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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

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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...
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; Padalabanarayanan 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 (Kawrowski 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 ingroup boundaries to block outgroup communication (e.g., xenophobia, prejudice, collectivism, philothropy)—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 natal locales in response to contagion threats 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 (Guittion, 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., 2021) 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; Sorkowksi 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; Husmayain 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; Kaminski 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 in the U.S. may use multiple languages to search information related to COVID-19, such as coronavirus or coronavirus); 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, Ptwo-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 \( \leq r_s \leq 0.96 \)) 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 \( \leq r_s \leq 0.93 \), 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, 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.

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 (Pyzczynski 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 (Kappoor 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 \( x - 1 \)); 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, $\hat{\beta} = 0.34, p_{\text{two-tailed}} < 0.001$, $95\% \text{ CI } = [0.28, 0.40]$, 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 SSI–SSS1 (Study 1 Supplementary Tables https://osf.io/w25kb/?view_only=cf42ed56bcebd791b4c20d44ed535d01) 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, $\hat{\beta} = 0.29, SE = 0.01, z = 41.62, p_{\text{two-tailed}} < 0.001$, $95\% \text{ CI } = [0.28, 0.30]$. Adding state-level infectious-disease contagion risk as a covariate for the meta-regression did not alter the significant and positive combined effect, $\hat{\beta} = 0.29, SE = 0.01, z = 41.62, p_{\text{two-tailed}} < 0.001$, $95\% \text{ CI } = [0.28, 0.30]$. As the effect of state-level infectious-disease contagion risk was significant and positive, $\hat{\beta} = 0.03, SE = 0.01, z = 2.54, p_{\text{two-tailed}} = 0.011$, $95\% \text{ CI } = [0.01, 0.04]$, 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, $\hat{\beta} = 0.07, SE = 0.01, z = 9.05, p_{\text{two-tailed}} < 0.001$, $95\% \text{ CI } = [0.06, 0.09]$. Adding state-level infectious-disease contagion risk as a covariate did not alter the significant and positive combined effect, $\hat{\beta} = 0.07, SE = 0.01, z = 9.01, p_{\text{two-tailed}} < 0.001$, $95\% \text{ CI } = [0.06, 0.09]$, and the effect of state-level infectious-disease contagion risk was non-significant, $\hat{\beta} = -0.01, SE = 0.01, z = -0.60, p_{\text{two-tailed}} = 0.548$, $95\% \text{ CI } = [-0.03, 0.01]$ (Fig. S1a; Supplementary File). As for case fatality rate, the combined effect was non-significant, $\hat{\beta} = -0.01, SE = 0.01, z = -1.41, p_{\text{two-tailed}} = 0.158$, $95\% \text{ CI } = [-0.03, 0.00]$, 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, $\hat{\beta} = 0.01, SE = 0.01, z = 1.95, p_{\text{two-tailed}} = 0.342$, $95\% \text{ CI } = [-0.01, 0.03]$, did not alter the non-significant combined association, $\hat{\beta} = -0.01, SE = 0.01, z = -1.26, p_{\text{two-tailed}} = 0.207$, $95\% \text{ CI } = [-0.02, 0.00]$ (Fig. S1b; Supplementary File).

Given that the combined effect of COVID-19 concerns (standardised estimate = 0.29) was larger than that of the actual coronavirus threat (e. g., COVID-19 cases per million standardised 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.

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, and the categorized search term Coronavirus, coronavirus (English) was used for English-speaking countries/territories (e.g., United Kingdom) and coronavirus (Portuguese) was used for Portuguese-speaking countries/territories (e.g., Portugal). Table SSS1 (Study 2 Supplementary Tables https://osf.io/w25kb/?view_only=cf42e6588ecb4791b4c20d4a4d535d01) 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 α = 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 α = 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

Table SSS2-SSS116 (Study 2 Supplementary Tables https://osf.io/w25kb/?view_only=cf42e6588ecb4791b4c20d4a4d535d01) shows 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 (Brookebank & 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) = 364.96, p 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 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 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 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 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 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 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 two-tailed = 0.318, 95% CI = [-0.01, 0.02], calculated from a restricted maximum likelihood method, Q (114) = 224.90, p 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 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 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
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 (Guittot, 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 (Broeklebank & 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; Maclnnis & 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 sociability (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 sociability (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 response 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 sociability 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 sociability 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 collectivist 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 sociability 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 (Lu 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 Guittot (2013), Guittot (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 sociability 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...
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