Computers in Human Behavior 127 (2022) 107059

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

COVID-19 concerns in cyberspace predict human reduced dispersal in the real world: Meta-regression analysis of time series relationships across American states and 115 countries/territories[☆]

Mac Zewei Ma

Department of Social and Behavioural Sciences, City University of Hong Kong, Hong Kong

ARTICLE INFO

Keywords:
COVID-19
Google trends
Parasite-stress theory of sociality
Behavioral immune system theory
Time series data
Reduced dispersal

ABSTRACT

On the basis of parasite-stress theory of sociality and behavioral immune system theory, this research examined how concerns regarding the Coronavirus disease 2019 (COVID-19) in cyberspace (i.e., online search volume for coronavirus-related keywords) would predict human reduced dispersal in the real world (i.e., human mobility trends throughout the pandemic) between January 05, 2020 and May 22, 2021. Multiple regression analyses controlling for COVID-19 cases per million, case fatality rate, death-thought accessibility, government stringency index, yearly trends, season, religious holidays, and reduced dispersal in the preceding week were conducted. Meta-regression analysis of the multiple regression results showed that when there were high levels of COVID-19 concerns in cyberspace in a given week, the amount of time people spent at home increased from the previous week across American states (Study 1) and 115 countries/territories (Study 2). Across studies, the associations between COVID-19 concerns and reduced dispersal were stronger in areas of higher historical risks of infectious-disease contagion. Compared with actual coronavirus threat, COVID-19 concerns in cyberspace had significantly larger effects on predicting human reduced dispersal in the real world. Thus, online query data have invaluable implications for predicting large-scale behavioral changes in response to life-threatening events in the real world and are indispensable for COVID-19 surveillance.

1. Introduction

Guitton (2013), the editor-in-chief of *Computers in Human Behavior* (*CHB*), proposes that virtual worlds broaden people's understanding of large-scale human behavioral changes in response to critical and threatening events. As such, can cyberpsychology research deepen the public understanding of the ongoing Coronavirus disease 2019 (COVID-19) and can online technologies help mitigate this pandemic? According to a recent editorial of *CHB* (Guitton, 2020), the answer is yes. Online technologies, such as social media and the Internet, help maintain social relationships during the pandemic (Guitton, 2020) and technological tracking techniques, such as Internet- and mobile-based strategies, are critically useful in surveilling and managing COVID-19 (Georgieva et al., 2021). Indeed, recently published studies in *CHB* reveal that analysis of big data related to online behavior can considerably broaden the public understanding of risks and crisis communications (Wang et al., 2021), citizen engagement (Chen et al., 2020), and death anxiety (Barnes, 2021) during the deadly pandemic. In addition to analyzing data sourced from social media websites, such as Twitter and Weibo (Barnes, 2021; Chen et al., 2020; Wang et al., 2021), another research approach is to focus on how online query data can track the public attention to COVID-19 (Brodeur et al., 2021; Hu et al., 2020; Muselli et al., 2021; Springer et al., 2020) and can be used for COVID-19 surveillance (Ayyoubzadeh et al., 2020; Ma, 2021; Mavragani & Gkillas, 2020; Nindrea et al., 2020).

Internet search engines naturally and anonymously capture millions of people's information-seeking behaviors (Lai et al., 2017), and thus tracking changes of public interest in specific search terms can be used as an acceptable means of technological tracking in the COVID-19 context (Georgieva et al., 2021). Computers and other digital devices (e.g., smartphone) are mediums of obtaining information online and conducting web searches occurs in daily life (Cervellin et al., 2017; Lai et al., 2017), online query data are indeed outcomes of human interactions with computers and all other Internet-accessible devices, which can be used to track anonymous online search behavior to reveal how computer and online technologies are important for professional practice, such as

[☆] This research received no specific grant from any funding agency, commercial or not-for-profit sectors.
E-mail address: mac.ma@cityu.edu.hk.

https://doi.org/10.1016/j.chb.2021.107059
Received 25 June 2021; Received in revised form 14 September 2021; Accepted 13 October 2021
Available online 14 October 2021

predicting human behavioral changes in response to large-scale catastrophic events (Guitton, 2013). Thus, this line of study is indeed consistent with Guitton (2020) and Georgieva et al. (2021) that online technologies, such as Internet-based strategies, provide political decision makers with informative implications for mitigating crisis.

This study attempts to investigate how online query data on COVID-19 predict societal-level mobility changes during the deadly pandemic, given that promoting stay-at-home behavior significantly contributes to the control of COVID-19 (Castillo et al., 2020; Gao et al., 2020; Medline et al., 2020; Padalabalanarayanan et al., 2020; Yilmazkuday, 2020). Online query data are publicly available, easily accessible, and of high anonymity (Lai et al., 2017), which make tracking online interests in specific search terms a powerful and socially acceptable means of tracking the societal changes of human behavior in response to large-scale life-threatening events (Guitton, 2013), such as the COVID-19 (Georgieva et al., 2021). In this regard, determining if the search of COVID-19 online can predict human dispersal behavior during the pandemic presents high practicality, given that policy makers can include such query data as an important part of preventive and control measures.

To track millions of hits on COVID-19 in cyberspace, scholars commonly use Google Trends, a big data tool tracking people's natural thoughts on specific topics over time (Arora et al., 2019). This tool is widely used to investigate how human interactions with computers can contribute to the understanding of various important research topics, such as pornography (e.g., Markey & Markey, 2011), death-thought accessibility (e.g., Pelham et al., 2018), mental health (e.g., Adam--Troian & Arciszewski, 2020), physical health (e.g., Flanagan et al., 2021), religiosity (e.g., Ma & Ye, 2021), basic human motivations (e.g., Ma, 2021), and the ongoing COVID-19 (Brodeur et al., 2021; Husnayain et al., 2020; Mavragani & Gkillas, 2020). Therefore, Google Trends data can be used to reveal psychological processes in cyberspace. For example, tracking web search data on specific terms has been successfully used to investigate how searching for major illnesses (e.g., cancer) online can induce people's death anxiety and activate terror management (Alper, 2019; Pelham et al., 2018).

Given that Google search terms serve as a reliable proxy for researchers to gain insight into the thoughts of millions of people (Alper, 2019; Du et al., 2020; Husnayain et al., 2020; Lai et al., 2017; Mavragani & Gkillas, 2020; Pelham et al., 2018; Senecal et al., 2020), the resulting data can provide much natural and ecological evidence for the examined relationships. Recently, Ma and Ye (2021) and Adam-Troian and Bagci (2021) have used Google Trends to track search volume for coronavirus-related keywords (e.g., *coronavirus*, *covid-19*) to obtain a measure of perceived coronavirus threat, given that online searches can assess a group-level spontaneous exposure to coronavirus-related information online (Adam-Troian & Bagci, 2021). Searching for (Sorokowski et al., 2020) and reading COVID-19 information (Karwowski et al., 2020; Kim et al., 2021) induce the perceived threat of the coronavirus. People might have different purposes for carrying out online searches, such as online searches for finding answers, reducing uncertainty, and sensemaking (Lai et al., 2017). Seeking coronavirus online at least captures people's psychological concerns regarding COVID-19 in cyberspace (Du et al., 2020; Muselli et al., 2021). Indeed, COVID-19 query data and coronavirus epidemiological data have a strong and positive correlation across different countries (Du et al., 2020; Mavragani & Gkillas, 2020; Muselli et al., 2021). Moreover, searching for religious terms online (e.g., *Jesus*, *God*, *prayer*) is part of terror management (Alper, 2019; Pelham et al., 2018), and thus the evidence that searching for COVID-19 in cyberspace is carried out with a similar online search for religious terms (Ma & Ye, 2021), suggesting that online query data optimally capture COVID-19 concerns.

Despite an increasing trend of examining how Internet data predict behavioral changes in response to COVID-19, few studies have provided an ecologically-sound theory or a well-framed social psychological model to deepen the public understanding of the examined relationships. Most of the studies using online query data are carried out at a population level to investigate how infectious-disease threats influence human psychology and behavior (e.g., Adam-Troian & Bagci, 2021; Brodeur et al., 2021; Du et al., 2020; Mavragani & Gkillas, 2020), and thus necessitate theories accounting for group-level phenomenon or models explaining human psychological and behavioral responses to infectious-disease threats. Similar to Ma and Ye (2021), the present study uses the parasite–stress theory of sociality, which considers how pathogen prevalence shapes human sociality and cultural diversity (Fincher et al., 2008; Fincher & Thornhill, 2008, 2012b; Thornhill & Fincher, 2014b), and the behavioral immune system theory, which focuses on the psychological and behavioral changes in response to pathogen threat, to examine the relationship between COVID-19 concern in cyberspace and stay-at-home behavior in the real world.

The parasite-stress theory of sociality proposes that strong ingroup assortative sociality is favored by natural selection for avoiding and managing novel infectious diseases in areas of high pathogen-stress (Thornhill & Fincher, 2014a). The reason is that ingroup assortative sociality creates strong intergroup boundaries to block outgroup communication (e.g., xenophobia, prejudice, collectivism, philopatry) to prevent their transmission of novel infectious diseases. The propositions that features of ingroup assortative sociality are adaptive (ancestrally) preferences/values and behaviors for infectious-disease avoidance and management (Thornhill & Fincher, 2014b) are consistent with the proactive responses postulated by the behavioral immune system theory (Ackerman et al., 2018), which aim to manage infectious diseases in the long term. The proactive role of ingroup assortative sociality in avoiding infectious diseases is supported by recent empirical studies showing that the Unites States (U.S.) (Ma & Ye, 2021) and countries (Gelfand et al., 2021; Gokmen et al., 2020; Maaravi et al., 2021; Rajkumar, 2021) of stronger ingroup assortative sociality had better control of COVID-19.

However, how ingroup assortative sociality becomes a reactive response to heightened parasite-stress at a group level remains unknown. According to the behavioral immune system theory, the presence of pathogen threat triggers reactive responses (Ackerman et al., 2018). For example, experimentally manipulating individuals to perceive an increased risk of parasitic infection results in their greater ingroup assortative sociality (Faulkner et al., 2004; Navarrete & Fessler, 2006; Wu & Chang, 2012). Recent studies have investigated the relationship between ingroup assortative sociality and COVID-19 from a perspective of proactive response (i.e., the effect of ingroup assortative sociality on COVID-19 pandemic) (Gelfand et al., 2021; Gokmen et al., 2020; Maaravi et al., 2021; Rajkumar, 2021), but provides limited insights for understanding this relationship from a reactive response perspective (i.e., the effect of COVID-19 pandemic on ingroup assortative sociality) (Ma & Ye, 2021).

One central feature of ingroup assortative sociality is reduced dispersal, which is the "*behaviours that reduce movements away from a central location*" (Fincher & Thornhill, 2008) and "*keeps people near to their natal locale and social community, and hence contributes to collectivism, ethnocentrism, and in-group assortative in general*" (Thornhill & Fincher, 2014a). According to Fincher and Thornhill (2008), reduced dispersal serves as an avoidance strategy for infectious diseases by increasing people's association with immunologically similar individuals, and thus prevent obtaining the parasite from immunologically distant others. Fincher and Thornhill (2008) found that people embedded more in their extended family in parasite–stressed societies and dispersed over shorter distances annually. Thornhill and Fincher (2014a) further showed that American states with higher pathogen prevalence had fewer residential emigration events. These findings suggest that contagion risks can promote reduced dispersal by keeping people near their natal locale as a means of avoiding novel infectious diseases.

Given that staying at home suggests embedding more in one's own family and dispersing for shorter distances from the natal locale (Alesina

& Giuliano, 2010; Fincher & Thornhill, 2008; Thornhill & Fincher, 2014a), this behavior captures strong philopatric values. In this regard, the increase in people's average amount of time spent at their residence in the context of COVID-19 (Bavadekar et al., 2020; Saha et al., 2020) can serve as a proxy for reduced dispersal during the pandemic. Reasonably, increasing the relative frequency, time, and duration of visits related to residences (Bavadekar et al., 2020; Saha et al., 2020) fundamentally reduces the contact with immunologically distant individuals outside. Therefore, this search provides an ecologically-sound perspective to track how psychological concerns regarding COVID-19 in cyberspace can predict mobility changes at a societal level during the pandemic.

Reduced mobility can be a consequence of the lethargy and incapacitation associated with high levels of pathogen prevalence (Fincher & Thornhill, 2008), reduced dispersal during the pandemic may not always reflect the increased philopatric values that serve to avoid the infectious diseases (Thornhill & Fincher, 2014a). As such, the present study on how online query data on COVID-19 predict human reduced dispersal can considerably enhance the understanding of how changes in the collective concerns on the pandemic can promote philopatry at a group level (Thornhill & Fincher, 2014a). More importantly, findings in the current study can show how Google Trends can be easily used as a tool for predicting human behavioral changes in response to large-scale catastrophic events (Guitton, 2013) and how online query data can be informative to policy makers in the context of COVID-19 (Georgieva et al., 2021). Given that time series data are analyzed, the effects of seasonality and autocorrelation are addressed by accounting for season, religious holidays, yearly trends, and reduced dispersal in the previous week (Alper, 2019; Pelham et al., 2018). The effects of stringency of COVID-19 policy (Saha et al., 2020) and terror management during the pandemic (Pyszczynski et al., 2020) are likewise accounted for to rule out alternative explanations.

Given that perceiving an increased risk of parasitic infection has a unique effect on ingroup assortative sociality (Faulkner et al., 2004; Karwowski et al., 2020; Navarrete & Fessler, 2006; Sorokowski et al., 2020; Wu & Chang, 2012) and that online query data capture millions of people's thoughts across a wide range of topics to effectively predict important psychological and behavioral changes in the real world (e.g., Adam-Troian & Arciszewski, 2020; Brodeur et al., 2021; Flanagan et al., 2021; Husnayain et al., 2020; Ma, 2021; Ma & Ye, 2021; Markey & Markey, 2011; Mavragani & Gkillas, 2020; Pelham et al., 2018), this study predicts that:

H1. *COVID-19 concerns in cyberspace uniquely predict reduced dispersal in the real world during the pandemic.*

As ingroup assortative sociality is predominantly valued in parasite-stressed areas due to its associated benefits when defending against novel infectious diseases (Fincher et al., 2008; Thornhill et al., 2009; Thornhill & Fincher, 2014b), a reduced dispersal is assumed to be favored by natural selection in such areas (Fincher & Thornhill, 2008; Thornhill & Fincher, 2014a). Thus, this study further hypothesizes that:

H2. *The associations between COVID-19 concerns in cyberspace and reduced dispersal in the real world are stronger in historically high-risk areas of infectious-disease contagion.*

2. Study 1

2.1. States and period

This study examined how COVID-19 concerns in cyberspace can predict stay-at-home behavior in Washington D.C. and each American state from January 05, 2020 (first week of 2020) to May 22, 2021 (i.e., 72 consecutive weeks).

2.2. Measures and procedure

2.2.1. Weekly-level variables

2.2.1.1. COVID-19 threat in the real world. This study sourced national- and state-level time series epidemiological data on COVID-19 from Our World in Data (https://ourworldindata.org/) and the New York Times (https://github.com/nytimes/COVID-19-data), respectively. New cases per million and fatality rate (i.e., ratio of COVID-19 deaths to cases) were calculated for each week to determine the prevalence and lethality of the novel coronavirus and capture its threat (Mazumder et al., 2020; Verity et al., 2020). For weeks (January and early February) with missing epidemiological data, the values were fixed to 0.

2.2.1.2. COVID-19 concerns in cyberspace. Recent studies used online query data on COVID-19 to obtain a measure of the perceived coronavirus threat (Adam-Troian & Bagci, 2021; Ma & Ye, 2021). Given that people have different purposes to search for COVID-19 online, which is by itself an information-seeking behavior to find answers, reduce uncertainty, and enhance sensemaking (Lai et al., 2017), online query data on COVID-19 can also capture people's concerns regarding the novel coronavirus in cyberspace. Indeed, a strong and positive correlation exists between online query data on COVID-19 and epidemiological data on coronavirus across different countries (Du et al., 2020; Mavragani & Gkillas, 2020; Muselli et al., 2021). Recent studies suggested that COVID-19 search volume could capture people's psychological concerns on COVID-19 (Du et al., 2020; Mavragani & Gkillas, 2020; Muselli et al., 2021) and related death anxiety (Ma & Ye, 2021). Therefore, operationalizing the current index as the COVID-19 concerns in cyberspace allows for greater validity and comprehensiveness of the research findings.

Given that Google Trends uses a natural language classification engine to categorize search terms that share similar concepts into specific topics (Choi & Varian, 2012), irrespective of their languages (Dilmaghani, 2020; Yeung, 2019), recent studies have utilized categorized search terms to improve the reliability and validity of their findings (Brodeur et al., 2021; Flanagan et al., 2021; Gianfredi et al., 2018; Kamiński et al., 2020; Ma & Ye, 2021; Strzelecki, 2020; Yeung, 2019). In the context of COVID-19, using only exact search terms, such as *covid-19*, presented at least two disadvantages: 1) obtaining search volume from people performing online searches with other languages within the investigated geographic region was difficult (e.g., people in the U.S. may use multiple languages to search information related to COVID-19, such as *coronavirus* or *coronavírus*); and 2) search volume of other terms that share similar concepts to the exact search terms used (e.g., *SARS-CoV-2*) would be excluded.

Accordingly, five exact search terms (i.e., *corona*, *coronavirus*, *covid19*, *covid 19*, and *covid-19*) (Adam-Troian & Bagci, 2021) plus one categorized search term (i.e., *Coronavirus*, the categorization 'Virus' of all search keywords related to the concept of the novel coronavirus) (Ma & Ye, 2021) were used to improve the reliability and validity of the study index. The search volume of several keywords that had values less than 1, often in the weeks of January, were fixed to 0. At the national level, the search terms had a Cronbach's α of 0.97, suggesting the plausibility to average the relative-search-volume (RSV) scores across the weekly search terms to capture COVID-19 concerns in cyberspace. As the lethality of the novel coronavirus was associated with people's concerns regarding COVID-19 (Muselli et al., 2021), this study found that the current index had a significant and positive correlation with COVID-19 case fatality rate that was analyzed with time series data, $r = 0.37$, $p_{\text{two-tailed}} = 0.001$. Furthermore, if searching for the novel coronavirus in Google indeed reflected people's concerns regarding COVID-19 in cyberspace, the current index should be significantly and positively associated with the search volume for fear-related emotions and help-seeking behaviors (i.e., helpline, fear, worry, panic, and death) and infectious-disease avoidance (i.e., hand washing, social distancing, and quarantine) (Du et al., 2020). Table S1 (below the diagonal; Supplementary File) shows that the correlations between the COVID-19 concerns index and external variables were significant (all $ps < .001$) and positive ($0.65 \leq rs \leq 0.96$) at a national level. Table S1 (above the diagonal; Supplementary File) also shows that accounting for the actual COVID-19 threat in a partial correlation analysis did not alter the significant and positive relationships between the study index and the external variables ($0.64 \leq rs \leq 0.93$, all $ps < 0.001$). Thus, the psychological process in cyberspace was unique and reflected people's concerns regarding COVID-19 in the virtual world. Therefore, the COVID-19 concerns index was computed for each American state.

2.2.1.3. Reduced dispersal in the real world. The daily COVID-19 Community Mobility Reports (CMR) from Google (https://www.google.com/covid19/mobility/) were sourced to track mobility changes during the pandemic. Google collects the movement data from users who have turned on their location history setting (Sulyok & Walker, 2020). By assessing the amount of time people spent at specific location categories (i.e., retail and recreation, grocery and pharmacy, parks, transit stations, workplace, and residential), Google calculates the percentage change in activity at each of the location categories in comparison with the median value of the baseline day from the 5-week period of 03 January to 06 February 2020 (Puppala et al., 2021) (for further details, see https://support.google.com/covid19-mobility/answer/9824897?hl=en&ref_topic=9822927). For each region (e.g., U.S.) and subregion (e.g., California), Google uses specific algorithms (Bavadekar et al., 2020) and the "same world-class anonymization technology" (https://www.google.com/covid19/mobility/?hl=en) to aggregate and anonymize individual data. Therefore, the mobility data released by Google are aggregated and anonymized at a regional level, which is important to protect the privacy of individual users when releasing data to the public (Bavadekar et al., 2020). Bavadekar et al. (2020) describes the detailed processes of aggregation and anonymization.

Huynh (2020) showed that residential movement was strongly and negatively related to all other types of movement. Thus, the present study averaged the daily mobility scores of retail and recreation, grocery and pharmacy, parks, transit stations, and workplace to compute a mean score of non-residential movement. The result was subtracted from the mobility score of residential movement to create a daily reduced dispersal index, which was further used to calculate a weekly-level measure such that a higher score indicates a greater level of reduced dispersal in a given week (i.e., spending more time at home; Alesina & Giuliano, 2010; Thornhill & Fincher, 2014a). Given that religiosity is an important element of ingroup assortative sociality (Fincher & Thornhill, 2012a), its significant and positive correlation with reduced dispersal would support the external validity of the present index. As such, the RSV scores of categorized search terms of *Jesus* (Preacher), *God* (Supreme being), and *Prayer* (Topic) were averaged to obtain a weekly religiosity index (Alper, 2019; Pelham et al., 2018). The results were found significantly and positively related to the weekly-level reduced dispersal index, $r = 0.58$, $p_{\text{two-tailed}} < 0.001$. This significant relationship persisted when accounting for COVID-19 cases per million and case fatality rate in a partial correlation analysis, $r = 0.55$, $p_{\text{two-tailed}} < 0.001$. Thus, the weekly reduced dispersal index of each American state was calculated by using the U.S. regional reports of the Google CMR. Given that no data were obtained between 01 January and 14 February 2020, the reduced dispersal scores of these weeks were fixed to 0.

2.2.1.4. Death-thought accessibility. Pelham et al. (2018) reported that search volume for hypertension, cancer, and diabetes induced death-thought accessibility at a group level. Given that reduced dispersal could also serve as a terror management process during the deadly pandemic (Pyszczynski et al., 2020), this study averaged the weekly RSV scores of the categorized search terms of *Hypertension* (Medical condition), *Cancer* (Disease) and *Diabetes* (Disorder) to obtain a major-illness index (Alper, 2019; Pelham et al., 2018) and account for the effect of death-thought accessibility on reduced dispersal.

2.2.1.5. Stringency of COVID-19 policy. Mobility changes were also affected by the societal responses to COVID-19 lockdown policy (Saha et al., 2020). As such, this study controlled for the government stringency index from The University of Oxford (https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-responsetracker) that has been widely used to account for COVID-19 policy (Kapoor et al., 2021; Sorci et al., 2020; Wang, 2021). For the weeks with missing stringency indices, the values were fixed to 0.

2.2.1.6. Season, religious holidays, and yearly trends. First, people commonly reduce their outdoor activities when the weather becomes colder. Thus, autumn and winter (from September to February) weeks were coded as 1 while other weeks were coded as 0 to account for the effect of seasons on reduced dispersal. Second, religious holidays were controlled because people may be less likely to stay at home during religious events. According to Pelham et al. (2018) and Alper (2019), weeks including Easter and Christmas days were coded as 1 while other weeks were coded as 0. Third, adjusting for yearly trends in reduced dispersal (Alper, 2019; Pelham et al., 2018) by treating the variable 'year' (2020 and 2021) as a covariate was an important factor.

2.2.2. Existing level of infectious-disease contagion risk

This study sourced the state-level parasite–stress index from Fincher and Thornhill (2012a) to proxy for the historical infectious-disease contagion risk. This parasite–stress index was created based on data (between 1993 and 2007) obtained from the annual Morbidity and Mortality Weekly Report, "Summary of Notifiable Diseases, United States", of the Centers for Disease Control and Prevention. Fincher and Thornhill (2012a) adjusted the number of cases of all infectious diseases for all states and then used *Z*-transformed scores to create a composite index that measures the pathogen prevalence of each state. In the present study, an Expectation–Maximization method was used to estimate the parasite–stress index for Washington D.C. to maximize the use of the data.

2.3. Analytical procedure

The statistical approaches in Pelham et al. (2018) and Alper (2019) were followed. First, with *week* as the unit of analysis, all weekly-level cases were considered the individual data points. Second, this study specified a regression model to predict level of reduced dispersal in the present week (week x) from several predictors: 1) year; 2) season and religious holidays; 3) reduced dispersal in the prior week (i.e., week x – 1), which allowed for the consideration for autocorrelation and assessed changes in reduced dispersal rather than its simple variation; 4) major-illness and stringency indices in the present week; 5) COVID-19 threat in the present week; and 6) COVID-19 concerns in the present week. This regression model was first analyzed with national-level data, then procedures were replicated separately for Washington D.C. and each American state. Specifically, variables were *Z*-transformed to obtain standardized betas and standard errors estimated from the scores to improve the legibility and allow for comparison. Based on the results of the multiple regressions, meta-regression was carried out to examine the moderating effect of state-level infectious-disease contagion risks on the combined association between COVID-19 concerns in cyberspace and stay-at-home behavior across American states (Alper, 2019). Two-tailed tests were carried out to avoid inaccurate and biased statistical results.

2.4. Results and discussion

The national level analysis showed that while actual coronavirus threat had no significant effect on reduced dispersal in the real world, the effect of the COVID-19 concerns index was significant, $\beta = 0.34$, $p_{\text{two-tailed}} < 0.001$, 95% CI = [0.28, 0.40], accounting for a series of covariates (Table S2; Supplementary File). The Durbin-Watson value was 2.10, which was close to the ideal value of 2.00, thus there was no evidence of autocorrelation (Brocklebank & Dickey, 2003; Pelham et al., 2018; Yaffee & McGee, 2000). Next, the multiple regression was run separately on data of Washington D.C. and each American state. The results are separately presented from Tables SS1–SS51 (Study 1 Supplementary Tables https://osf.io/w25kb/?view_only=cf42e658bceb4791b4c20d4a4d535d01) to make the present study more transparent. Across analyses, the mean Durbin-Watson value was 2.14 ($SD = 0.31$) and the median value was 2.13, suggesting that autocorrelation was not an issue. Based on the results of the 51 multiple regressions, meta-regression examining the moderating effect of state-level infectious-disease contagion risk on the combined association was conducted.

The first meta-regression analysis examined the combined association between COVID-19 concern in cyberspace and reduced dispersal in the real world, which showed a non-significant heterogeneity in the associations across states, after accounting for covariates, $Q(50) = 50.19$, $p_{\text{two-tailed}} = 0.466$. Thus, a fixed-effect method was used (Alper, 2019), showing a significant combined effect of the COVID-19 concerns index on the reduced dispersal index across states, $Estimate = 0.29$, $SE = 0.01$, $z = 41.62$, $p_{\text{two-tailed}} < 0.001$, 95% CI = [0.28, 0.30]. Adding state-level infectious-disease contagion risk as a covariate for the meta-regression did not alter the significant and positive combined effect, $Estimate = 0.29$, $SE = 0.01$, $z = 41.62$, $p_{\text{two-tailed}} < 0.001$, 95% CI = [0.28, 0.30]. As the effect of state-level infectious-disease contagion risk was significant and positive, $Estimate = 0.03$, $SE = 0.01$, $z = 2.54$, $p_{\text{two-tailed}} = 0.011$, 95% CI = [0.01, 0.04], the associations between COVID-19 concerns in cyberspace and reduced dispersal in the real world were stronger in states of higher historical risks of infectious-disease contagion (Fig. 1).

The second meta-regression analysis was conducted to investigate the combined effect of COVID-19 cases per million on reduced dispersal. Due to the non-significant heterogeneity in the associations across states, after accounting for covariates, $Q(50) = 29.71$, $p = 0.990$, a fixed-effect method was employed, showing a significant combined effect of COVID-19 cases per million on reduced dispersal across states, $Estimate = 0.07$, $SE = 0.01$, $z = 9.05$, $p_{\text{two-tailed}} < 0.001$, 95% CI = [0.06, 0.09]. Adding state-level infectious-disease contagion risk as a covariate did not alter the significant and positive combined effect, $Estimate = 0.07$, $SE = 0.01$, $z = 9.01$, $p_{\text{two-tailed}} < 0.001$, 95% CI = [0.06, 0.09], and the effect of state-level infectious-disease contagion risk was non-significant, $Estimate = -0.01$, $SE = 0.01$, $z = -0.60$, $p_{\text{two-tailed}} = 0.548$, 95% CI = [−0.03, 0.01] (Fig. S1a; Supplementary File). As for case fatality rate, the combined effect was non-significant, $Estimate = -0.01$, $SE = 0.01$, $z = -1.41$, $p_{\text{two-tailed}} = 0.158$, 95% CI = [−0.03, 0.00], calculated from a fixed-effect method, $Q(50) = 46.46$, $p_{\text{two-tailed}} = 0.620$, and it was found that adding the state-level infectious-disease contagion risk as a covariate, $Estimate = 0.01$, $SE = 0.01$, $z = 0.95$, $p_{\text{two-tailed}} = 0.342$, 95% CI = [−0.01, 0.03], did not alter the non-significant combined association, $Estimate = -0.01$, $SE = 0.01$, $z = -1.26$, $p_{\text{two-tailed}} = 0.207$, 95% CI = [−0.02, 0.00] (Fig. S1b; Supplementary File).

Given that the combined effect of COVID-19 concerns (*standardized estimate* = 0.29) was larger than that of the actual coronavirus threat (e.g., COVID-19 cases per million *standardized estimate* = 0.07), H1 was supported. Moreover, the associations between COVID-19 concerns and reduced dispersal were stronger in states of higher risks of infectious-disease contagion, supporting H2. With the parasite–stress theory of sociality supported cross-nationally (Fincher et al., 2008; Fincher & Thornhill, 2008, 2012a; Murray & Schaller, 2010; Thornhill et al., 2010), the findings in Study 1 can be examined across different countries/territories.

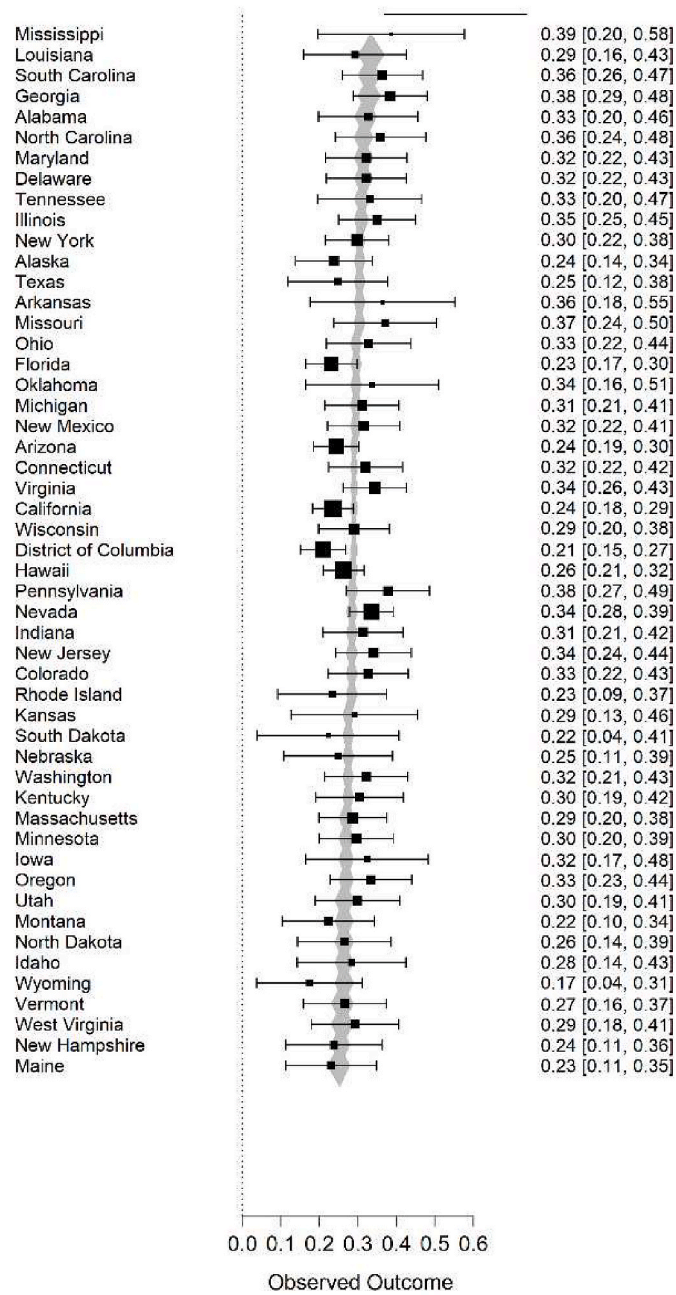

Fig. 1. The distribution of standardized regression coefficients predicting reduced dispersal in the real world from COVID-19 concerns in cyberspace in Study 1 ($N = 51$). Whiskers represent 95% CIs for the standardized regression coefficients. Grey diamonds indicate the predictions from historical risk of infectious-disease contagion. States are ranked from the most parasite-stressed (Mississippi) to the least parasite-stressed (Maine).

3. Study 2

Study 2 examined whether the effect of the COVID-19 concerns index on the reduced dispersal index could also be found in different countries/territories. How this effect would depend on the country-level risk of infectious-disease contagion was examined by replicating the research design and analytical procedure of Study 1 to determine the generalizability of the findings.

3.1. Countries/territories and period

Country selection was based on 1) Google CMR data availability; 2) Google Trends data availability; 3) COVID-19 epidemiological data availability; and 4) availability of data on covariates. A total of 115 countries/territories were investigated from January 05, 2020 to May 22, 2021, the same 72 consecutive weeks in Study 1.

3.2. Measures and procedure

All measures were identical to those used in Study 1 except for several minor modifications for 1) religious holidays; 2) autumn and winter weeks; 3) languages used for searching the word *coronavirus*, and 4) historical infectious-disease contagion risk index. First, the CIA WORLD FACTBOOK (https://www.cia.gov/the-world-factbook/) was used to identify the predominant religion of each country. Subsequently, 1) Easter and Christmas days were controlled for Christian countries/territories; 2) Ramadan, Eid al-Fitr, and Eid al-Adha were controlled for Islamic countries/territories; and 3) Diwali was controlled for countries/territories predominated by Hinduism (Alper, 2019; Pelham et al., 2018). For Buddhist countries, Buddha's Birthday was controlled. Passover, Rosh Hashanah, Yom Kippur, and Hanukkah were controlled for Judaism. The Bon festival was controlled for Japan (Pelham et al., 2018). For Nepal, the Dashain festival was controlled. For Vietnam, the Hung Kings Temple Festival was controlled. The exact dates of the religious holidays in each year were tracked by an online calendar tool (https://www.officeholidays.com/). For seasons, autumn and winter weeks (from September to February for countries/territories in the northern hemisphere; from March to August for countries/territories in the southern hemisphere) were coded as 1 while other weeks were coded as 0.

People in different countries/territories might have different expressions for the word *coronavirus*, and thus two strategies were used to minimize the linguistic influences. First, the categorized search term *Coronavirus* (Virus topic) was used to capture all relevant search volume related to keywords similar to the coronavirus concept (see Study 1 for details). Therefore, as a topic categorization, the search volume for the term *Coronavirus* was not influenced by linguistic differences across countries/territories. Second, the most widely spoken language or official language of each country was identified using the CIA WORLD FACTBOOK. Then, the Google Translator (https://translate.google.com/) was used to translate the English word *coronavirus* to other languages. For example, when creating the COVID-19 concerns index from the RSVs of exact search terms of *corona*, *coronavirus*, *covid19*, *covid 19*, *covid-19*, and the categorized search term *Coronavirus*, *coronavirus* (English) was used for English-speaking countries/territories (e.g., United Kingdom) and *coronavírus* (Portuguese) was used for Portuguese-speaking countries/territories (e.g., Portugal). Table SSS1 (Study 2 Supplementary Tables https://osf.io/w25kb/?view_only=cf42e658bceb4791b4c20d4a4d535d01) shows the word *coronavirus* in other languages. The internal reliability of the COVID-19 concerns index was found satisfactory across different countries/territories (mean Cronbach $\alpha = 0.92$, $SD = 0.04$).

The historical parasite-stress index in Murray and Schaller (2010) and the infectious disease richness index in Fincher and Thornhill (2008) were used to create a country-level infectious-disease contagion risk index (Cronbach $\alpha = 0.74$). A high score indicated a high historical risk of infectious-disease contagion.

3.3. Analytical approach

The analytical procedures for Study 2 were identical to those of Study 1.

3.4. Results and discussion

Tables SSS2–SSS116 (Study 2 Supplementary Tables https://osf.io/w25kb/?view_only=cf42e658bceb4791b4c20d4a4d535d01) show the results of the 115 multiple regression analyses. Across analyses, the mean Durbin-Watson value was 2.01 ($SD = 0.27$) and the median value was 2.02, suggesting that autocorrelation was not an issue (Brocklebank & Dickey, 2003; Pelham et al., 2018; Yaffee & McGee, 2000).

The first meta-regression analysis examined the combined effect of the COVID-19 concerns index on the reduced dispersal index. Because the heterogeneity in the associations across countries/territories was significant, after accounting for covariates, $Q(114) = 363.95$, $p_{\text{two-tailed}} < 0.001$, a restricted maximum likelihood method was employed, showing a significant combined effect, $Estimate = 0.28$, $SE = 0.01$, $z = 31.37$, $p_{\text{two-tailed}} < 0.001$, 95% CI = [0.26, 0.30]. This combined association remained significant when adding the country-level infectious-disease contagion risk as a covariate, $Estimate = 0.28$, $SE = 0.01$, $z = 32.03$, $p_{\text{two-tailed}} < 0.001$, 95% CI = [0.26, 0.29]. Given that the effect of the existing-level of infectious-disease contagion risk was significant and positive, $Estimate = 0.02$, $SE = 0.01$, $z = 2.34$, $p_{\text{two-tailed}} = 0.019$, 95% CI = [0.00, 0.04], the associations between COVID-19 concerns in cyberspace and reduced dispersal in the real world were stronger in countries/territories of higher historical risks of infectious-disease contagion (Fig. 2).

The second meta-regression analysis examined the combined effect of COVID-19 cases per million on reduced dispersal. Because the heterogeneity in the associations across countries/territories was significant, after accounting for covariates, $Q(114) = 364.96$, $p_{\text{two-tailed}} < 0.001$, a restricted maximum likelihood method was employed, showing a significant combined effect, $Estimate = 0.06$, $SE = 0.01$, $z = 6.56$, $p_{\text{two-tailed}} < 0.001$, 95% CI = [0.04, 0.08]. This combined effect remained significant when accounting for country-level infectious-disease contagion risk, $Estimate = 0.06$, $SE = 0.01$, $z = 6.63$, $p < 0.001$, 95% CI = [0.04, 0.08], but this effect did not depend on the existing level of infectious-disease contagion risk, $Estimate = -0.02$, $SE = 0.01$, $z = -1.66$, $p_{\text{two-tailed}} = 0.100$, 95% CI = [−0.04, 0.00] (Fig. S2a; Supplementary File). Moreover, the combined effect of COVID-19 case fatality rate on reduced dispersal was non-significant, $Estimate = 0.01$, $SE = 0.01$, $z = 1.00$, $p_{\text{two-tailed}} = 0.318$, 95% CI = [−0.01, 0.02], calculated from a restricted maximum likelihood method, $Q(114) = 224.90$, $p_{\text{two-tailed}} < 0.001$, and it was found that adding the country-level infectious-disease contagion risk as a covariate, $Estimate = -0.00$, $SE = 0.01$, $z = -0.68$, $p_{\text{two-tailed}} = 0.498$, 95% CI = [−0.02, 0.01], did not alter this non-significant combined association, $Estimate = 0.01$, $SE = 0.01$, $z = 0.98$, $p_{\text{two-tailed}} = 0.325$, 95% CI = [−0.01, 0.02] (Fig. S2b; Supplementary File).

Study 2 showed that high levels of COVID-19 concerns in cyberspace were major causes of reduced dispersal in the real world across different countries/territories, supporting H1. Compared with the effect of the COVID-19 concerns index (*standardized estimate* = 0.28), the COVID-19 threat in the real world showed an extremely small effect (e.g., COVID-19 cases per million *standardized estimate* = 0.06), revealing that tracking the former could be a more effective approach of predicting people's behavioral response to the coronavirus. Fig. 3 presents the combined time series association between the COVID-19 concerns index and the reduced dispersal index for 72 consecutive weeks across countries/territories. This association was stronger in countries/territories of high historical risks of infectious-disease contagion. Thus, reduced dispersal could serve as a mechanism of the behavioral immune system at a group level and was favored by natural selection in areas of high pathogen-stress, supporting H2.

4. General discussion

As a response to Guitton (2020) and Georgieva et al. (2021) that online technologies are useful for mitigating the ongoing COVID-19

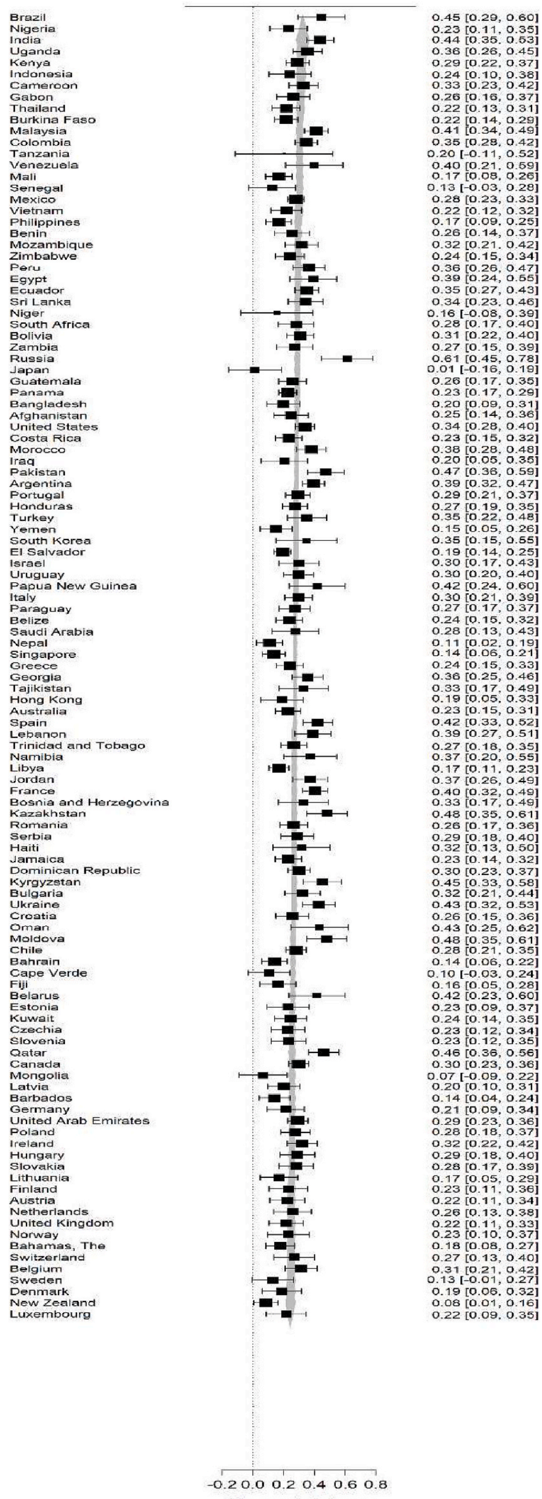

Fig. 2. The distribution of standardized regression coefficients predicting reduced dispersal in the real world from COVID-19 concerns in cyberspace in Study 2 ($N = 115$). Whiskers represent 95% CIs for the standardized regression coefficients. Grey diamonds indicate the predictions from historical risk of infectious-disease contagion of the country/territory. Countries/territories are ranked from the most parasite-stressed (Brazil) to the least parasite-stressed (Luxembourg).

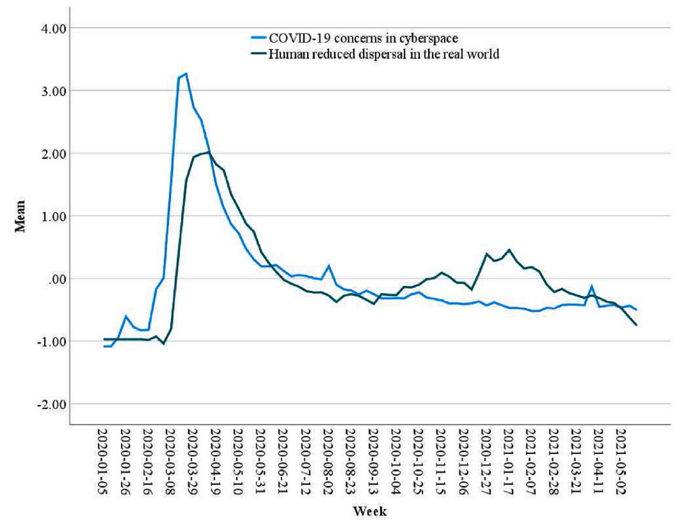

Fig. 3. Graph representing the combined time series association between the COVID-19 concerns index and the reduced dispersal index across 115 countries/territories between January 05, 2020 and May 22, 2021 (Study 2). Standardized scores are shown.

pandemic, the present study is the first to document that when people have high levels of COVID-19 concerns in cyberspace in a given week, the amount of time they spend at home in the real world increases from the previous week across American states (Study 1) and 115 countries/territories (Study 2), controlling for a series of covariates. Given that both online query and mobility data are outcomes of human interactions with computers or other Internet-accessible devices, the present findings are consistent with the recent editorial of *CHB* (Guitton, 2020) that cyberpsychology research and online technologies deepen the public understanding of the ongoing COVID-19 and help mitigate this pandemic. Indeed, given that the effect of the COVID-19 concerns index on predicting reduced dispersal in the real world is significantly larger than that of the actual coronavirus threat (i.e., COVID-19 cases per million and case fatality rate) across studies, online query data provide an invaluable implication for predicting large-scale behavioral changes in response to catastrophic events (Guitton, 2013) and are indispensable for COVID-19 surveillance (Georgieva et al., 2021). From a theoretical perspective, the present research extends the parasite–-stress theory of sociality (Thornhill & Fincher, 2014b) by showing that a high level of concern about parasitic infection promotes a high level of reduced dispersal, which is a reactive response of the behavioral immune system (Ackerman et al., 2018). Moreover, as the combined association between COVID-19 concerns and reduced dispersal is stronger in American states (Study 1) and countries/territories (Study 2) with high historical risks of infectious-disease contagion, the present research supports the proposal that reduced dispersal is favored by natural selection in areas of high pathogen-stress (Fincher & Thornhill, 2008; Thornhill & Fincher, 2014a).

Given that reduced dispersal in the form of staying at home is shown to decrease the transmission of the novel coronavirus (Castillo et al., 2020; Gao et al., 2020; Medline et al., 2020; Padalabalanarayanan et al., 2020; Yilmazkuday, 2020) and that searching for coronavirus-related keywords in Google uniquely predicts such dispersal behavior, the present findings are consistent with early (Carneiro & Mylonakis, 2009; Zhou et al., 2011) and recent studies (Fantazzini, 2020; Peng et al., 2021; Venkatesh & Gandhi, 2020). Thus, web search data have important implications for the control of novel infectious diseases. Online query data are publicly available, easily accessible, and have high anonymity (Lai et al., 2017), the significant effect of the COVID-19 concerns index on dispersal behavior in the real world suggests that tracking online interests in specific search terms can be a powerful and socially acceptable means of tracking societal changes of human behaviors in response to large-scale life-threatening events (Guitton, 2013), such as COVID-19 (Georgieva et al., 2021). In this regard, policy makers can use COVID-19 search query data to predict the likelihood of future mobility changes at the societal level to reach better control of COVID-19. Moreover, with the analysis of mobility data obtained from millions of people's individual devices, such as smartphones that allow recording of location history (Sulyok & Walker, 2020), the current research suggests that the Internet- and mobile-based strategies can serve as effective tracking and technological surveillance strategies of the population in the context of COVID-19 (Georgieva et al., 2021).

The present research design is consistent with the growing literature that uses big data to capture the thoughts (Alper, 2019; Du et al., 2020; Husnayain et al., 2020; Lai et al., 2017; Mavragani & Gkillas, 2020; Pelham et al., 2018; Senecal et al., 2020) and behaviors (Huynh, 2020; Saha et al., 2020; Wang, 2021; Yilmazkuday, 2020) of millions of people to test a wide range of important research topics. Thus, the big data increase the objectivity and ecological validity of the present findings in comparison with those relying on traditional self-report measures and experimental designs. In addition, ruling out alternative explanations by controlling constructs that were relevant to reduced dispersal in the context of COVID-19 (Pyszczynski et al., 2020; Saha et al., 2020) strengthens the validity of the findings, and thereby decrease the chances of drawing fallible conclusions. Moreover, the present findings cannot be interpreted as artifacts of common method variance and serial autocorrelation. First, reduced dispersal is estimated using Google mobility data, which are anonymized and aggregated from the number of requests for directions in Google maps (Saha et al., 2020). The COVID-19 concerns index is estimated with online query data on the coronavirus. Thus, the present significant findings are less likely to be attributed to the common method variance (Lindell & Whitney, 2001). Second, the effects of season, religious holidays, yearly trends, and reduced dispersal index in the previous week are effectively controlled. Subsequently, the Durbin-Watson values across studies are close to the ideal value of 2.00, suggesting the absence of autocorrelation (Brocklebank & Dickey, 2003; Pelham et al., 2018; Yaffee & McGee, 2000). Thus, COVID-19 concerns in cyberspace indeed uniquely predict reduced dispersal in the real world, supporting that big data such as online query data can be applied to account for various group-level processes that are hardly examined using traditional research methods (Alper, 2019; Du et al., 2020; Husnayain et al., 2020; Huynh, 2020; Lai et al., 2017; MacInnis & Hodson, 2015; Mavragani & Gkillas, 2020; Pelham et al., 2018; Saha et al., 2020; Senecal et al., 2020; Wang, 2021; Yilmazkuday, 2020).

In addition to their practical implications, the present findings also provide implications for social psychological theories regarding the role of pathogen threat in shaping human psychology and behaviors. Reduced dispersal is a reactive response of the behavioral immune system (Ackerman et al., 2018) at a group level, which is consistent with the individual-level finding that inducing a high risk perception on infectious diseases results in an increased level of ingroup assortative sociality (Faulkner et al., 2004; Karwowski et al., 2020; Navarrete & Fessler, 2006; Sorokowski et al., 2020; Wu & Chang, 2012). Given that reduced dispersal is proposed to contribute to ingroup assortative sociality (Thornhill & Fincher, 2014a), the current and recent findings regarding the COVID-19 pandemic (Gelfand et al., 2021; Gokmen et al., 2020; Maaravi et al., 2021; Rajkumar, 2021) could jointly suggest that the population-level reactive and proactive responses of the behavioral immune system may sustain the predictive power of the parasite-stress theory of sociality and infectious-disease avoidance at a group level (Fincher et al., 2008; Fincher & Thornhill, 2008, 2012a; Murray & Schaller, 2010; Thornhill et al., 2010).

Given that the relationship between COVID-19 concern in cyberspace and reduced dispersal in the real world is stronger in areas with high historical risks of infectious-disease contagion, the mitigating effect of ingroup assortative sociality on COVID-19 (Gokmen et al., 2020; Maaravi et al., 2021; Rajkumar, 2021) may be rooted in the reactive responses activated in these high parasite-stressed regions. For example, collectivism reflects ingroup assortative sociality and is predominately valued in areas of high pathogen-stress (Fincher et al., 2008; Fincher & Thornhill, 2012a; Murray & Schaller, 2010; Thornhill et al., 2010), and thus people in more collectivistic countries/territories may react more strongly to avoid the novel coronavirus, such as by wearing medical masks (Lu et al., 2021), although Lu et al. (2021) interpreted their results on the basis of cultural differences. Thus, the present findings reveal that the study of the relationship between ingroup assortative sociality and COVID-19 needs to consider alternative explanation(s).

Social media data also capture psychological and behavioral changes to COVID-19 (Barnes, 2021; Chen et al., 2020; Wang et al., 2021). Thus, the validity and reliability of the present findings can be examined by analyzing social media data on COVID-19 concerns. Moreover, despite being a representative search engine, Google is not widely used in several countries (Jun et al., 2018). As such, using only Google search volume data may not fully explain the variations in COVID-19 concerns during the deadly pandemic. Future research is encouraged to collect online data from other search engines to cross-validate the present findings. For example, the Baidu Index, which tracks Chinese people's online search behaviors (Liu et al., 2019), can be utilized in future studies. Online query data are widely used across different disciplines to predict important research topics (Adam-Troian & Arciszewski, 2020; Brodeur et al., 2021; Flanagan et al., 2021; Husnayain et al., 2020; Ma, 2021; Ma & Ye, 2021; Markey & Markey, 2011; Mavragani & Gkillas, 2020; Pelham et al., 2018), and thus those on COVID-19 can be used to explain other related issues. For example, future studies may investigate whether a high level of COVID-19 concern in cyberspace predicts a high likelihood of wearing medical masks in the real world. Indeed, search engines are used for finding answers, reducing uncertainties, and sensemaking, and searching for information online occurs in daily life (Lai et al., 2017), thus online query data can provide insights on important human psychological and behavioral changes. Furthermore, given the significant cultural differences in COVID-19 severity (e.g., Gelfand et al., 2021; Gokmen et al., 2020; Maaravi et al., 2021; Rajkumar, 2021) and preventive behaviors (e.g., Lu et al., 2021), future studies may investigate how cultural factors moderate the association between COVID-19 concerns and dispersal behavior. Another research direction relates to the parasite-stress theory, because individual-level findings show that inducing a high level of risk perception on the coronavirus increases ingroup favoritism and outgroup avoidance (Karwowski et al., 2020; Sorokowski et al., 2020). Future studies may test how COVID-19 concerns in cyberspace predict other ingroup assortative sociality features.

5. Conclusion

In summary, this research shows that online query data on COVID-19 are effective in predicting human reduced dispersal in the real world at a population level across American states (Study 1) and 115 countries/territories (Study 2). Across studies, the associations between COVID-19 concerns in cyberspace and reduced dispersal in the real world are stronger in areas of high historical risks of infectious-disease contagion, suggesting that reduced dispersal is favored by natural selection in areas of high pathogen-stress. Thus, this study supports Guitton (2013), Guitton (2020), and Georgieva et al. (2021) that online technological tools are indispensable for tracking human behavioral changes in response to large-scale life-threatening events. Cyberpsychology is important for deepening the public understanding of the ongoing COVID-19 pandemic. From a theoretical perspective, this study extends parasite–stress theory of sociality via connection with behavioral immune system theory in the context of COVID-19 (Ma & Ye, 2021). Strong ingroup assortative sociality is a reactive response to a high level of concern regarding parasitic infection at a group level, which serves to defend people against the transmission of novel infectious diseases from the outgroup, particularly in high parasite-stressed areas.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2021.107059.

References

Ackerman, J. M., Hill, S. E., & Murray, D. R. (2018). The behavioral immune system: Current concerns and future directions. *Social and Personality Psychology Compass, 12*(2), Article e12371. https://doi.org/10.1111/spc3.12371

Adam-Troian, J., & Arciszewski, T. (2020). Absolutist words from search volume data predict state-level suicide rates in the United States. *Clinical Psychological Science, 8*(4), 788–793. https://doi.org/10.1177/2167702620916925

Adam-Troian, J., & Bagci, C. (2021). The pathogen paradox: Evidence that perceived COVID-19 threat is associated with both pro-and anti-immigrant attitudes. *International Review of Social Psychology, 34*(1), 11. https://doi.org/10.5334/irsp.469

Alesina, A., & Giuliano, P. (2010). The power of the family. *Journal of Economic Growth, 15*(2), 93–125. https://doi.org/10.1007/s10887-010-9052-z

Alper, S. (2019). Does the association between illness-related and religious searches on the Internet depend on the level of religiosity? *Social Psychological and Personality Science, 12*(4), 497–505. https://doi.org/10.1177/1948550620923233

Arora, V. S., McKee, M., & Stuckler, D. (2019). Google Trends: Opportunities and limitations in health and health policy research. *Health Policy, 123*(3), 338–341. https://doi.org/10.1016/j.healthpol.2019.01.001

Ayyoubzadeh, S. M., Ayyoubzadeh, S. M., Zahedi, H., Ahmadi, M., & Kalhori, S. R. N. (2020). Predicting COVID-19 incidence through analysis of google trends data in Iran: Data mining and deep learning pilot study. *JMIR Public Health and Surveillance, 6*(2), Article e18828. https://doi.org/10.2196/18828

Barnes, S. J. (2021). Understanding terror states of online users in the context of COVID-19: An application of Terror Management Theory. *Computers in Human Behavior, 125*, 106967. https://doi.org/10.1016/j.chb.2021.106967

Bavadekar, S., Dai, A., Davis, J., Desfontaines, D., Eckstein, I., Everett, K., Fabrikant, A., Flores, G., Gabrilovich, E., & Gadepalli, K. (2020). *Google COVID-19 search trends symptoms dataset: Anonymization process description (version 1.0)*. arXiv preprint arXiv:2009.01265.

Brocklebank, J. C., & Dickey, D. A. (2003). *SAS for forecasting time series*. John Wiley & Sons.

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). COVID-19, lockdowns and well-being: Evidence from google trends. *Journal of Public Economics, 193*, 104346. https://doi.org/10.1016/j.jpubeco.2020.104346

Carneiro, H. A., & Mylonakis, E. (2009). Google trends: A web-based tool for real-time surveillance of disease outbreaks. *Clinical Infectious Diseases, 49*(10), 1557–1564. https://doi.org/10.1086/630200

Castillo, R. C., Staguhn, E. D., & Weston-Farber, E. (2020). The effect of state-level stay-at-home orders on COVID-19 infection rates. *American Journal of Infection Control, 48*(8), 958–960. https://doi.org/10.1016/j.ajic.2020.05.017

Cervellin, G., Comelli, I., & Lippi, G. (2017). Is google trends a reliable tool for digital epidemiology? Insights from different clinical settings. *Journal of epidemiology and global health, 7*(3), 185–189. https://doi.org/10.1016/j.jegh.2017.06.001

Chen, Q., Min, C., Zhang, W., Wang, G., Ma, X., & 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. https://doi.org/10.1016/j.chb.2020.106380

Choi, H., & Varian, H. (2012). Predicting the present with google trends. *The Economic Record, 88*, 2–9. https://doi.org/10.1111/j.1475-4932.2012.00809.x

Dilmaghani, M. (2020). Who is not afraid of richard dawkins? Using google trends to assess the reach of influential atheists across Canadian secular groups. *Studies in Religion/Sciences Religieuses, 49*(2), 268–289. https://doi.org/10.1177/0008429819854353

Du, H., Yang, J., King, R. B., Yang, L., & Chi, P. (2020). COVID-19 increases online searches for emotional and health-related terms. *Applied Psychology: Health and Well-Being, 12*(4), 1039–1053. https://doi.org/10.1111/aphw.12237

Fantazzini, D. (2020). Short-term forecasting of the COVID-19 pandemic using Google Trends data: Evidence from 158 countries. *Applied Econometrics, 59*, 33–54. https://doi.org/10.22394/1993-7601-2020-59-33-54

Faulkner, J., Schaller, M., Park, J. H., & Duncan, L. A. (2004). Evolved disease-avoidance mechanisms and contemporary xenophobic attitudes. *Group Processes & Intergroup Relations, 7*(4), 333–353. https://doi.org/10.1177/1368430204046142

Fincher, C. L., & Thornhill, R. (2008). Assortative sociality, limited dispersal, infectious disease and the genesis of the global pattern of religion diversity. *Proceedings of the Royal Society B: Biological Sciences, 275*(1651), 2587–2594. https://doi.org/10.1098/rspb.2008.0688

Fincher, C. L., & Thornhill, R. (2012a). Parasite-stress promotes in-group assortative sociality: The cases of strong family ties and heightened religiosity. *Behavioral and Brain Sciences, 35*(2), 61–79. https://doi.org/10.1017/s0140525x11000021

Fincher, C. L., & Thornhill, R. (2012b). The parasite-stress theory may be a general theory of culture and sociality. *Behavioral and Brain Sciences, 35*(2), 99–119. https://doi.org/10.1017/s0140525x11001774

Fincher, C. L., Thornhill, R., Murray, D. R., & Schaller, M. (2008). Pathogen prevalence predicts human cross-cultural variability in individualism/collectivism. *Proceedings of the Royal Society B: Biological Sciences, 275*(1640), 1279–1285. https://doi.org/10.1098/rspb.2008.0094

Flanagan, R., Kuo, B., & Staller, K. (2021). Utilizing Google Trends to assess worldwide interest in irritable bowel syndrome and commonly associated treatments. *Digestive Diseases and Sciences, 66*(3), 814–822. https://doi.org/10.1007/s10620-020-06290-7

Gao, S., Rao, J., Kang, Y., Liang, Y., Kruse, J., Dopfer, D., Sethi, A. K., Reyes, J. F. M., Yandell, B. S., & Patz, J. A. (2020). Association of mobile phone location data indications of travel and stay-at-home mandates with covid-19 infection rates in the us. *JAMA Network Open, 3*(9), Article e2020485. https://doi.org/10.1001/jamanetworkopen.2020.20485

Gelfand, M. J., Jackson, J. C., Pan, X., Nau, D., Pieper, D., Denison, E., Dagher, M., Van Lange, P. A., Chiu, C.-Y., & Wang, M. (2021). The relationship between cultural tightness–looseness and COVID-19 cases and deaths: A global analysis. *The Lancet Planetary Health, 5*(3), e135–e144. https://doi.org/10.1016/s2542-5196(20)30301-6

Georgieva, I., Beaunoyer, E., & Guitton, M. J. (2021). Ensuring social acceptability of technological tracking in the COVID-19 context. *Computers in Human Behavior, 116*, 106639. https://doi.org/10.1016/j.chb.2020.106639

Gianfredi, V., Bragazzi, N., Mahamid, M., Bisharat, B., Mahroum, N., Amital, H., & Adawi, M. (2018). Monitoring public interest toward pertussis outbreaks: An extensive Google Trends–based analysis. *Public Health, 165*, 9–15. https://doi.org/10.1016/j.puhe.2018.09.001

Gokmen, Y., Baskici, C., & Ercil, Y. (2020). The impact of national culture on the increase of COVID-19: A cross-country analysis of European countries. *International Journal of Intercultural Relations, 81*, 1–8. https://doi.org/10.1016/j.ijintrel.2020.12.006

Guitton, M. J. (2013). Developing tools to predict human behavior in response to large-scale catastrophic events. *Computers in Human Behavior, 6*(29), 2756–2757. https://doi.org/10.1016/j.chb.2013.07.027

Guitton, M. J. (2020). Cyberpsychology research and COVID-19. *Computers in Human Behavior, 111*, 106357. https://doi.org/10.1016/j.chb.2020.106357

Hu, D., Lou, X., Xu, Z., Meng, N., Xie, Q., Zhang, M., Zou, Y., Liu, J., Sun, G., & Wang, F. (2020). More effective strategies are required to strengthen public awareness of COVID-19: Evidence from Google Trends. *Journal of Global Health, 10*(1), Article 011003. https://doi.org/10.7189/jogh.10.011003

Husnayain, A., Fuad, A., & Su, E. C.-Y. (2020). Applications of google search trends for risk communication in infectious disease management: A case study of COVID-19 outbreak in taiwan. *International Journal of Infectious Diseases, 95*, 221–223. https://doi.org/10.1016/j.ijid.2020.03.021

Huynh, T. L. D. (2020). Does culture matter social distancing under the COVID-19 pandemic? *Safety Science, 130*, 104872. https://doi.org/10.1016/j.ssci.2020.104872

Jun, S.-P., Yoo, H. S., & Choi, S. (2018). Ten years of research change using Google Trends: From the perspective of big data utilizations and applications. *Technological Forecasting and Social Change, 130*, 69–87. https://doi.org/10.1016/j.techfore.2017.11.009

Kamiński, M., Skonieczna-Żydecka, K., Nowak, J. K., & Stachowska, E. (2020). Global and local diet popularity rankings, their secular trends, and seasonal variation in Google Trends data. *Nutrition, 79–80*, 110759. https://doi.org/10.1016/j.nut.2020.110759

Kapoor, H., Ticku, A., Tagat, A., & Karandikar, S. (2021). Innovation in isolation? COVID-19 lockdown stringency and culture-innovation relationships. *Frontiers in Psychology, 12*, 83. https://doi.org/10.3389/fpsyg.2021.593359

Karwowski, M., Kowal, M., Groyecka, A., Białek, M., Lebuda, I., Sorokowska, A., & Sorokowski, P. (2020). When in danger, turn right: Does covid-19 threat promote social conservatism and right-wing presidential candidates. *Human Ethology, 35*, 37–48. https://doi.org/10.31234/osf.io/pjfhs

Kim, J., Lee, J., Jhang, J., Park, J., & Lee, J. C. J. J. o. H. M., & Management. (2021). The impact of the COVID-19 threat on the preference for high versus low quality/price options. *Journal of Hospitality Marketing & Management, 30*(6), 699–716. https://doi.org/10.1080/19368623.2021.1884163

Lai, K., Lee, Y. X., Chen, H., & Yu, R. (2017). Research on web search behavior: How online query data inform social psychology. *Cyberpsychology, Behavior, and Social Networking, 20*(10), 596–602. https://doi.org/10.1089/cyber.2017.0261

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121. https://doi.org/10.1037/0021-9010.86.1.114

Liu, Y., Peng, G., Hu, L., Dong, J., & Zhang, Q. (2019). Using Google trends and Baidu index to analyze the impacts of disaster events on company stock prices. *Industrial Management & Data Systems, 120*(2), 350–365. https://doi.org/10.1108/imds-03-2019-0190

Lu, J. G., Jin, P., & English, A. S. (2021). Collectivism predicts mask use during COVID-19. *Proceedings of the National Academy of Sciences, 118*(23), Article e2021793118. https://doi.org/10.1073/pnas.2021793118

Ma, M. Z. (2021). *Group-level human values estimated with web search data and archival data explain the geographic variation in COVID-19 severity in the United States* (pp. 1–20). Psychology & Health. https://doi.org/10.1080/08870446.2021.1952582

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. https://doi.org/10.3389/fpubh.2021.627559

MacInnis, C. C., & Hodson, G. (2015). Do American states with more religious or conservative populations search more for sexual content on Google? *Archives of Sexual Behavior, 44*(1), 137–147. https://doi.org/10.1007/s10508-014-0361-8

Markey, P., & Markey, C. (2011). Pornography-seeking behaviors following midterm political elections in the United States: A replication of the challenge hypothesis.

Computers in Human Behavior, 27(3), 1262–1264. https://doi.org/10.1016/j.chb.2011.01.007

Mavragani, A., & Gkillas, K. (2020). COVID-19 predictability in the United States using Google Trends time series. *Scientific Reports, 10*(1), 1–12. https://doi.org/10.1038/s41598-020-77275-9

Ma, M. Z., & Ye, S. (2021). The role of ingroup assortative sociality in the COVID-19 pandemic: A multilevel analysis of google trends data in the United States. *International Journal of Intercultural Relations, 84*, 168–180. https://doi.org/10.1016/j.ijintrel.2021.07.010

Mazumder, A., Arora, M., Sra, M., Gupta, A., Behera, P., Gupta, M., Agarwal, M., Rao, A., Mohanta, S., & Parameswaran, G. (2020). Geographical variation in case fatality rate and doubling time during the COVID-19 pandemic. *Epidemiology and Infection, 148* (E163). https://doi.org/10.1017/s0950268820001685

Medline, A., Hayes, L., Valdez, K., Hayashi, A., Vahedi, F., Capell, W., Sonnenberg, J., Glick, Z., & Klausner, J. D. (2020). Evaluating the impact of stay-at-home orders on the time to reach the peak burden of Covid-19 cases and deaths: Does timing matter? *BMC Public Health, 20*(1), 1750. https://doi.org/10.1186/s12889-020-09817-9

Murray, D. R., & Schaller, M. (2010). Historical prevalence of infectious diseases within 230 geopolitical regions: A tool for investigating origins of culture. *Journal of Cross-Cultural Psychology, 41*(1), 99–108. https://doi.org/10.1177/0022022109349510

Muselli, M., Cofini, V., Desideri, G., & Necozione, S. (2021). Coronavirus (Covid-19) pandemic: How may communication strategies influence our behaviours? *International Journal of Disaster Risk Reduction, 53*(1), 101982. https://doi.org/10.1016/j.ijdrr.2020.101982

Navarrete, C. D., & Fessler, D. M. (2006). Disease avoidance and ethnocentrism: The effects of disease vulnerability and disgust sensitivity on intergroup attitudes. *Evolution and Human Behavior, 27*(4), 270–282. https://doi.org/10.1016/j.evolhumbehav.2005.12.001

Nindrea, R. D., Sari, N. P., Lazuardi, L., & Aryandono, T. (2020). Validation: The use of google trends as an alternative data source for COVID-19 surveillance in Indonesia. *Asia-Pacific Journal of Public Health, 32*(6–7), 368–369. https://doi.org/10.1177/1010539520940896

Padalabalanarayanan, S., Hanumanthu, V. S., & Sen, B. (2020). Association of state stay-at-home orders and state-level african American population with COVID-19 case rates. *JAMA Network Open, 3*(10), Article e2026010. https://doi.org/10.1001/jamanetworkopen.2020.26010

Pelham, B. W., Shimizu, M., Arndt, J., Carvallo, M., Solomon, S., & Greenberg, J. (2018). Searching for God: Illness-related mortality threats and religious search volume in Google in 16 nations. *Personality and Social Psychology Bulletin, 44*(3), 290–303. https://doi.org/10.1177/0146167217736047

Peng, Y., Chen, X., Rong, Y., Pang, C. P., & Chen, H. (2021). Real-time prediction of the daily incidence of COVID-19 in 215 countries and territories using machine learning: Model development and validation. *Journal of Medical Internet Research, 23*(6), Article e24285. https://doi.org/10.2196/24285

Puppala, H., Bheemaraju, A., & Asthana, R. (2021). A GPS data-based index to determine the level of adherence to COVID-19 lockdown policies in India. *Journal of Healthcare Informatics Research, 5*, 151–167. https://doi.org/10.1007/s41666-020-00086-0

Pyszczynski, T., Lockett, M., Greenberg, J., & Solomon, S. (2020). Terror management theory and the COVID-19 pandemic. *Journal of Humanistic Psychology, 61*(2), 173–189. https://doi.org/10.1177/0022167820959488

Rajkumar, R. P. (2021). The relationship between measures of individualism and collectivism and the impact of COVID-19 across nations. *Public Health in Practice, 2*, 100143. https://doi.org/10.1016/j.puhip.2021.100143

Saha, J., Barman, B., & Chouhan, P. (2020). Lockdown for COVID-19 and its impact on community mobility in India: An analysis of the COVID-19 Community Mobility Reports, 2020. *Children and Youth Services Review, 116*, 105160. https://doi.org/10.1016/j.childyouth.2020.105160

Senecal, C., Gulati, R., & Lerman, A. (2020). Google trends insights into reduced acute coronary syndrome admissions during the COVID-19 pandemic: Infodemiology study. *JMIR Cardio, 4*(1), Article e20426. https://doi.org/10.2196/20426

Sorci, G., Faivre, B., & Morand, S. (2020). Explaining among-country variation in COVID-19 case fatality rate. *Scientific Reports, 10*(1), 1–11. https://doi.org/10.1038/s41598-020-75848-2

Sorokowski, P., Groyecka, A., Kowal, M., Sorokowska, A., Białek, M., Lebuda, I., Dobrowolska, M., Zdybek, P., & Karwowski, M. (2020). Can information about pandemics increase negative attitudes toward foreign groups? A case of COVID-19 outbreak. *Sustainability, 12*(12), 4912. https://doi.org/10.31234/osf.io/j23vt

Springer, S., Menzel, L. M., & Zieger, M. (2020). Google Trends provides a tool to monitor population concerns and information needs during COVID-19 pandemic. *Brain, Behavior, and Immunity, 87*, 109–110. https://doi.org/10.1016/j.bbi.2020.04.073

Strzelecki, A. (2020). The second worldwide wave of interest in coronavirus since the COVID-19 outbreaks in South Korea, Italy and Iran: A google trends study. *Brain, Behavior, and Immunity, 88*, 950–951. https://doi.org/10.1016/j.bbi.2020.04.042

Sulyok, M., & Walker, M. (2020). Community movement and COVID-19: A global study using google's community mobility reports. *Epidemiology and Infection, 148*(e284), 1–9. https://doi.org/10.1017/s0950268820002757

Thornhill, R., & Fincher, C. L. (2014a). Collectivism–individualism, family ties, and philopatry. In *The parasite-stress theory of values and sociality* (pp. 113–170). Springer. https://doi.org/10.1007/978-3-319-08040-6_5.

Thornhill, R., & Fincher, C. L. (2014b). The parasite-stress theory of values. In *The parasite-stress theory of values and sociality* (pp. 59–82). Springer. https://doi.org/10.1007/978-3-319-08040-6_3.

Thornhill, R., Fincher, C. L., & Aran, D. (2009). Parasites, democratization, and the liberalization of values across contemporary countries. *Biological Reviews, 84*(1), 113–131. https://doi.org/10.1111/j.1469-185x.2008.00062.x

Thornhill, R., Fincher, C. L., Murray, D. R., & Schaller, M. (2010). Zoonotic and non-zoonotic diseases in relation to human personality and societal values: Support for the parasite-stress model. *Evolutionary Psychology, 8*(2). https://doi.org/10.1177/147470491000800201, 147470491000800201.

Venkatesh, U., & Gandhi, P. A. (2020). Prediction of COVID-19 outbreaks using google trends in India: A retrospective analysis. *Healthcare informatics research, 26*(3), 175–184. https://doi.org/10.4258/hir.2020.26.3.175

Verity, R., Okell, L. C., Dorigatti, I., Winskill, P., Whittaker, C., Imai, N., Cuomo-Dannenburg, G., Thompson, H., Walker, P. G., & Fu, H. (2020). Estimates of the severity of coronavirus disease 2019: A model-based analysis. *The Lancet Infectious Diseases, 20*(6), 669–677. https://doi.org/10.1016/s1473-3099(20)30243-7

Wang, Y. (2021). Government policies, national culture and social distancing during the first wave of the COVID-19 pandemic: International evidence. *Safety Science, 135*, 105138. https://doi.org/10.1016/j.ssci.2020.105138

Wang, Y., Hao, H., & Platt, L. S. (2021). Examining risk and crisis communications of government agencies and stakeholders during early-stages of COVID-19 on Twitter. *Computers in Human Behavior, 114*, 106568. https://doi.org/10.1016/j.chb.2020.106568

Wu, B.-P., & Chang, L. (2012). The social impact of pathogen threat: How disease salience influences conformity. *Personality and Individual Differences, 53*(1), 50–54. https://doi.org/10.1016/j.paid.2012.02.023

Yaffee, R. A., & McGee, M. (2000). *An introduction to time series analysis and forecasting: With applications of SAS® and SPSS®*. Elsevier.

Yeung, T. Y.-C. (2019). Measuring christian religiosity by google trends. *Review of Religious Research, 61*(3), 235–257. https://doi.org/10.1007/s13644-019-00379-w

Yilmazkuday, H. (2020). Stay-at-home works to fight against COVID-19: International evidence from Google mobility data. *Journal of Human Behavior in the Social Environment, 31*(1–4), 210–220. https://doi.org/10.1080/10911359.2020.1845903

Zhou, X., Ye, J., & Feng, Y. (2011). Tuberculosis surveillance by analyzing Google trends. *IEEE Transactions on Biomedical Engineering, 58*(8), 2247–2254. https://doi.org/10.1109/tbme.2011.2132132