trend (i.e., increases due to interpersonal infections). This may be due to the fact that most intervention policies are non-pharmaceutical interventions, including isolation and social distancing (Wang et al., 2020), so that citizens' greater awareness and compliance from Internet Use may complement these policies and enhance their effectiveness. Furthermore, for the collective effects of the effective Internet use and intervention to manifest, there is a need for people to figure out how to combine home isolation with ways to live their online life more fruitfully (e.g., getting accustomed to online meetings), or to combine social distancing with ways to engage in safe interactions at a distance (e.g., wearing appropriate types of mask).

4.2. Heterogeneity of intervention policies

Table 4 summarizes the heterogeneity results and reveals the potential fit between effective Internet use and intervention policies implemented. Three categories of policies are examined in this section: policy objectives, difficulty of implementation and primitive-crisis orientation. These categories could provide important insights for policy makers. A comprehensive view of the Internet use and policy can inform the plausible fit to promote success.

As the results in Columns 1–5 suggest, effective Internet use could enhance social-distancing ($Coef. = -0.00455, P\text{-value} < 0.1$), closure-type ($Coef. = -0.00994, P\text{-value} < 0.001$), movement restriction ($Coef. = -0.00659, P\text{-value} < 0.01$) policies. The underlying logic is that effective Internet use could increase citizen's awareness and compliance behaviours through social learning, hence enhancing the policy effectiveness. In terms of the difficulty of implementation, it is indicated that effective Internet use is a great fit for difficult-to-implement policies ($Coef. = -0.00273, P\text{-value} < 0.01$). When fuzzy procedures and efforts are highly demanded for a successful implementation, taking advantage of the internet channel would pay off. For the orientation of the policy, we investigate the primitive and secondary crisis orientation. Result in Column 8 and 9 suggests the primitive-orientation policies could be complemented by effective internet use ($Coef. = -0.00197, P\text{-value} < 0.01$).

These results are consistent with our arguments in the Literature

¹⁰ Information about the intervention dates was gathered based on a search of the global and domestic news websites including the New York Times and CNN news.

Table 3
Internet use and its effects on pandemic spread.

VARIABLES	(1) CR	(2) CR	(3) CR	(4) CR	(5) CR
Internet Use (IU)	-0.0342* (0.0200)	-0.0408** (0.0203)			
Sum_Intensity	-0.00570 (0.00359)	-0.0102*** (0.00390)	-0.00570 (0.00359)	-0.00609* (0.00359)	-0.00534 (0.00359)
IU × Sum_Intensity		-0.0309*** (0.0108)			
Effective Internet Use (EIU)			-0.00938* (0.00509)	-0.0109** (0.00519)	
EIU × Sum_Intensity				-0.00746** (0.00347)	
Ineffective Internet Use (IIU)					-0.00246 (0.00352)
Departure	0.0551*** (0.0153)	0.0571*** (0.0155)	0.0535*** (0.0150)	0.0542*** (0.0152)	0.0505*** (0.0149)
Arrival	0.00407 (0.00808)	0.00735 (0.00826)	0.00352 (0.00784)	0.00605 (0.00802)	-5.84e-05 (0.00769)
Health_Index	-0.00138** (0.000593)	-0.00137** (0.000598)	-0.00160*** (0.000599)	-0.00168*** (0.000606)	-0.00149** (0.000600)
Deathrate_newborn	0.0409*** (0.00825)	0.0404*** (0.00823)	0.0408*** (0.00825)	0.0404*** (0.00824)	0.0413*** (0.00825)
Population Density	-0.00430 (0.00637)	-0.00445 (0.00644)	-0.00446 (0.00635)	-0.00474 (0.00642)	-0.00349 (0.00633)
Unemployment	0.00360 (0.00560)	0.00338 (0.00565)	0.00393 (0.00555)	0.00404 (0.00560)	0.00483 (0.00553)
Culture-individualism	7.76e-05 (0.000382)	8.37e-05 (0.000385)	5.72e-05 (0.000381)	1.66e-05 (0.000385)	9.32e-05 (0.000380)
Pct_mobile	0.000374*** (0.000139)	0.000378*** (0.000140)	0.000382*** (0.000138)	0.000383*** (0.000140)	0.000377*** (0.000138)
Income	0.00476 (0.0110)	0.00461 (0.0111)	0.00490 (0.0109)	0.00530 (0.0110)	0.00267 (0.0109)
GDP per capita	0.0143 (0.00977)	0.0144 (0.00986)	0.0135 (0.00975)	0.0135 (0.00985)	0.0141 (0.00975)
GDP increase	0.00675 (0.00597)	0.00723 (0.00602)	0.00801 (0.00584)	0.00873 (0.00591)	0.00861 (0.00583)
Gov_respo_chang	-0.0204*** (0.00762)	-0.0203*** (0.00770)	-0.0204*** (0.00759)	-0.0207*** (0.00761)	-0.0208*** (0.00761)
Gov_trans	-0.0382* (0.0198)	-0.0398** (0.0200)	-0.0375* (0.0198)	-0.0374* (0.0200)	-0.0395** (0.0198)
Gov_management	0.0563*** (0.0196)	0.0577*** (0.0198)	0.0551*** (0.0196)	0.0549*** (0.0197)	0.0555*** (0.0196)
Temperature	-0.00605 (0.00565)	-0.00600 (0.00568)	-0.00614 (0.00564)	-0.00608 (0.00567)	-0.00608 (0.00564)
Precipitation	-0.000833 (0.00318)	-0.000861 (0.00317)	-0.000862 (0.00318)	-0.000847 (0.00318)	-0.000852 (0.00318)
Time Effects	Yes	Yes	Yes	Yes	Yes
Constant	0.314*** (0.0383)	0.310*** (0.0387)	0.328*** (0.0384)	0.332*** (0.0388)	0.320*** (0.0383)
Observations	1756	1756	1756	1756	1756

Note: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Review. It is well recognized that the prevention and control policies of the government need to be timely and effective. During this fight against the virus, these findings shed light on how the policy tools could be combined with online information, and further how this mix may take effect as the crisis unfolded.

5. Additional analyses

5.1. Impact of different socio-economic states on the internet role

In this section, we delve into the boundary conditions for Internet use to take effects. A country's socio-economic conditions might pave the way or act as impediments to facilitate social learning. First, we divided the countries into two groups by their relative social factors (e.g., GDP per capita, unemployment rate, hygiene condition) as they may potentially affect citizens' Internet behaviours and the epidemic spread. We reduced the multi-dimensional representations in each category using principle components analysis (PCA), which is a dimension reduction technique to bring out strong patterns in a dataset (with multi-

dimension information of GDP per capita, development extent, income class in economics; unemployment, CPIA economic management cluster average in societal and the newborn death rate in hygiene). The aim of the PCA is to explain as much of the variance of the observed variables as possible using few composite variables (referred to as components) (Lever, Krzywinski, & Altman, 2017a; Wold, Esbensen, & Geladi, 1987), by performing eigenvalue decomposition on the covariance matrix. We extracted the first principal component that can explain 72.2% and more variation of the dataset and divided the countries into two subgroups according to the mean value of the first principal component.

The results in Table 5 point out two findings. First, the complementarity of effective Internet use and policy tools are embodied in low-hygiene (Coef. = -0.00649, P -value < 0.1) and high-economics features (Coef. = -0.00627, P -value < 0.1). Second, in certain cases effective Internet use would backfire to worsen the policy effectiveness. When countries have strong hygiene support, the effective use may marginally lessen the policy consequences (Coef. = 0.0443, P -value < 0.01). Citizens in such countries often possess enough medical strength and resolution. However, over propaganda or information absorbed may reduce their

Table 4
Heterogeneity of the Intervention Policy and Effective Internet Use.

	Policy objectives					Difficulty of implementation		Primitive and secondary-orientation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Effective Internet Use (EIU)	-0.00382 (0.00580)	0.0124* (0.00647)	0.0191* (0.0105)	-0.0108** (0.00453)	-0.0306 (0.178)	-0.0142** (0.00713)	0.0157* (0.00828)	0.00493 (0.00708)	-0.0155** (0.00691)
SDE	-0.00660* (0.00378)								
EIU × SDE	-0.00455* (0.00240)								
CLO		-0.000321 (0.00405)							
EIU × CLO		-0.00994*** (0.00205)							
MOV			0.00521 (0.00333)						
EIU × MOV			-0.00659*** (0.00215)						
FIN				0.00290 (0.00755)					
EIU × FIN				0.00875 (0.00819)					
INF					0.0347 (0.0297)				
EIU × INF					0.0207 (0.178)				
Easy						0.00947* (0.00552)			
EIU × Easy						0.00406 (0.00500)			
Hard							-9.37e-06 (0.00147)		
EIU × Hard							-0.00273*** (0.000735)		
PRIM								-0.00137* (0.000752)	
EIU × PRIM								-0.00197*** (0.000677)	
SECD									-0.000264 (0.00189)
EIU × SECD									0.00387 (0.00261)
Controls	Yes					Yes		Yes	
Constant	0.367*** (0.0353)	0.364*** (0.0366)	0.343*** (0.0382)	0.346*** (0.0354)	0.325*** (0.0466)	0.336*** (0.0366)	0.362*** (0.0382)	0.322*** (0.0401)	0.343*** (0.0388)
Observations	1611	1611	1611	1611	1611	1611	1611	1756	1756

Note: *: p < 0.1, **: p < 0.05, ***: p < 0.01.

alert to the virus. For example, Filsinger and Freitag (2021) find that information about a positive economic outlook and governmental support to mitigate the crisis actually promotes people’s subjective feelings of disadvantage rather than reducing them. Pan et al. (2020) also indicate that higher overall information exposure was associated with higher depressive symptoms among participants who were less likely to carefully consider the veracity of the information to which they were exposed. The similar result holds when the countries belong to low-level economic conditions (Coef. =-0.0957, P-value < 0.01). More often, these countries face huge financial budgets to conquer the pandemic and represent worse social learning, so it is hard for them to promote the sharing and diffusion of suitable knowledge. Effective Internet use and sufficient information is not on an equal basis. Increasing effective use might still lead to low-quality precautionary measures and awareness. The heterogeneity induced by country-level factors deserves further investigation.

5.2. Weighted intervention intensity

Moreover, we used the sum of policy types and intensity as indicators for intervention intensity, which is a coarse measure by treating each policy with the same weight. To validate the results, we turned to modeling literatures towards policy impacts on containing the spread of the pandemic. Part of the summary is listed in Table 6-7. However,

models conduct in different contexts (pandemic stages, countries) indicate inconsistent results. Consolidating the findings, we gave each policy a fixed rating based on the relative importance weight. Aggregating the weighted intensity across intervention types, we could witness consistent results with the previous main analysis (the coefficient of the interaction term is -0.0030, P-value < 0.01).

Overall, these results provide further confidence to the effects of citizens’ effective Internet information on the epidemic spread, and such effects are generally significant and stable across different countries’ geographic and social-economic conditions, and the extent and type of interventions.

5.3. Alternative measure of internet use

We took advantage of the Google Trends Index¹¹ related to coronavirus as a measure of Internet search intensity. To adjust for the effective information, we calculate the effective internet search as:

$$Effective\ Internet\ Search = GoogleSearch_index * Infodemic_index$$

We also address the endogenous problem with the two-stage method for calculating Internet search. In the first stage we Derive the residuals

¹¹ <https://trends.google.com/trends/>

Table 5
Impact of Internet behaviours on the epidemic in countries with different social-economic states.

Outcome	Hygiene		Societal		Economics	
	Low CR	High CR	Low CR	High CR	Low CR	High CR
EIU	-0.0196*** (0.00492)	0.0714 (0.0684)	-0.0115* (0.00640)	0.00391 (0.00855)	-0.0514 (0.0964)	-0.0208*** (0.00482)
Sum_intensity	-0.00585 (0.00462)	0.0131* (0.00687)	-0.00157 (0.00650)	-0.00909** (0.00460)	0.0223*** (0.00689)	-0.00620 (0.00449)
EIU × Sum_intensity	-0.00649* (0.00363)	0.0443*** (0.0167)	-0.00157 (0.00587)	0.00175 (0.00496)	0.0957*** (0.0248)	-0.00627* (0.00363)
Departure	0.0813*** (0.0169)	0.0791 (0.0561)	0.0486*** (0.0171)	0.107*** (0.0213)	0.0460 (0.0624)	0.0723*** (0.0169)
Arrival	0.00567 (0.00731)	-0.0471 (0.0585)	0.00656 (0.0289)	-0.0210** (0.00972)	-0.0636 (0.0493)	0.0105 (0.00784)
Health_Index	-0.00325*** (0.000735)	0.00230 (0.00157)	-0.00373*** (0.00144)	-0.00113 (0.000703)	0.00155 (0.00255)	-0.00249*** (0.000705)
Deathrate_newborn	0.0411*** (0.0106)	0.0341*** (0.0129)	0.0271** (0.0121)	0.0419*** (0.0110)	0.0291** (0.0122)	0.0462*** (0.0110)
Population Density	-0.00943* (0.00571)	0.0341 (0.0983)	0.274*** (0.0907)	-0.0105* (0.00599)	-0.0254 (0.0607)	-0.00747 (0.00628)
Unemployment	0.0213*** (0.00813)	-0.0137 (0.0106)	0.0802*** (0.0178)	-0.000497 (0.00676)	0.00752 (0.0123)	0.00267 (0.00977)
Culture-individualism	0.000186 (0.000471)	0.00168*** (0.000633)	9.64e-05 (0.000629)	-7.56e-05 (0.000416)	0.000728 (0.000707)	-0.000107 (0.000445)
Pct_mobile	0.000367** (0.000145)	0.000211 (0.000222)	0.00125*** (0.000305)	0.000487*** (0.000135)	0.000337 (0.000268)	0.000318** (0.000148)
Income	0.0183 (0.0162)	0.0249 (0.0220)	0.00900 (0.0181)	0.0296** (0.0121)	-0.0125 (0.0152)	0.0164 (0.0148)
GDP per capita	0.00734 (0.00978)	-0.0594 (0.0526)	-0.0163 (0.0169)	0.0150 (0.00987)	-0.115* (0.0691)	0.0110 (0.00978)
GDP increase	-0.000574 (0.00920)	-0.00325 (0.0120)	0.0400*** (0.0127)	0.00569 (0.00681)	0.0236 (0.0200)	0.000998 (0.00739)
Gov_respo_chang	0.00525 (0.0111)	-0.0202** (0.00959)	-0.0291* (0.0149)	-0.0239*** (0.00776)	-0.0171 (0.0114)	-0.0115 (0.0102)
Gov_trans		-0.0580*** (0.0156)	-0.0423** (0.0174)		-0.0615*** (0.0150)	
Gov_management		0.0705*** (0.0194)	0.0332* (0.0181)		0.0577*** (0.0205)	
Temperature	0.00101 (0.00674)	-0.0114 (0.00982)	-0.0228** (0.0114)	0.00825 (0.00707)	-0.0133 (0.00912)	-0.00534 (0.00650)
Precipitation	-0.000187 (0.00320)	0.000252 (0.0125)	-0.00162 (0.00317)	0.0415 (0.145)	-0.00251 (0.00311)	0.00853 (0.145)
Time Effects	Yes		Yes		Yes	
Constant	0.313*** (0.0400)	0.135 (0.0967)	0.456*** (0.103)	0.358*** (0.0473)	0.0390 (0.0802)	0.354*** (0.0560)
Observations	1129	627	615	1141	590	1166

Note: *: p < 0.1, **: p < 0.05, ***: p < 0.01.

of regressions after regressing on policy intensity variable, meanwhile controlling for country-level socio-economic factors that might determine the development of Internet infrastructures. We substitute the residuals for original internet search measures in the second stage.

In Table 8, we replicate the main results with the alternative measure of Internet use. Concretely, effective Internet search interacts with the intervention policies in lessening the spread of the COVID-19. The joint effects of effective Internet search with the interventions are significant to reduce the spread (Coef. = - 0.0141, P-value < 0.05). Regarding the heterogeneity of the intervention policy, we consistently confirm that effective internet search could complement certain policies in particular: social distancing- (Coef. = - 0.00832, P-value < 0.05), movement restriction- (Coef. = - 0.00711, P-value < 0.05), closure- (Coef. = - 0.0121, P-value < 0.01) types of policies are strengthened; Difficult-to-implement policies (Coef. = - 0.0040, P-value < 0.01) are better coped with; Primitive-crisis orientation policies Coef. = - 0.00327, P-value < 0.01) are promoted better by the Internet behaviours.

5.4. Alternative measure of intervention policy objectives

We examine five types of policies according to their objectives. An alternative simplified version is to divide the policies based on their targeting governance subjects. That is, market department in charge of

economic emphasis(including financial measures, monetary measures, emergency investment in healthcare, school and workplace closure), hygiene department responsible of medication input and scientific isolation (including public event cancellations, public transportation closures, restrictions on domestic and international travel), as well as investment in vaccines), and support department incorporating information campaigns and supporting technology (public information campaigns, testing framework and contact tracing).

Results in Table 9 confirm the main findings. Effective Internet use exert significant complementary effects of market (Coef. = - 0.00734, P-value < 0.001) and hygiene (Coef. = - 0.00491, P-value < 0.01) policies.

6. Discussions and conclusion

The consequences of Internet behaviours during the pandemic have been understudied in the literature. This research disentangles the relationship between Internet use behaviours and pandemic containment and concentrates on national-level effects of Internet behaviours on pandemic containment. Our main objective was to investigate the interaction of Internet behaviours with public health interventions during the ongoing COVID-19 pandemic on a global scale. We assessed two aspects of such behaviours: (1) Internet use, proxied by daily network traffic and speed, and (2) Internet search, with people's

Table 6
Summary of modeling work on intervention efficacy.

Paper	Method	country	interventions	Conclusion
Dehning et al. (2020)	Bayesian framework	Germany	Cancel large public events; Stop childcare facilities, Launch many stores and far-reaching contact ban	λ decreased from 0.43 to 0.25 when canceling large public events; λ decreased to 0.15 when canceling childcare facilities; λ reduced to 0.9 when launching the contact ban.
Giordano et al. (2020)	SEIR	Italy	basic social-distancing measures; policy limiting screening to symptomatic individuals only; lockdown; lockdown is fully operational and gets stricter; a wider testing campaign is launched	basic $R_0 = 2.38$; $R_0 = 1.66$ when policy limiting screening to symptomatic individuals only; $R_0 = 1.8$ when lockdown; $R_0 = 1.6$ when lockdown is fully operational and gets stricter; $R_0 = 0.99$ when a wider testing campaign is launched
Chang, Harding, Zachreson, Cliff, & Prokopenko, 2020	agent-based modeling, AceMod	Australia	(i) case isolation, (ii) in-home quarantine of household contacts of confirmed cases, and (iii) school closures, combined with (i) and (ii)	the effectiveness of school closures is limited, producing a four-week delay in epidemic peak; s, increasing a compliance level just by 10%, from 70% to 80%, may effectively control the spread;
Aleta et al. (2020)	SEIR	High-income countries: Europe and US	Lift scenario (LIFT): the stay-at-home order is lifted after eight weeks by reopening all work and community places, except for mass-gathering; Lift and enhanced tracing (LET): The stay-at-home order is lifted as in the previous scenario, plus testing policies	(1) R_0 dropped by around 75% and reached values below 1 with the intervention, increases to values up to 2.05 (2) quarantining households of symptomatic individuals alone is not sufficient to substantially change the course of the epidemic and the conclusions reached for the first of these scenarios.
Davies et al. (2020)	age-structured transmission model	UK	School closures, physical distancing, shielding of people aged 70 years or older, and self-isolation of symptomatic cases.	The combined intervention was more effective at reducing R_0 , but only lockdown periods were sufficient to bring R_0 near or below 1; school closures had little effect in our projections, physical distancing measures were most effective if the staggered return to work was at the beginning of April;
Prem et al. (2020)	SEIR	China	school closures, extended workplace closures, and a reduction in mixing in the general community.	Relative impact: PC 14%; CI 33%; CI_HQ 53%; CI_HQ_SD 33%; CI_SD 53%; CI_HQ_SDOL70 67%; PC_CI_HQ_SDOL70 69%
Ferguson et al. (2020)	individual-based simulation model	UK	school and university closure (PC); home isolation of cases (CI); household quarantine (HQ);social distancing of the entire population (SD);social distancing of those over 70 years for 4 month (SDOL70)	

Table 7
Efficacy rating for each intervention type.

policy	Rating
school closing	0.8
workplace closing	0.8
cancel public events	0.8
close public transport	0.8
public information campaigns	0.8
restrictions on internal movement	1
international travel controls	1
fiscal measures	0.6
monetary measures	0.6
emergency investment in healthc	0.5
investment in vaccines	0.5
testing framework	1
contact tracing	0.8

interests indexed in term of pandemic-related keywords.

We constructed a unique data set containing data on Internet usage from M-lab, Internet search data from Google Trends, and national-level policy interventions from the Oxford COVID-19 Government Response Tracker and the GardaWorld Crisis24 portal (Hale et al., 2021). We employed a single-group interrupted time-series experimental design to empirically evaluate the significance of behavioural interventions and Internet behaviours. We find that both the intervention and behaviour significantly reduce the epidemic spread. Besides, Internet use and public policies exerted joint effects. Our results suggest that the COVID-19 confirm rate was reduced by the combination of effective Internet use and public health interventions. Our findings pave the path for future researchers to investigate the interaction of online and offline behaviours during a crisis.

6.1. Theoretical contributions

This study has several theoretical contributions. First, social learning theory was well leveraged to explain the mechanism by which effective Internet use influenced pandemic containment. A deeper understanding of the motivation and efficacy of implemented interventions leads to stronger subjective compliance, especially when policy information dissemination and relevant promotional campaigns are mainly conducted through the Internet. Although various interventions that involve offline behavioural changes, such as isolation and social distancing, have been shown to be effective in reducing COVID-19 spread (Anderson, Heesterbeek, Klinkenberg, & Hollingsworth, 2020; Pan et al., 2020; Prem et al., 2020; West, Susan Michie, Rubin, & Amlôt, 2020;), we demonstrated that public Internet behaviours may also play crucial roles in this regard. Under social learning theory, people who actively or passively receive relevant information regarding a crisis through the Internet tend to realise the urgency and importance of intervention policies.

Second, we examined social learning theory in a cross-country context, suggesting that Internet use moderates policy effects consistently across countries. Past research has addressed social learning from an individual perspective and explored the effects of learning on a wide range of individual behaviours besides compliance to policies (e.g. adoption, crime behaviours). However, the present study is the first to confirm these effects on a global scale. Our study extends the applicability of social learning theory to a cross-country context and the finding is robust to alternative measures of key Internet use behaviours. Following Liu and San (2006), we determined that a country's socio-economic conditions (regarding economic and hygiene factors) constitute a strong driver of that country's social learning, which in turn influences pandemic outcomes there. The findings enrich the literature on infodemic research by extrapolating the effects of effective Internet use in a cross-country context. Studies have focused more on these

Table 8
Regression results for the alternative effective internet search.

	Sum_Intensity		Policy objectives				Difficulty of implementation		Primitive and secondary-orientation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Effective Internet Search (EIS)	-0.00638	0.00909	0.0247	0.0256*	-0.0160**	0.0110	-0.000190	0.0374**	0.0212	-0.00939
Sum_Intensity	(0.00596)	(0.0127)	(0.0192)	(0.0153)	(0.00712)	(0.0376)	(0.0127)	(0.0185)	(0.0131)	(0.00926)
EIS × Sum_Intensity	-0.000264									
	(0.00336)									
SDE	-0.0141**	-0.00272								
	(0.00556)	(0.00352)								
EIS × SDE		-0.00832**								
		(0.00419)								
CLO				-0.000521						
				(0.00367)						
EIS × CLO				-0.0121***						
				(0.00439)						
MOV			0.00345							
			(0.00318)							
EIS × MOV			-0.00711**							
			(0.00335)							
FIN					-0.000697					
					(0.00711)					
EIS × FIN					0.00279					
					(0.00760)					
Easy							0.00871*			
							(0.00517)			
EIS × Easy							-0.00853			
							(0.00702)			
Hard								-0.000410		
								(0.00136)		
EIS × Hard								-0.0040***		
								(0.00138)		
PRIM									-0.000201	
									(0.000700)	
EIS × PRIM									-0.00327***	
									(0.00114)	
SECD										-8.12e-06
										(0.00174)
EIS × SECD										-0.00151
										(0.00261)
INF						0.0496**				
						(0.0206)				
EIS × INF						-0.0259				
						(0.0379)				
Time Effects	Yes	Yes						Yes	Yes	
Controls	Yes	Yes					Yes	Yes	Yes	
Constant	0.283***	0.300***	0.285***	0.297***	0.292***	0.253***	0.284***	0.305***	0.283***	0.279***
	(0.0382)	(0.0344)	(0.0354)	(0.0348)	(0.0344)	(0.0377)	(0.0349)	(0.0357)	(0.0385)	(0.0409)
Observations	1572	1458	1458	1458	1458	1458	1458	1458	1572	1572

Note: *: p < 0.1, **: p < 0.05, ***: p < 0.01.

effects at the individual level and collected survey data (Fernández-Torres, Almansa-Martínez, & Chamizo-Sánchez, 2021; Gavaravarapu, Seal, Banerjee, Reddy, & Pittla, 2022; Olatunji, Ayandele, Ashirudeen, & Olaniru, 2020). Only a few studies have employed user data regarding social media such as Twitter and Facebook to probe the impacts of the infodemic on the COVID-19 crisis (Mourad, Srour, Harmanani, Jenainati, & Arafah, 2020; Yang et al., 2021). Mourad et al. (2020) reported that the widespread dissemination of inaccurate or false medical information on precautions and other measures to take during the pandemic on Twitter undermined efforts to combat the pandemic. Herein, we demonstrated the importance of effective Internet use (as a measure of information quality) in curbing pandemic spread.

Third, this study extended the stream of research on health crisis management to general Internet use and considered an online–offline complementarity. Although social media communication in crisis situations has generated intense scholarly interest, relatively few studies have examined online information in general as a means of managing such situations (Alexander, 2014; Soroya et al., 2021; Yu et al., 2021). A

few studies have investigated this topic at the individual level, and its comprehensive impacts remain to be evaluated (Pierewan & Tampubolon, 2014; Soroya et al., 2021). We probed the joint effects of Internet use behaviour with offline interventions. Effective Internet use may help enhance the effects of interventions introduced, particularly for those that have primary crisis orientations or specific objectives (or are simply difficult to implement). We examined this understudied subject, determining a potential fit between online behaviour and offline public policies. The findings serve as a reference for the integration of online and offline data for crisis management. This discussion serves as a springboard for future researchers to take a holistic perspective in determining the consequences of online information.

6.2. Practical implications

This study also bears implications for policymakers. First, the results highlight the importance of the Internet and online behaviours during the COVID-19 pandemic. The dissemination of information through the

Table 9
Results for alternative measures of policy Objectives.

	Market (1)	Support (2)	Hygiene (3)
Effective Internet Use (IU)	0.00722 (0.00621)	-0.0214** (0.0102)	0.0142* (0.00791)
Market	0.00247 (0.00328)		
EIU × Market	-0.00734*** (0.00182)		
Support		0.00989*** (0.00335)	
EIU × Support		0.00351 (0.00293)	
Hygiene			-0.00391* (0.00235)
EIU × Hygiene			-0.00491*** (0.00130)
Time Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Constant	0.354*** (0.0366)	0.330*** (0.0361)	0.382*** (0.0371)
Observations	1611	1611	1611

Note: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Internet can potentially be leveraged to promote public awareness of the pandemic and facilitate public adherence to interventions. For example, the timely reporting of the current situation, the motivations and rationale underlying interventions, and instructions for policy implementation can inform the public and thereby improve policy effects. From the government perspective, in line with the observation that governments can use various digital strategies to fight the pandemic (Kummitha, 2020), we further observed the potential complementarity of the government policies and Internet use. People’s information behaviours during global health crises can help both individuals and societies conquer global health crises; therefore, this topic merits investigation.

Second, our analysis confirmed the joint effects of effective Internet use with policy interventions. This further demonstrates the substitutive effects of subjective force in acknowledging reality and the importance of complying with policy interventions. When policies are premature, such as those introduced at the beginning of the pandemic, the dissemination of accurate information on transmission, self-protection, and other relevant topics is pivotal. Governments can optimise the results of policy interventions by coordinating implementation with the spread of such accurate Internet information (Zeemering, 2021). A comprehensive examination of policy characteristics highlights the synergy between online information and offline prevention. When the government launches policies, especially those that are primary crisis

Appendix A. Effects of the intervention policies and internet information

The internal and external validity is significant in the causal evaluation of policies. Hence, with the single-group interrupted design, the estimation equation is presented in the following form:

$$y_{it} = \alpha + \beta Treat_{it} + \sum_{k=1}^3 \gamma_k DayDif_t^k + \sum_{k=1}^3 \delta_k DayDif_t^k \times Treat_{it} + \epsilon_{it}$$

Here, $DayDif_t$ is coded as the day of observation relative to the policy implementation day, and $Treat_{it}$ is an indicator variable that equals to one of the observations after the implementation. Following previous design (Cavusoglu et al., 2016), we fit a separate third-degree polynomial trend on each side of the intervention declaration. The coefficient of interest β reflects the size of the discontinuity in the outcome variable at the cutoff time.

We started by analyzing the effects of the intervention policies, since they are likely to show most immediate effects on the epidemic spread. Consistent with the recent research (Kraemer et al., 2020; Tian et al., 2020), the Treat variable holds negative significance in the 2 models, showing strong power to contain the pandemic development.

oriented, difficult to implement, and carrying specific objectives, the dissemination of accurate information through the Internet should be coordinated with medical education. Thus, policy effects can be enhanced. Further research on the boundary conditions for these findings would reveal the importance of a country’s socioeconomic status. The greatest synergy between effective Internet use and policy interventions can be achieved in countries with low-hygiene and high-economics features.

This study has some limitations. First, owing to seasonal factors that influence susceptibility and transmission, regional efforts to fight the COVID-19 pandemic may not be successful in the long term. Therefore, caution should be exercised when extrapolating our findings to longer time periods. Second, reliability concerns related to the number of confirmed cases remain. Third, the high-quality information reflected in effective Internet use may call for more detailed examination. As our results suggest, effective Internet use is a relative measure of information quality. However, online information available in some countries is of extremely low quality. Furthermore, examining the intervention implementation process and related efforts more comprehensively may increase the rigour and power of the present analyses. Fourth, measuring Internet use across countries is a formidable challenge. We proxied this variable with multisource macroscopic data to ensure reliable cross-country comparisons. However, considering the possibility of data distortion, this macroscopic calculation may not reflect the true Internet usage status.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Qi Zhang: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **Chee Wei Phang:** Data curation, Resources, Supervision, Writing – original draft. **Cheng Zhang:** Conceptualization, Funding acquisition, Resources, Supervision, Investigation, Writing – review & editing.

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Table A1
Effects of Intervention Policies and Internet Behaviours on the Pandemic.

	(1)	(2)
Effective Internet Use	-0.00805* (0.00478)	
Effective Internet Search		-0.0130** (0.00521)
Treat	-0.0495*** (0.0129)	-0.0368*** (0.0120)
Departure	0.0508*** (0.0141)	0.0368** (0.0147)
Arrival	0.00180 (0.00736)	0.00132 (0.00722)
Health_Index	-0.00142** (0.000562)	-0.00121** (0.000580)
Deathrate_newborn	0.0423*** (0.00818)	0.0380*** (0.00799)
Population Density	-0.00411 (0.00596)	0.00197 (0.00615)
Unemployment	0.00510 (0.00517)	0.00512 (0.00537)
Culture-individualism	0.000108 (0.000357)	0.000215 (0.000371)
Pct_mobile	0.000367*** (0.000128)	0.000346** (0.000135)
Income	-0.00224 (0.00951)	-0.00505 (0.00966)
GDP per capita	0.0164* (0.00901)	0.00676 (0.00934)
GDP increase	0.00759 (0.00550)	0.0128** (0.00586)
Gov_respo_chang	-0.0203*** (0.00713)	-0.0178** (0.00744)
Gov_trans	-0.0388** (0.0188)	-0.0314 (0.0202)
Gov_management	0.0540*** (0.0186)	0.0412** (0.0198)
Temperature	-0.00765 (0.00541)	-0.0129** (0.00535)
Precipitation	-0.00111 (0.00316)	-0.00140 (0.00270)
Constant	0.342*** (0.0368)	0.291*** (0.0379)
Observations	1782	1594

*, p < 0.1, **, p < 0.05, ***, p < 0.01.

We then assessed the effects of effective Internet use, which is one of our focal variables related to Internet behaviours. Result in Table A1 (columns 1) indicates that an increased daily effective Internet use intensity was associated with a slowdown of the epidemic growth ($Coef. = -0.00805$, $P\text{-value} < 0.1$). As the intensity of effective Internet use may reflect the extent to which citizens are exposed to effective overall information, this should make them less exposed to the risks of the COVID-19 virus. Thus, increased effective Internet information load (that displaced physical contacts) may reduce the epidemic spread significantly.

Next, we assessed the effects of the Internet search, which is the other focal Internet behaviour in this study. Result in Table A1 (columns 2) indicates that an increased daily effective Internet search intensity is also associated with a slowdown of the epidemic growth ($Coef. = -0.0130$, $P\text{-value} < 0.05$). As the intensity of informative Internet search on the epidemic-related information may heighten “correct” public awareness of the epidemic situation in their country, citizens with higher such awareness may be better able to adopt measures to protect themselves, and are thus less susceptible to the infection risks.

Appendix B. Supplementary data

Supplementary materials to this article can be found online at <https://doi.org/10.1016/j.giq.2022.101749>.

References

- Abbas, J., Wang, D., Su, Z., & Ziapour, A. (2021). The role of social media in the advent of COVID-19 pandemic: crisis management, mental health challenges and implications. *Risk Management and Healthcare Policy*, 14, 1917.
- Alamsyah, N., & Zhu, Y.-Q. (2021). We shall endure: Exploring the impact of government information quality and partisanship on citizens' well-being during the Covid-19 pandemic. *Government Information Quarterly*, 101646.
- Aleta, A., Martin-Corral, D., Piontti, A. P., Ajelli, M., Litvinova, M., Chinazzi, M., ... Moreno, Y. (2020). Modelling the impact of testing, contact tracing and household quarantine on second waves of COVID-19. *Nature Human Behaviour*, 4(9), 964–971.
- Alexander, D. E. (2014). Social media in disaster risk reduction and crisis management. *Science and Engineering Ethics*, 20(3), 717–733.
- Al-Surimi, K., Khalifa, M., Bahkali, S., EL-Metwally, A., & Househ, M. (2017). The potential of social media and internet-based data in preventing and fighting infectious diseases: from internet to Twitter. *Advances in Experimental Medicine and Biology*, 972, 131–139.
- Anderson, R. M., Heesterbeek, H., Klinkenberg, D., & Hollingsworth, T. D. (2020). How will country-based mitigation measures influence the course of the COVID-19 epidemic? *The Lancet*, 395(10228), 931–934.
- Balcan, D., Colizza, V., Gonçalves, B., Hu, H., Ramasco, J. J., & Vespignani, A. (2009). Multiscale mobility networks and the spatial spreading of infectious diseases. *Proceedings of the National Academy of Sciences*, 106(51), 21484–21489.
- Bandura, A., & Walters, R. H. (1977). *Social learning theory*. 1. Englewood cliffs: Prentice Hall.

- Banerjee, D., & Meena, K. S. (2021). COVID-19 as an "infodemic" in public health: critical role of the social media. *Frontiers in Public Health*, 9, 231. <https://doi.org/10.3389/fpubh.2021.610623>
- Barabas, J., & Jerit, J. (2009). Estimating the causal effects of media coverage on policy-specific knowledge. *American Journal of Political Science*, 53(1), 73–89.
- Beck, N., Katz, J. N., & Tucker, R. (1998). Taking time seriously: Time-series-cross-section analysis with a binary dependent variable. *American Journal of Political Science*, 42(4), 1260–1288.
- Bonneux, L., & Van Damme, W. (2006). An iatrogenic pandemic of panic. *Bmj*, 332(7544), 786–788.
- Bunker, D. (2020). Who do you trust? The digital destruction of shared situational awareness and the Covid-19 infodemic. *International Journal of Information Management*, 55, Article 102201.
- Cai, H., Chen, Y., & Fang, H. (2009). Observational learning: Evidence from a randomized natural field experiment. *American Economic Review*, 99(3), 864–882. <https://www.aeaweb.org/articles?id=10.1257/aer.99.3.864>.
- Campbell, D. T., & Stanley, J. C. (2015). *Experimental and quasi-experimental designs for research*. Ravenio Books.
- Cavusoglu, H., Phan, T. Q., Cavusoglu, H., & Airoldi, E. M. (2016). Assessing the impact of granular privacy controls on content sharing and disclosure on Facebook. *Information Systems Research*, 27(4), 848–879.
- Chang, S. L., Harding, N., Zachreson, C., Cliff, O. M., & Prokopenko, M. (2020). Modelling transmission and control of the COVID-19 pandemic in Australia. *Nature Communications*, 11(1), 1–13.
- Chatfield, A. T., & Reddick, C. G. (2017). All hands on deck to Tweet #Sandy: Networked governance of citizen coproduction in turbulent times. *Government Information Quarterly*, 35(2), 259–272.
- Chen, Q., Min, C., Zhang, W., Wang, G., & Evans, R. (2020). Unpacking the black box: How to promote citizen engagement through government social media during the Covid-19 crisis. *Computers in Human Behavior*, 110, 106380.
- Chernozhukov, V., Kasahara, H., & Schrimpf, P. (2021). Causal impact of masks, policies, behavior on early Covid-19 pandemic in the US. *Journal of Econometrics*, 220(1), 23–62.
- Chiou, L., & Tucker, C. (2020). *Social distancing*. Cambridge, MA: Internet Access and Inequality.
- Cook, T. D., Campbell, D. T., & Shadish, W. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. MA: Houghton Mifflin Boston.
- Cook, T. D., & Campbell, D. T. (1979b). The design and conduct of true experiments and quasi-experiments in field settings. In *Reproduced in part in research in organizations: Issues and controversies*. <https://www.scholars.northwestern.edu/en/publications/the-design-and-conduct-of-true-experiments-and-quasi-experiments.-3>.
- Davies, N. G., Kucharski, A. J., Eggo, R. M., Gimma, A., Edmunds, W. J., Jombart, T., O'Reilly, K., Endo, A., Hellewell, J., & Nightingale, E. S. (2020). Effects of non-pharmaceutical interventions on Covid-19 cases, deaths, and demand for hospital services in the UK: A modelling study. *The Lancet Public Health*, 5(7), e375–e385.
- Dehning, J., Zierenberg, J., Spitzner, F. P., Wibral, M., Neto, J. P., Wilczek, M., & Priesemann, V. (2020). Inferring change points in the spread of COVID-19 reveals the effectiveness of interventions. *Science*, 369(6500).
- Denecke, K., & Atique, S. (2016). Social media and health crisis communication during epidemics. In *Participatory health through social media* (pp. 42–66). Academic Press.
- Duhon, J., Bragazzi, N., & Kong, J. D. (2021). The impact of non-pharmaceutical interventions, demographic, social, and climatic factors on the initial growth rate of Covid-19: A cross-country study. *Science of the Total Environment*, 760, 144325.
- Effenberger, M., Kronbichler, A., Shin, J. I., Mayer, G., Tilg, H., & Perco, P. (2020). Association of the COVID-19 pandemic with internet search volumes: A google Trends™ analysis. *International Journal of Infectious Diseases: IJID: Official Publication of the International Society for Infectious Diseases*, 95, 192–197.
- Elbanna, A., Bunker, D., Levine, L., & Sleigh, A. (2019). Emergency management in the changing world of social media: Framing the research agenda with the stakeholders through engaged scholarship. *International Journal of Information Management*, 47.
- Fang, H., Wang, L., & Yang, Y. (2020). Human mobility restrictions and the spread of the novel coronavirus (2019-nCoV) in China. *Journal of Public Economics*, 191, Article 104272.
- Farooq, A., Laato, S., & Islam, A. (2020). Impact of online information on self-isolation intention during the COVID-19 pandemic: Cross-sectional study. *Journal of Medical Internet Research*, 22(5).
- Feng, S., & Kirkley, A. (2021). Integrating online and offline data for crisis management: Online geolocalized emotion, policy response, and local mobility during the COVID crisis. *Scientific Reports*, 11(1), 1–14.
- Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunuba Perez, Z., & Cuomo-Dannenburg, G. (2020). *Report 9: impact of non-pharmaceutical interventions (Npis) to reduce Covid19 mortality and healthcare demand*.
- Fernández-Torres, M. J., Almansa-Martínez, A., & Chamizo-Sánchez, R. (2021). Infodemic and fake news in Spain during the COVID-19 pandemic. *International Journal of Environmental Research and Public Health*, 18(4), 1781.
- Filsinger, M., & Freitag, M. (2021). When good news backfires: Feelings of disadvantage in the Corona crisis. *International Political Science Review*, 42(3), 367–382.
- Galaz, V. (2009). Pandemic 2.0: Can information technology help save the planet? *Environment: Science and Policy for Sustainable Development*, 51(6), 20–28.
- Gavaravarapu, S. M., Seal, A., Banerjee, P., Reddy, T., & Pittla, N. (2022). Impact of 'infodemic in pandemic' on food and nutrition related perceptions and practices of Indian internet users. *PLoS One*, 17(4), Article e0266705.
- Gillings, D., Makuc, D., & Siegel, E. (1981). Analysis of interrupted time series mortality trends: an example to evaluate regionalized perinatal care. *American Journal of Public Health*, 71(1), 38–46.
- Giordano, G., Blanchini, F., Bruno, R., Colaneri, P., Di Filippo, A., Di Matteo, A., & Colaneri, M. (2020). Modelling the COVID-19 epidemic and implementation of population-wide interventions in Italy. *Nature Medicine*, 26(6), 855–860.
- Glowacki, E. M., Lazard, A. J., Wilcox, G. B., Mackert, M., & Bernhardt, J. M. (2016). Identifying the public's concerns and the centers for disease control and prevention's reactions during a health crisis: An analysis of a Zika live Twitter chat. *American Journal of Infection Control*, 44(12), 1709–1711.
- Gong, X., & Ye, X. (2021). Governors fighting crisis: Responses to the COVID-19 pandemic across US states on Twitter. *The Professional Geographer*, 73(4), 683–701.
- Gottlieb, J., Townsend, R., & Xu, T. (2016). *Experimenting with entrepreneurship: the effect of job-protected leave* (No. id: 11142).
- Graham, M. W., Avery, E. J., & Park, S. (2015). The role of social media in local government crisis communications. *Public Relations Review*, 41(3), 386–394.
- Haas, P. M. (2000). International institutions and social learning in the management of global environmental risks. *Policy Studies Journal*, 28(3), 558–575.
- Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., ... Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, 5(4), 529–538.
- Hale, T., Petherick, A., Phillips, T., & Webster, S. (2020). "Variation in government responses to COVID-19" version 4.0. Blavatnik School of Government Working Paper. April 7. Available www.bsg.ox.ac.uk/covidtracker.
- Heshmati, A., Al-Hammadani, F. H., & Bany-Mohammed, A. (2013). Analysis of internet usage intensity in Iraq: An ordered logit model. *Journal of Knowledge Management, Economics and Information Technology*, 3(3), 1–21.
- Ho, C. S., Chee, C. Y., & Ho, R. C. (2020). Mental health strategies to combat the psychological impact of COVID-19 beyond paranoia and panic. *Annals of the Academy of Medicine, Singapore*, 49(1), 1–3.
- Howlett, M., Ramesh, M., & Perl, A. (2009). *Studying public policy: Policy cycles and policy subsystems* (vol. 3). Oxford: Oxford university press.
- Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., Druckenmiller, H., Huang, L. Y., Hultgren, A., & Krasovich, E. (2020). The effect of large-scale anti-contagion policies on the Covid-19 pandemic. *Nature*, 584(7820), 262–267.
- Hsiang, S. M., Burke, M., & Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151), 1235367.
- Islam, M. S., Sarkar, T., Khan, S. H., Kamal, A.-H. M., Hasan, S. M., Kabir, A., Yeasmin, D., Islam, M. A., Chowdhury, K. I. A., & Anwar, K. S. (2020). Covid-19-related infodemic and its impact on public health: A global social media analysis. *The American Journal of Tropical Medicine and Hygiene*, 103(4), 1621.
- Islam, N., Sharp, S. J., Chowell, G., Shabnam, S., Kawachi, I., Lacey, B., Massaro, J. M., D'Agostino, R. B., & White, M. (2020). Physical distancing interventions and incidence of Coronavirus disease 2019: Natural experiment in 149 countries. *bmj*, 370.
- Kavanaugh, A. L., Fox, E. A., Sheetz, S. D., Yang, S., Li, L. T., Shoemaker, D. J., ... Xie, L. (2012). Social media use by government: From the routine to the critical. *Government Information Quarterly*, 29(4), 480–491.
- Kim, S. C., & Hawkins, K. H. (2020). The psychology of social media communication in influencing prevention intentions during the 2019 U.S. measles outbreak. *Computers in Human Behavior*, 111, Article 106428.
- Kraemer, M. U., Yang, C. H., Gutierrez, B., Wu, C. H., Klein, B., Pigott, D. M., ... Scarpino, S. V. (2020). The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science*, 368(6490), 493–497.
- Kubota, Y., Shiono, T., Kusumoto, B., & Fujinuma, J. (2020). Multiple drivers of the Covid-19 spread: The roles of climate, international mobility, and region-specific conditions. *PLoS One*, 15(9), e0239385.
- Kummitha, R. K. R. (2020). Smart technologies for fighting pandemics: The techno-and human-driven approaches in controlling the virus transmission. *Government Information Quarterly*, 37(3), Article 101481.
- Lakshmi Priyadarsini, S., & Suresh, M. (2020). Factors influencing the epidemiological characteristics of pandemic COVID 19: A TISM approach. *International Journal of Healthcare Management*, 13(2), 89–98.
- Lever, J., Krzywinski, M., & Altman, N. (2017a). Points of significance: Principal component analysis. *Nature Methods*, 14(7), 641–643.
- Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., Ren, R., Leung, K. S. M., Lau, E. H. Y., Wong, J. Y., Xing, X., Xiang, N., Wu, Y., Li, C., Chen, Q., Li, D., Liu, T., Zhao, J., Li, M., ... Feng, Z. (2020). Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. *The New England Journal of Medicine*. <https://doi.org/10.1056/NEJMoa2001316>. published online Jan 29.
- Linden, A. (2013). Assessing regression to the mean effects in health care initiatives. *BMC Medical Research Methodology*, 13(1), 1–7.
- Linden, A. (2015). Conducting interrupted time-series analysis for single-and multiple-group comparisons. *The Stata Journal*, 15(2), 480–500.
- Linden, A., Adams, J. L., & Roberts, N. (2004). Generalizing disease management program results: How to get from here to there. *Managed Care Interface*, 17(7), 38–45.
- Lindsay, B. R. (2011). Social media and disasters: Current uses, future options, and policy considerations. In *US congressional research service, report for congress*.
- Liu, M.-c., & San, G. (2006). Social learning and digital divides: A case study of internet technology diffusion. *Kyklos (Basel)*, 59(2), 307–321.
- Maaravi, Y., Levy, A., Gur, T., Confino, D., & Segal, S. (2021). "The tragedy of the commons": How individualism and collectivism affected the spread of the COVID-19 pandemic. *Frontiers in Public Health*, 9, 37.
- McDonnell, L. M., & Elmore, R. F. (1987). *Alternative policy instruments*. Santa Monica CA: Rand Corp.
- Menebo, M. M. (2020). Temperature and precipitation associate with Covid-19 new daily cases: A correlation study between weather and Covid-19 pandemic in Oslo, Norway. *Science of the Total Environment*, 737, 139659.

- Moon, M. J. (2020). Fighting COVID-19 with agility, transparency, and participation: Wicked policy problems and new governance challenges. *Public Administration Review*, 80(4), 651–656.
- Mourad, A., Srour, A., Harmanani, H., Jenainati, C., & Arafeh, M. (2020). Critical impact of social networks infodemic on defeating coronavirus COVID-19 pandemic: Twitter-based study and research directions. *IEEE Transactions on Network and Service Management*, 17(4), 2145–2155.
- Munster, V. J., Koopmans, M., van Doremalen, N., van Riel, D., & de Wit, E. (2020). A novel Coronavirus emerging in China—Key questions for impact assessment. *New England Journal of Medicine*, 382(8), 692–694.
- Nguyen, M. H., Hargittai, E., & Marler, W. (2021). Digital inequality in communication during a time of physical distancing: The case of Covid-19. *Computers in Human Behavior*, 120, 106717.
- Oh, O., Agrawal, M., & Rao, H. R. (2013). Community intelligence and social media services: A rumor theoretic analysis of tweets during social crises. *MIS Quarterly*, 407–426.
- Oh, S. H., Lee, S. Y., & Han, C. (2020). The effects of social media use on preventive behaviors during infectious disease outbreaks: The mediating role of self-relevant emotions and public risk perception. *Health Communication*, 4, 1–10.
- Olatunji, O. S., Ayandele, O., Ashirudeen, D., & Olaniru, O. S. (2020). “Infodemic” in a pandemic: COVID-19 conspiracy theories in an african country. *Social Health and Behavior*, 3(4), 152.
- Pan, Y., Xin, M., Zhang, C., Dong, W., Fang, Y., Wu, W., & He, Y. (2020). Associations of mental health and personal preventive measure compliance with exposure to COVID-19 information during work resumption following the COVID-19 outbreak in China: cross-sectional survey study. *Journal of Medical Internet Research*, 22(10), Article e22596.
- Paules, C. I., Marston, H. D., & Fauci, A. S. (2020). Coronavirus infections—more than just the common cold. *Jama*, 323(8), 707–708.
- Pierewan, A. C., & Tampubolon, G. (2014). Internet use and well-being before and during the crisis in Europe. *Social Indicators Research*, 119(2), 647–662.
- Prem, K., Liu, Y., Russell, T. W., Kucharski, A. J., Eggo, R. M., Davies, N., ... Hellewell, J. (2020). The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: A modelling study. *The Lancet Public Health*, 5(5), e261–e270.
- Ragonnet-Cronin, M., Boyd, O., Geidelberg, L., Jorgensen, D., Nascimento, F. F., Siveroni, I., Johnson, R. A., Baguelin, M., Cucunubá, Z. M., & Jauneikaite, E. (2021). Genetic evidence for the association between Covid-19 epidemic severity and timing of non-pharmaceutical interventions. *Nature Communications*, 12(1), 1–7.
- Rapp, D. N., & Salovich, N. A. (2018). Can't we just disregard fake news? The consequences of exposure to inaccurate information. *Policy Insights From the Behavioral and Brain Sciences*, 5, 232–239.
- Sajadi, M. M., Habibzadeh, P., Vintzileos, A., Shokouhi, S., Miralles-Wilhelm, F., & Amoroso, A. (2020). *Temperature, humidity and latitude analysis to predict potential spread and seasonality for Covid-19*. <https://doi.org/10.2139/ssrn.3550308>
- Scheffran, J., Brzoska, M., Kominek, J., Link, P. M., & Schilling, J. (2012). Climate change and violent conflict. *Science*, 336(6083), 869–871.
- Schneider, A., & Ingram, H. (1990). Behavioral assumptions of policy tools. *The Journal of Politics*, 52(2), 510–529.
- Sharma, M., Yadav, K., Yadav, N., & Ferdinand, K. C. (2017). Zika virus pandemic—analysis of Facebook as a social media health information platform. *American Journal of Infection Control*, 45(3), 301–302.
- Soroya, S. H., Farooq, A., Mahmood, K., Isoaho, J., & Zara, S. E. (2021). From information seeking to information avoidance: Understanding the health information behavior during a global health crisis. *Information Processing & Management*, 58(2), Article 102440.
- Stagl, S. (2006). Multicriteria evaluation and public participation: the case of UK energy policy. *Land Use Policy*, 23(1), 53–62. <http://sro.sussex.ac.uk/id/eprint/19941/>.
- Stojkoski, V., Utkovski, Z., Jolakoski, P., Tevdovski, D., & Kocarev, L. (2020). *The socio-economic determinants of the coronavirus disease (COVID-19) pandemic*. Available at SSRN 3576037.
- Sun, Y., Li, Y., Bao, Y., Meng, S., Sun, Y., Schumann, G., Kosten, T., Strang, J., Lu, L., & Shi, J. (2020). Brief report: Increased addictive internet and substance use behavior during the COVID-19 pandemic in China. *The American Journal on Addictions*, 29(4).
- Tian, H., Liu, Y., Li, Y., Wu, C.-H., Chen, B., Kraemer, M. U. G., ... Dye, C. (2020). An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science (New York, N.Y.)*, 368(6491), 638–642.
- Wang, J., Tang, K., Feng, K., & Lv, W. (2020). *High temperature and high humidity reduce the transmission of Covid-19*. <https://doi.org/10.2139/ssrn.3551767>
- Waszak, P. M., Kasprzycka-Waszk, W., & Kubanek, A. (2018). The spread of medical fake news in social media—the pilot quantitative study. *Health Policy and Technology*, 7(2), 115–118.
- West, R., Susan Michie, G., Rubin, J., & Amlôt, R. (2020). Applying principles of behaviour change to reduce SARS-CoV-2 transmission. *Nature Human Behaviour*, 4(5), 451–459.
- Wold, S., Esbensen, K., & Geladi, P. (1987). Principal component analysis. *Chemometrics and Intelligent Laboratory Systems*, 2(1-3), 37–52.
- Wu, J. T., Leung, K., & Leung, G. M. (2020). Nowcasting and forecasting the potential domestic and international spread of the 2019-Ncov outbreak originating in Wuhan, China: A modelling study. *The Lancet*, 395(10225), 689–697.
- Wu, S., Neill, R., De Foo, C., Chua, A. Q., Jung, A.-S., Haldane, V., ... Nordström, A. (2021). Aggressive containment, suppression, and mitigation of Covid-19: lessons learnt from eight countries. *bmj*, 375.
- Xie, X., Zang, Z., & Ponzio, J. M. (2020). The information impact of network media, the psychological reaction to the Covid-19 pandemic, and online knowledge acquisition: Evidence from Chinese college students. *Journal of Innovation & Knowledge*, 5(4), 297–305.
- Yang, K. C., Pierri, F., Hui, P. M., Axelrod, D., Torres-Lugo, C., Bryden, J., & Menczer, F. (2021). The COVID-19 infodemic: Twitter versus facebook. *Big Data & Society*, 8(1), 20539517211013861.
- Yu, M., Li, Z., Yu, Z., He, J., & Zhou, J. (2021). Communication related health crisis on social media: a case of COVID-19 outbreak. *Current Issues in Tourism*, 24(19), 2699–2705.
- Zarocostas, J. (2020). How to fight an infodemic. *Lancet*, 395, 676.
- Zeemering, E. S. (2021). Functional fragmentation in city hall and Twitter communication during the Covid-19 pandemic: Evidence from Atlanta, San Francisco, and Washington, Dc. *Government Information Quarterly*, 38:1, 101539.
- Zhang, J. (2021). People's responses to the COVID-19 pandemic during its early stages and factors affecting those responses. *Humanities and Social Sciences Communications*, 8(1), 1–13.

Qi Zhang is a doctoral student in Department of Information Management & Information Systems, Fudan University. Her research interests are in the areas of human-AI interaction, business analytics and machine learning.

Chee Wei Phang is currently a Professor in the Business School of University of Nottingham Ningbo Campus (UNNC), China. Prior to joining UNNC, he was Professor in Information Systems in the School of Management of Fudan University. His research interests include mobile commerce, social media, and societal impact of IT. His works have appeared in top-tier journals including the Management Science, MIS Quarterly (MISQ), Information Systems Research (ISR), Journal of Marketing, Journal of Management Information Systems (JMIS), Journal of Association for Information Systems, and Communications of the ACM, among others. He is currently serving as Senior Editor for *Electronic Commerce Research and Application (ECRA)*, Associate Editor for *Information & Management*, and on the editorial review board of *JAIS* and *IEEE Transactions on Engineering Management*.

Cheng Zhang is a professor at Department of Information Management & Information Systems, Fudan University. His research interests include IT business value, data-driven business value and platform strategy. His works have been published by >20 journals including MIS Quarterly, INFORMS Journal on Computing, Journal of Management Information Systems, Marketing Science and Journal of Marketing.