Received: 18 October 2022 | Accepted: 1 December 2022
DOI: 10.1002/jmv.28382

RESEARCH ARTICLE

JOURNAL OF MEDICAL VIROLOGY WILEY

Association between public attention and monkeypox epidemic: A global lag‐correlation analysis

Wenxin Yan[1] | Min Du[1] | Chenyuan Qin[1] | Qiao Liu[1] | Yaping Wang[1] | Wannian Liang[2] | Min Liu[1] | Jue Liu[1,3,4]

[1]Department of Epidemiology and Biostatistics, School of Public Health, Peking University, Beijing, China
[2]Vanke School of Public Health, Tsinghua University, Beijing, China
[3]Institute for Global Health and Development, Peking University, Beijing, China
[4]Global Center for Infectious Disease and Policy Research & Global Health and Infectious Diseases Group, Peking University, Beijing, China

Correspondence
Jue Liu, Department of Epidemiology and Biostatistics, School of Public Health, Peking University, Beijing 100191, China.
Email: jueliu@bjmu.edu.cn

Funding information
National Natural Science Foundation of China, Grant/Award Numbers: 72122001, 72211540398, 71934002; National Key Research and Development Project of China, Grant/Award Numbers: 2021ZD0114101, 2021ZD0114104, 2021ZD0114105; National Statistical Science Research Project, Grant/Award Number: 2021LY038; Global Center for Infectious Disease and Policy Research & Global Health and Infectious Diseases Group of Peking University, Grant/Award Number: 202204; Developing China‐ASEAN Public Health Research and Development Collaborating Center, Grant/Award Number: KY202101004

Abstract
The human monkeypox has become a public health problem globally. Google Trends Index (GTI) is an indicator of public attention, being potential for infectious disease outbreak surveillance. In this study, we used lag‐correlation analysis to evaluate the spearman correlation coefficients between public attention and monkeypox epidemic by −36 to +36 days‐lag in top 20 countries with most cumulated cases until September 30, 2022, the meta‐analyses were performed to pool the coefficients of countries among all lags. We also constructed vector autoregression model and Granger‐causality test to probe the significance of GTI in monkeypox forecasting. The strongest spearman correlation was found at lag +13 day ($r = 0.53$, 95% confidence interval: 0.371–0.703, $p < 0.05$). Meta‐analysis showed significantly positive correlation when the lag was from −12 to +36 day, which was most notable on the third posterior day (lag +3 day). The pooled spearman correlation coefficients were all above 0.200 when the lag ranged from +1 to +20 day, and the causality of GTI for daily case was significant in worldwide and multiple countries. The findings suggested a robust association between 13‐days‐priority GTI and daily cases worldwide. This work introduced a potential monitor indicator on the early warning and surveillance of monkeypox outbreak.

KEYWORDS
Google Trends, lag‐correlation, monkeypox, public attention

1 | INTRODUCTION

Human monkeypox as a zoonotic disease was caused by monkeypox virus (MPXV), which was first reported in central Africa in 1970.[1] The disease mortality was around 1%–10%.[2,3] Nearly 5 months on, as the World Health Organization (WHO) reported over 72 000 confirmed cases (as of October 14, 2022) in 109 countries in Europe, the America, the Eastern Mediterranean, the Western Pacific, Africa and Southeast Asia region.[4] And the new, unusual, multi‐country monkeypox outbreak was unfolding rapidly. In the current 2022 epidemic, the presentation of most monkeypox patients was atypical.[5] In addition, patients may begin after the onset of a localized rash, and only present with mild or no prodromal symptoms.[5] Nowadays, new cases could be detected outside the traditional endemic areas of monkeypox, underlining the fact that rapid identification and diagnosis of cases were needed to curb further community transmission.[6] Due to the increasing number of global confirmed cases, the WHO had declared the monkeypox outbreak as a Public Health Emergency of International Concern (PHEIC) on July 23, 2022.[7] Early detection and curbing the spread of monkeypox is of great global concern.

Monkeypox had been detected in 11 African countries in recent years, with the most reported cases in the Democratic Republic of Congo. Human monkeypox infections are rare, especially outside of Central and Western Africa region where the virus is endemic in animals and circulates primarily in forested areas before 2022. Whereas this monkeypox outbreak occurred in Europe and North America, the chain of transmission was irrelevant to West and Central Africa. The first reported case of monkeypox outbreak 2022 was men who have sex with men (MSM) with a high risk of transmission in a close contact setting. The changes in the geographical epidemic area and the changes of characteristics in the cases both indicated very important hints. Early identification of signals for monkeypox outbreaks was important. Public attention has been used by some scholars[8–11] to pre-identify outbreak signals of infectious diseases. However, there is no relevant study exploring the relationship of internet attention behavior with the onset of monkeypox.

Along with the Internet development, public attention could refer to matters of concern. Google Trend Index (GTI) is a commonly used indicator for internet attention behavior. Over recent years, the Google Trend Index (GTI) as a dissemination indicator was widely used to explore the association of internet attention behavior and early detection of infectious disease. GTI had been used to predict the trend of confirmed cases and deaths in the COVID-19 epidemic 3 weeks in advance,[8] also served as a predictor of COPD,[9] Norovirus,[10] HIV[11] and other infectious disease prevalence. Some studies[12,13] suggested that Google Trend Index had some significances in forecasting the epidemiology of common diseases with less media coverage, or the epidemiology of rare diseases with a larger audience, as a digital epidemiology tool.[12,13] Although the former Google Index prediction study underestimated the first wave of the H1N1 epidemic in the United States, it reflected the true epidemic situation in the second wave,[14] the Google index was of interest for the timely prediction of emerging infectious diseases. The previous study Effenberger et al.[15] conducted only time-lagged correlation tests for GTI and daily cases of Emerging Infectious Disease (EID), which provided limited evidence for surveillance significance. Therefore, based on their work, we innovatively added meta-analyses to combine the correlations across countries to map out the universal pattern, and in addition, we supplemented the Granger causality tests to improve the sensitivity of correlation test for forecasting and monitoring EID by detecting the causality between two time series.

Human monkeypox posed unique challenge, even to resourceful health-care systems with high consequence infectious diseases network.[16] Regarding search indices as an innovative approach to grab effective information support, it can be used to provide clinical epidemiologists with timely alerts of disease outbreaks or changes in treatment regimens with much earlier response than traditional health epidemiology.[17] Therefore, to address the noteworthy geographical distribution characteristics and specific population distribution of present monkeypox epidemic, we assessed the Google Trends Index into the study for exploring whether public attention was useful for early prediction of monkeypox epidemic.

2 | METHODS

2.1 | Study design and data sources

We conducted an observational study to assess the lag-correlation between public attention and monkeypox epidemic in 20 countries from May to September. Data on public attention about monkeypox was extracted from Google Trends (https://trends.google.com/trends/).[18] Data on monkeypox epidemic was extracted from Our World in Data (https://ourworldindata.org/monkeypox).[19] This study met the requirements of the Declaration of Helsinki and no ethical approval was required for this study because of its public secondary data.

2.2 | Public attention on monkeypox

The Google Trends tool was utilized to retrieve data on Internet patron search activity in the context of Monkeypox, reflecting public attention. Google Trends empowered researchers to study patterns and tendencies in Google search queries.[20] The GTI was assisted to compare search volume between terms, time, and location. It was constrained to a range of 0–100, and an index of 100 indicated the highest search count for a given period (week, month, or year), while in other periods, search counts were scaled to a lower number. For further information on Google Trends, please refer to the website on Google Trends (https://support.google.com/trends/).[21]

Global and national GTIs were retrieved from May 1, 2022 to September 30, 2022 using the search term "Monkeypox." Considering countries with less cases nearly had no search records and we aimed to perform correlation tests and remind countries to be aware of public search interests, so we retrieved Google Trend index for six countries from Region of the Americas (United States, Brazil, Peru, Canada, Chile, and Argentina), 12 countries from European Region (Spain, France, United Kingdom, Germany, Netherlands, Portugal, Italy, Belgium, Switzerland, Austria, Israel, and Sweden), and two from African Region (Nigeria and Democratic Republic of Congo).

2.3 | Monkeypox epidemic data

In this study, we collected daily confirmed cases, daily confirmed cases per million capita, 7-day average confirmed cases and 7-day average confirmed cases per million capita of monkeypox. Data were retrieved from the Oxford Our World in Data for the time from the May 1, 2022 to September 30, 2022 (https://ourworldindata.org/monkeypox).[19] Worldwide data were retrieved as well as data for the top 20 countries in terms of cumulative number of confirmed cases.

2.4 | Statistical analysis

We presented daily GTI and 7-day average confirmed monkeypox cases from May to September in total 20 countries and territories. Monthly number of confirmed cases and confirmed cases per million people by countries were calculated. Since the data were not normally distributed, we picked the Spearman correlation instead of Pearson correlation[22] to test the time-lag correlations between GTI and 7-average daily cases by −36 to +36 days-lag (Figure 1A). The positive lags corresponded to the time-lag effect of GTI on daily cases, on the contrary, the negative ones represented the time-lag effect of daily cases on GTI. Meta-analysis was constructed to show 95% confidence intervals (CIs) for the spearman correlation coefficients of GTI and daily confirmed cases from 20 countries with lags ranging −36 to +36, and the combined correlation coefficient for each lag (Figure 1B).[23] Heterogeneity between studies was evaluated by the I^2 statistic, which denotes the total variation explained by the variation among studies.[24] An I^2 values ranging about 25%–50% were considered as low heterogeneity, 50%–75% as moderate and ≥75% as high heterogeneity. A random-effects model was performed if significant heterogeneity existed between studies ($I^2 > 50\%$, $p < 0.10$), otherwise, a fixed-effects model was applied ($I^2 < 50\%$, $p > 0.10$).[24,25]

In the confirmatory test of causality, we evaluated two series with an augmented Dickey–Fuller (ADF) test using R package *tseries*[26] to examine whether the sequence was stationary (Figure 1C). If the series was not considered stationary, the sequence was further differenced so that the differenced series became stationary (as confirmed by the ADF test again). Our differencing procedures comprise 1–6 steps, respectively first-order, second-order and third-order differencing. Next, the temporal relationship between the GTI and number of the daily confirmed case was analyzed with the Vector autoregressive (VAR) model,[27] using R package *vars*,[28] the maximum lag in VAR model was set as 24 days (Figure 1D). Using the obtained VAR model, we assessed whether the GTI trend Granger-caused the daily confirmed trends (Figure 1E).[27,29]

All Spearman correlation test, ADF test, and Granger-causality test were performed using R, version 4.2.1 and meta-analyses were performed using Stata/SE, version 17.0.

3 | RESULTS

3.1 | Trends in global and national GTI and daily confirmed monkeypox cases

Worldwide interest in Monkeypox started on May 1 and reached its first peak on May 2, the first reported global case of monkeypox outside of Africa was confirmed by experts in the UK on May 7. By May 20, the cases spread to 14 countries, reaching a total of 100 cases worldwide, and the global GTI suddenly peaked (Figure 2). After May 24, a large number of the public had learned about the characteristics of monkeypox transmission, the interest rate began to wane. Up to July 23, the Director-General of the World Health Organization (WHO), Tedros Adhanom Ghebreyesus, declared the outbreak a public health emergency of international concern (PHEIC).[7] GTI peaked again on the 24, at 71% of its former maximum. On August 1, 2022 India confirmed its first monkeypox death, a 22-year-old male who died in Thrissur, Kerala on July 30.[30] After then, Google trends declined and gradually leveled off, while the

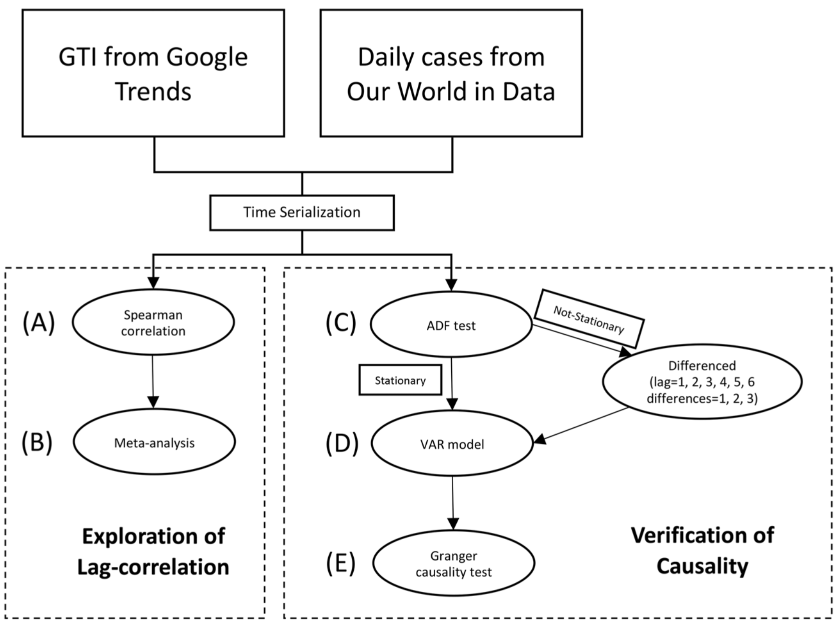

FIGURE 1 Outline of preprocessing flow.

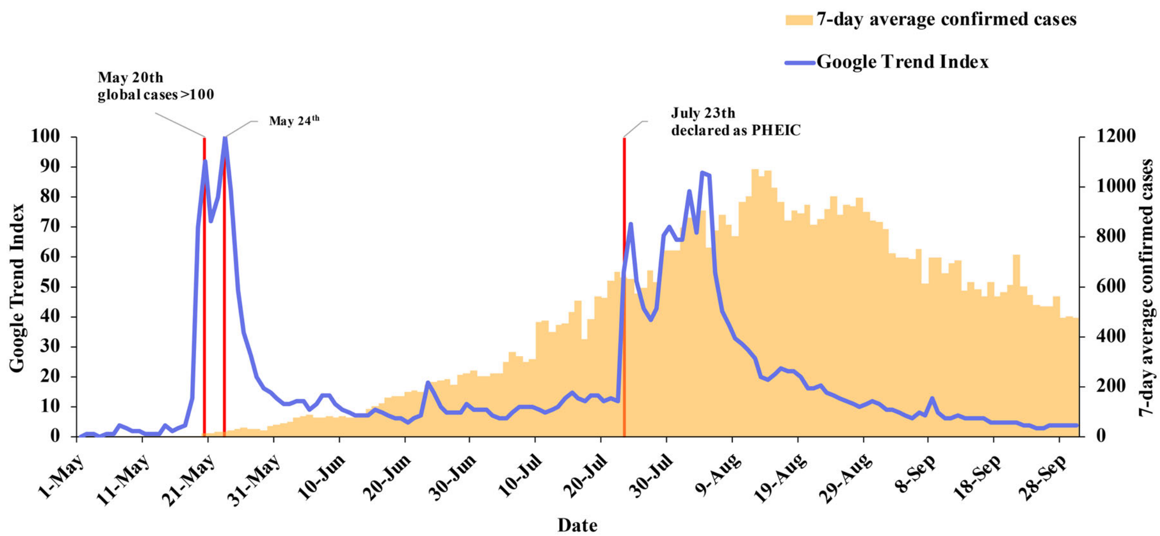

FIGURE 2 Worldwide Google Trend Index (GTI) for "Monkeypox" and 7-day average daily confirmed Monkeypox cases.

number of new confirmed cases per day was still fluctuating steadily, with the rolling number of new cases peaking on August 14 and then slowly declining (Figure 2).

As shown in Table 1, in terms of epidemic prevalence, On May, the cases occurred mainly in the European region, with the United Kingdom recording the greatest number of cases (190 cases), Portugal suffered from the highest incidence of the disease, with 9.72 cases/million. As of June, the epidemic spread to regions of the Americas, but remained relatively severe in the UK and Portugal. In July and August, the epidemic spread in Spain, with the prevalence reaching 61.87 and 59.07 cases/million. Meanwhile, the United States recorded the highest number of cases, accumulating 4591 (13.63 cases per million) and 13 097 (38.86 cases per million) cases respectively in each month. Peru also reached a prevalence rate of 35.42 cases/million in August. By September, the outbreak in Spain had improved significantly, with a slight decrease of confirmed cases in the United States and a twofold increase in Chile and Argentina compared to the past month, while the number of new cases in Peru was unchanged from the previous month. The number of cases worldwide also declined after peaking in August. Peru remained constant with the previous month. The number of global cases had declined as well, after peaking in August.

3.2 | Lag-correlations between global/national GTI and daily confirmed monkeypox cases

As we can see in Figure 3, there was some variations in the correlation between the Google Trends index and daily monkeypox cases across countries. A negative correlation was observed when lag was −36 to −15 based on the overall global data ($p < 0.05$). This illustrated that the more daily cases, the relatively lower the Google trends will be observed in the next 15–36 days.

When the lag ranged from −6 to +36, there was a positive correlation between the two, indicating that the more daily cases, the higher the Google trend indices from 0 to 6 days thereafter. While the higher the Google trends, the correlation was consistently significant followed by higher cases of subsequent 0–36 days, the strongest spearman correlation was 0.537 (95% CI = 0.371–0.703, $p < 0.001$) at Day 13 (Table S1). Among the top 8 countries in terms of total number of cases, all of them showed an overall positive time-series correlation of Google trends on daily confirmed cases.

The most same situation as the world toke place in the United States, and when lag was +20, it revealed the maximum positive correlation (COR = 0.658, 95% CI = 0.511–0.804, $p < 0.001$). The exception was Brazil, where the positive correlation was consistently strong with lags of −36 to +36, the COR ranged from 0.313 (95% CI = 0.120–0.506, $p < 0.001$, lag = −36) to 0.750 (95% CI = 0.665–0.835, $p < 0.001$, lag = +9). Both France and Canada resembled the United States in correlation regularity. From the heat plot (Figure 4), we were able to see that there was a significant adverse lag correlation of new cases on the Google trend, especially when the lag was less than −12. Focusing on the lag range from +6 to +24 in the figure, we could see that the time lag correlation effect of Google trends on new cases was significantly stronger in the countries of the Americas region, and the time correlation effect was unstable in two countries of Africa.

We performed meta-analyses and merged the correlations of GTI and daily cases across time lags (−36 to +36) for the 20 countries (Figure 5). When the lag extent was from −12 to +36, the correlations were significantly positive, ranging from 0.051 (0.011–0.091) to 0.218 (0.182–0.253). The GTI correlated most significantly with the number of confirmed cases 3 days later (lag = +3). When the lag ranged from +1 to +20, the pooled Spearman correlations were all above 0.200.

Table S2 presented the positive time series groups with processing of difference and the *p*-values of the Granger causality

TABLE 1 Total number of cases and cases per million in 20 countries, in duration from May to September

	Total	Months May	June	July	August	September
World	68 246 (8.629)	535 (0.068)	4991 (0.632)	16 054 (2.031)	28 876 (3.651)	17 790 (2.247)
Region of the Americas						
United States	25 434 (75.476)	-	306 (0.910)	4591 (13.626)	13 097 (38.863)	7440 (22.077)
Brazil	7687 (35.866)	-	36 (0.170)	942 (4.395)	3715 (17.332)	2994 (13.969)
Peru	2480 (73.559)	-	3 (0.089)	266 (7.890)	1194 (35.415)	1017 (30.165)
Canada	1396 (36.589)	-	278 (7.286)	525 (13.760)	425 (11.140)	168 (4.403)
Chile	880 (45.142)	-	6 (0.307)	49 (2.514)	289 (14.824)	536 (27.497)
Argentina	396 (8.744)	-	4 (0.088)	16 (0.352)	113 (2.496)	263 (5.808)
European Region						
Spain	7188 (151.369)	98 (2.063)	702 (14.785)	2938 (61.871)	2805 (59.068)	645 (13.582)
France	3999 (59.312)	17 (0.253)	481 (7.133)	1339 (19.861)	1710 (25.362)	452 (6.703)
United Kingdom	3635 (54.023)	190 (2.823)	1045 (15.531)	1197 (17.790)	981 (14.580)	222 (3.299)
Germany	3625 (43.463)	33 (0.396)	936 (11.224)	1626 (19.491)	872 (10.456)	158 (1.896)
Netherlands	1219 (69.650)	26 (1.485)	231 (13.199)	622 (35.540)	281 (16.055)	59 (3.371)
Portugal	926 (89.991)	100 (9.720)	302 (29.347)	231 (22.448)	213 (20.700)	80 (7.776)
Italy	850 (14.350)	14 (0.237)	145 (2.447)	267 (4.507)	334 (5.640)	90 (1.519)
Belgium	770 (66.313)	10 (0.860)	107 (9.214)	276 (23.770)	313 (26.957)	64 (5.512)
Switzerland	513 (59.018)	4 (0.460)	79 (9.089)	181 (20.825)	192 (22.087)	57 (6.557)
Austria	313 (35.076)	1 (0.112)	19 (2.130)	98 (10.982)	147 (16.476)	48 (5.376)
Israel	250 (26.910)	2 (0.216)	40 (4.307)	79 (8.502)	113 (12.162)	16 (1.723)
Sweden	195 (18.635)	4 (0.383)	24 (2.294)	57 (5.445)	72 (6.882)	38 (3.631)
African Region						
Nigeria	385 (1.802)	6 (0.028)	41 (0.191)	55 (0.258)	103 (0.482)	180 (0.843)
Democratic Republic of Congo	190 (1.981)	-	10 (0.104)	153 (1.595)	11 (0.115)	16 (0.167)

Note: Total number of cases (cases per million).

tests, indicating whether the GTI Granger-cause (i.e., predict) daily confirmed Monkeypox cases. The GTI was generally found to granger-cause the daily cases at the World level as well as in 10/20 countries after differential smoothing and stationary test, the number of lags used in stationary VAR models ranged from 13 to 24 days.

4 | DISCUSSION

To our knowledge, this was the first study that assessed the association between public attention and monkeypox epidemic globally. In the present study, we found a significant increase in Google Trends for monkeypox searching worldwide with the robust association between Google Trends index with around 13 days priority and the daily diagnosed cases all over the world, and the causality was tested to demonstrate a certain forecast capability of GTI to daily cases, which highlights the significance of concern for lag-correlation. The correlation test has been detected early in the preceding and ongoing PHEIC, the COVID-19 outbreak. A slightly positive correlation between daily RSV about COVID-19 and the daily number of confirmed cases was observed ($p < 0.05$).[31] The results were used as a prompt for governments to raise awareness of emerging infectious disease outbreaks nationwide.[31] The innovation was that based on our exploration of lag-correlation, we made a meta-analysis of correlation coefficients and performed causality tests on serial data across countries. In this way, Google Trends index could be used to correlate and predict the outbreak in many countries and worldwide. The application of internet data in health concern research was also known as digital Epidemiology.

Nonpharmacological interventions (NPIs) were important actions to prevent infections when confronting emerging infectious diseases, and national action plans were widely implemented during the COVID-19 pandemic as the only viable option to reduce virus transmission in the population.[32] Nevertheless, monkeypox required

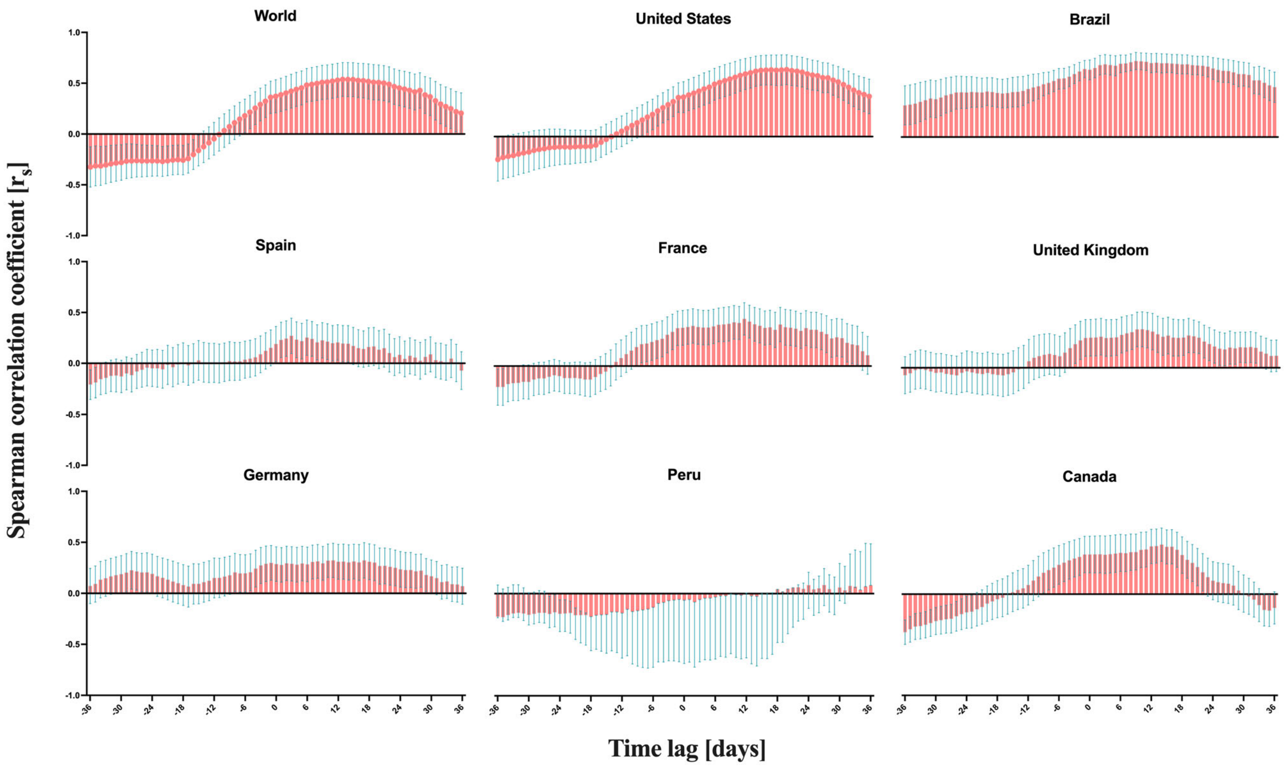

FIGURE 3 Time-lag correlations of Google Trend Index (GTI) for "Monkeypox" and 7-day average daily confirmed Monkeypox cases for eight countries with the most confirmed cases.

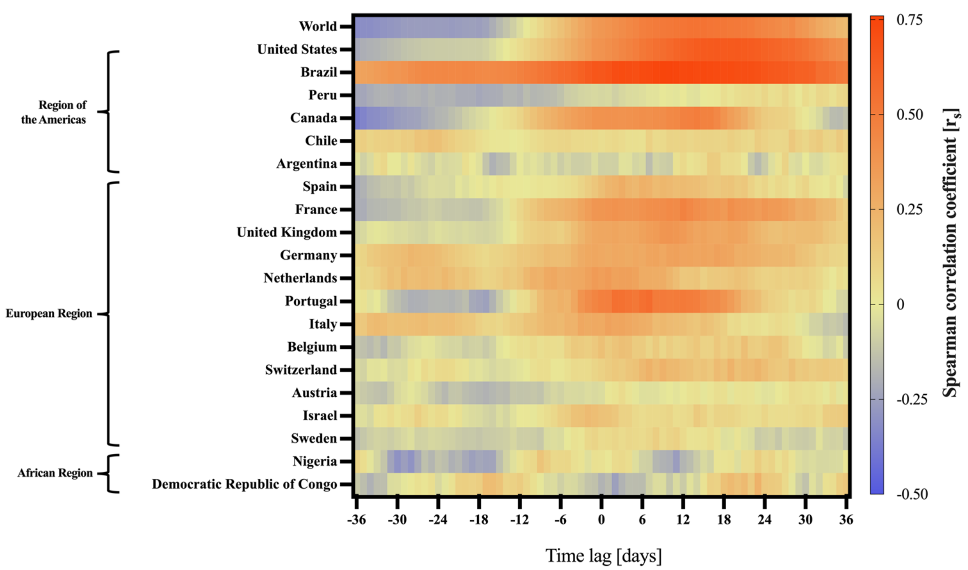

FIGURE 4 Heat plot of the time lag correlation of the Google Trends Index (GTI) and daily cases in 20 countries.

no implementation of the very strict NPI (e.g., closure of offices and educational institutions) imposed in the first wave of the COVID-19 pandemic. The major approach to preventing monkeypox was to adopt NPI strategies in daily life.[33] During an outbreak, NPIs should be routinely used in the home and workplace, in travel, and in community and social settings. A first essential step was educating individuals and communities to mitigate the risk of exposure to MPXV.[33]

The web-based tools were becoming powerful platforms not just for the general public, but also for science and medicine, social media and search engines already had potential to accelerate the discovery of new and undiagnosed diseases.[34] Google trends tended to correlate positively with daily confirmed cases in the days or weeks following, this strongly endorsed our findings that the Google Trend index was a useful tool to monitor global and regional outbreaks of

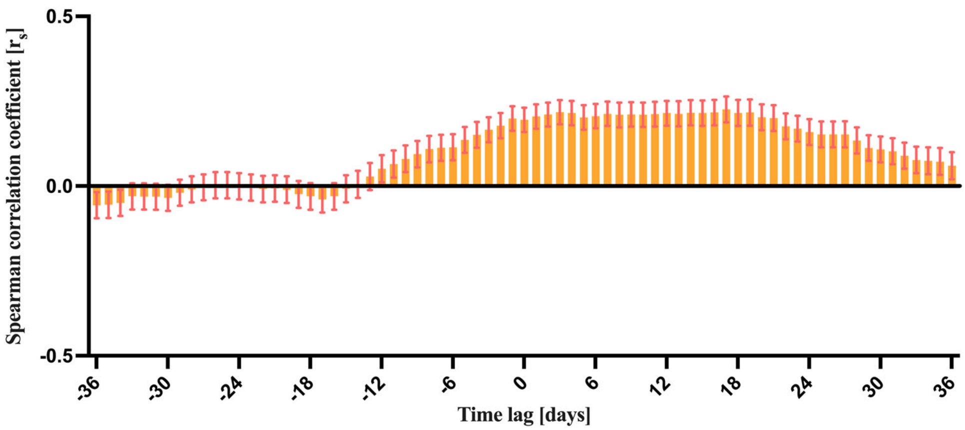

FIGURE 5 Pooled correlations for 20 countries of GTI and daily cases with lag ranging from −36 to + 36.

infectious diseases. Differences in the public opinion environment, government attention, media focus and population characteristics (e.g., education level, scientific awareness, cultural background, etc.) in different countries had led to significant differences in the speed of response and intensity of attention to the monkeypox epidemic in different countries.

Google was now the most important web search engine. With the rapid development of the internet, its role in the monitoring and early warning of infectious diseases had become increasingly evident in recent years. Many studies[35,36] had shown that the frequency of queries for diseases and related symptom keywords were highly correlated with the incidence, reflecting the true searchers' need trends. Whilst Google Trends cannot be used for real-time epidemiological surveillance of monkeypox, it could be exploited to capture the public's response to the outbreak. The search behavior reflected the concern for knowledge. The further people with less knowledge or higher risk, the more they would search, so it was essential that the accurate messages are released officially in a timely manner. Public health providers should be aware of this because information and communication technologies were available to communicate with users, assuage their concerns, and empower them to make decisions protecting their health. Our meta results indicated that in the countries where the outbreak occurred, the Google trends index fluctuated from 1 to 20 days after the diagnosed cases would have certain fluctuations, reminding countries to monitor the rising search index within 2 weeks after the epidemic. There was a need to maintain close attention to the epidemic, early detection, diagnosis, prevention and control, making contingency plans in advance, as well as promoting public knowledge and so on.

In addition, we shall know that the rapid spread of information and misinformation about the epidemic creates public panic, which was faster than the spread of the virus. This put forward two requirements, on the one hand, timely correcting errors to alleviate panic, and also to spread proper knowledge, keeping the public properly vigilant, as well as master the necessary knowledge stock. On the other hand, the early appearance of public search interest has also afforded public health workers and government managers a long window period. Our findings have largely demonstrated the time-lag correlation between the Google Trend and the onset of monkeypox, so we should seize the opportunity to prevent external importation, strengthen public awareness of self-observation and reporting, to intensify the awareness of doctors and nurses, to report and control the disease ahead of time. Emergency management and health departments shall jointly prepare emergency management schemes and emergency treatment programs sufficiently in advance to minimize the possibility of an outbreak, the impact of a monkeypox epidemic, and the public panic following an outbreak. Ultimately, we could protect the rights of public and the rights of infected people.

Thirdly, as MPX and its symptoms were highly visible worldwide, the impact of media coverage on Google trends for symptom keywords was inevitable.[12] Faced with emerging infectious diseases and a lack of relevant information among the public, timely and effective risk communication was necessary. News media was a pivotal resource for shaping public risk awareness and conveying relevant health messages. Its potential to be an effective partner in health communication was enormous, which fostered the implementation of risk communication, disease prevention and control strategies.[37,38] Some research works[37] recommended that state agencies unite with the news media to closely monitor changes in the public interest by testing Google Trends search data and media coverage, map out the nature and content of news items, and provide the publicly desirable information in more reasonable forms, to better prevent and control epidemics at an early stage.

Facing threats from infectious diseases, we wished the future to be predictable, the risks to be assessed, and the solutions to be reasonable, policy-makers required mastering these.[39] We should also focus on relevant search terms and protect the privacy of special groups, to avoid social consequences, as well as reducing discrimination. Apart from web searches, social media tools ought to be noticed and appropriately used to support public health measures. Well-planned analysis of global online conversations, enabling swift assessment of transmission and possible changes in public attitudes and behavior (e.g., self-isolating, handwashing, and accessing health care), as well as the knowledge, belief and behavior concerning the epidemic and its symptoms.[40] Positive feedback from community outreach was visible, with the results of a small web-based survey of MSM in United States,[41] indicating half of the survey population reduced the number of sextual partners and one-time sexual intercourse after informed of the MPX outbreak, and one-fifth of the respondents receipt the vaccination. Government continued to provide targeted, respectful, harmless messages to diverse MSM communities that do not cause stigma in local public health programs. At the same time, community-dependent health communication was important in response to epidemic.[41] Additionally, stigma and equity should be considered in the context of monkeypox prevention, testing, and vaccination.[42] The development and promotion of vaccines could reduce stress and anxiety, and the development of artificial intelligence was promising for predicting the spread of monkeypox infection and developing early warning systems.

In particular, when multiple PHEIC were spreading globally at the same time, it was worthwhile to consider whether there was some interaction among public attitudes towards the two infectious diseases. The impact of regionally important initiatives (e.g., quarantine measures, development of new vaccines, internationally coordinated responses) on public perceptions and attitudes also mattered.[40] Administrators should make full use of information sources and the public health department shall enhance proper understanding, purposeful and optimal planning of the media, to raise self-awareness of the public and high-risk populations, and keep them away from potential harm and danger.[43] We anticipated that Google Trends would be engaged in the future as an informative tool to drive change and track progress, potentially helping to improve planning to offset the current lack of public awareness of monkeypox.

There were limitations of this study. There is no information about the individual searches for the analyzed topics. Search behavior for monkeypox may be influenced by individual economic level and literacy, but the high interest group cannot be pinpointed, the association between high-risk behavior and searching, the association between high-risk behavior and morbidity cannot be analyzed in depth, and other confounding factors cannot be controlled. Google Trends-based research was increasing in volume, but so far there had not been a standardized data collection process. To help researchers establish optimal search strategies, Google was expected to provide more guidance.[44] Google search index was a relative number, no absolute value data for intercountry comparison, but our innovation was to merge the correlations between Google index and new cases in each country by meta gathering to draw informative results.

In conclusion, Google Trend Index can help to monitor the outbreak of monkeypox. The significant lag-correlation between GTI and daily monkeypox cases, changes in cases within 1–3 weeks after the anomalous search volume merited close attention. And these results are indicative of early monitoring of abnormalities and response were necessary, especially in countries that were not normally endemic.

AUTHOR CONTRIBUTIONS

Conceptualization: Wenxin Yan, Min Liu, and Jue Liu. Methodology and analysis: Wenxin Yan, Min Liu, and Jue Liu. Visualization: Wenxin Yan and Qiao Liu. Writing-original draft preparation: Wenxin Yan and Min Du. Review and editing: Min Du, Chenyuan Qin, Qiao Liu, Yaping Wang, Wannian Liang, and Min Liu. Supervision: Wannian Liang, Min Liu, and Jue Liu. All authors have read and agreed to the published version of the manuscript.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (grant numbers 72122001, 72211540398, 71934002), the National Key Research and Development Project of China (grant number 2021ZD0114101, 2021ZD0114104, 2021ZD0114105), National Statistical Science Research Project (grant numbers 2021LY038) and the Fundamental Research Funds for the Central Universities supported by Global Center for Infectious Disease and Policy Research & Global Health and Infectious Diseases Group of Peking University (grant number 202204), National Science and Technology Project on Development Assistance for Technology, Developing China-ASEAN Public Health Research and Development Collaborating Center (grant number KY202101004). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the paper. No payment was received by any of the co-authors for the preparation of this article.

DATA AVAILABILITY STATEMENT

All data in the study are available at https://trends.google.com/trends/, https://ourworldindata.org/monkeypox.

ORCID

Min Liu http://orcid.org/0000-0002-5059-3743
Jue Liu http://orcid.org/0000-0002-1938-9365

REFERENCES

1. Marennikova SS, Seluhina EM, Mal'ceva NN, Cimiskjan KL, Macevic GR. Isolation and properties of the causal agent of a new variola-like disease (monkeypox) in man. *Bull World Health Organ*. 1972;46(5):599-611.
2. Dou YM, Yuan H, Tian HW. Monkeypox virus: past and present. *World J Pediatr*. 2022:1-7.
3. Petersen E, Kantele A, Koopmans M, et al. Human monkeypox. *Infect Dis Clin North Am*. 2019;33(4):1027-1043.
4. World Health Organization. Monkeypox Outbreak: Global Trends, October 14, 2022. Accessed October 16, 2022. https://worldhealthorg.shinyapps.io/mpx_global/
5. Centers for Disease Control and Prevention (CDC). Monkeypox Virus Infection in the United States and Other Non-endemic Countries—May 20, 2022. Accessed October 4, 2022. https://emergency.cdc.gov/han/2022/han00466.asp
6. Thornhill JP, Barkati S, Walmsley S, et al. Monkeypox virus infection in humans across 16 countries-April-June 2022. *N Engl J Med*. 2022;387(8):679-691.
7. World Health Organization. WHO Director-General declares the ongoing monkeypox outbreak a Public Health Emergency of International Concern. July 23, 2022. Accessed October 4, 2022. https://www.who.int/europe/news/item/23-07-2022-who-director-general-declares-the-ongoing-monkeypox-outbreak-a-public-health-event-of-international-concern

8. Abbas M, Morland TB, Hall ES, El-Manzalawy Y. Associations between Google Search Trends for symptoms and COVID-19 confirmed and death cases in the United States. *Int J Environ Res Public Health*. 2021;18(9):4560.
9. Boehm A, Pizzini A, Sonnweber T, et al. Assessing global COPD awareness with Google Trends. *Eur Respir J*. 2019;53(6):1900351.
10. Yuan K, Huang G, Wang L, et al. Predicting norovirus in the United States using Google Trends: infodemiology Study. *J Med Internet Res*. 2021;23(9):e24554.
11. Adhikari T, Juneja A, Kaur A, Rao M. Forecasting HIV Prevalence in India and States Using Online Search Traffic Data. 2019.
12. Cervellin G, Comelli I, Lippi G. Is Google Trends a reliable tool for digital epidemiology? Insights from different clinical settings. *J Epidemiol Global Health*. 2017;7(3):185-189.
13. Adawi M, Bragazzi NL, Watad A, Sharif K, Amital H, Mahroum N. Discrepancies between classic and digital epidemiology in searching for the Mayaro virus: preliminary qualitative and quantitative analysis of Google Trends. *JMIR Public Health Surveill*. 2017;3(4):e93.
14. Olson DR, Konty KJ, Paladini M, Viboud C, Simonsen L. Reassessing Google Flu Trends data for detection of seasonal and pandemic influenza: a comparative epidemiological study at three geographic scales. *PLoS Comput Biol*. 2013;9(10):e1003256.
15. Effenberger M, Kronbichler A, Shin JI, Mayer G, Tilg H, Perco P. Association of the COVID-19 pandemic with Internet search volumes: a Google Trends(TM) analysis. *Int J Infect Dis*. 2020;95:192-197.
16. Adler H, Gould S, Hine P, et al. Clinical features and management of human monkeypox: a retrospective observational study in the UK. *Lancet Infect Dis*. 2022;22(8):1153-1162.
17. Lippi G, Mattiuzzi C, Cervellin G. Is digital epidemiology the future of clinical epidemiology? *J Epidemiol Global health*. 2019;9(2):146.
18. Google. Google Trends. Accessed October 4, 2022. https://trends.google.com/trends/
19. Edouard Mathieu FS, Dattani S, Ritchie H, Roser M. Monkeypox Our World in Data. 2022.
20. Arora VS, McKee M, Stuckler D. Google Trends: opportunities and limitations in health and health policy research. *Health Policy*. 2019;123(3):338-341.
21. Google. Google Trends Help. Accessed October 4, 2022. https://support.google.com/trends/
22. Schober P, Vetter TR. Correlation analysis in medical research. *Anesth Analg*. 2020;130(2):332.
23. Li Y, Shi B, Li S. Association between serum chemerin concentrations and clinical indices in obesity or metabolic syndrome: a meta-analysis. *PLoS One*. 2014;9(12):e113915.
24. Higgins JPT, Thompson SG. Controlling the risk of spurious findings from meta-regression. *Stat Med*. 2004;23(11):1663-1682.
25. Higgins JPT, Thompson SG. Quantifying heterogeneity in a meta-analysis. *Stat Med*. 2002;21(11):1539-1558.
26. Trapletti A, Hornik K. Tseries: time series analysis and computational finance. *R package version*. 2019:010-035.
27. Sato K, Mano T, Iwata A, Toda T. Need of care in interpreting Google Trends-based COVID-19 infodemiological study results: potential risk of false-positivity. *BMC Med Res Methodol*. 2021;21(1):147.
28. Pfaff B. VAR, SVAR and SVEC models: implementation within R package vars. *J Stat Softw*. 2008;27:1-32.
29. Crowson MG, Witsell D, Eskander A. Using Google Trends to predict pediatric respiratory syncytial virus encounters at a major health care system. *J Med Syst*. 2020;44(3):57.
30. Youth who died in Kerala's Thrissur succumbed to monkeypox, says health dept after NIV confirms. *Indian Express*. August 2, 2022. Accessed October 4, 2022. https://indianexpress.com/article/cities/thiruvananthapuram/kerala-thrissur-monkeypox-death-8063699/
31. Hu D, Lou X, Xu Z, et al. More effective strategies are required to strengthen public awareness of COVID-19: evidence from Google Trends. *J Glob Health*. 2020;10(1):011003.
32. Haug N, Geyrhofer L, Londei A, et al. Ranking the effectiveness of worldwide COVID-19 government interventions. *Nature Human Behaviour*. 2020;4(12):1303-1312.
33. Ejaz H, Junaid K, Younas S, et al. Emergence and dissemination of monkeypox, an intimidating global public health problem. *J Infect Public Health*. 2022;15(10):1156-1165.
34. Costa FF. Social networks, web-based tools and diseases: implications for biomedical research. *Drug Discov Today*. 2013;18(5):272-281.
35. Jiang L, Ma Q, Wei S, Che G. Online public attention of COVID-19 vaccination in Mainland China. *Digital Health*. 2022;8:20552076211070704.
36. Chen S, Liu X, Wu Y, et al. The application of meteorological data and search index data in improving the prediction of HFMD: a study of two cities in Guangdong Province, China. *Sci Total Environ*. 2019;652:1013-1021.
37. Smith KC, Rimal RN, Sandberg H, et al. Understanding newsworthiness of an emerging pandemic: international newspaper coverage of the H1N1 outbreak. *Influenza Other Respir Viruses*. 2013;7(5):847-853.
38. Verma M, Kishore K, Kumar M, Sondh AR, Aggarwal G, Kathirvel S. Google Search Trends predicting disease outbreaks: an analysis from India. *Healthc Inform Res*. 2018;24(4):300-308.
39. Ferguson N. Capturing human behaviour. *Nature*. 2007;446(7137):733.
40. Depoux A, Martin S, Karafillakis E, Preet R, Wilder-Smith A, Larson H. The pandemic of social media panic travels faster than the COVID-19 outbreak. *J Travel Med*. 2020;27(3):taaa031.
41. Delaney KP, Sanchez T, Hannah M, et al. Strategies adopted by gay, bisexual, and other men who have sex with men to prevent monkeypox virus transmission-United States, August 2022. *MMWR Morb Mortal Wkly Rep*. 2022;71(35):1126-1130.
42. Hubach RD, Owens C. Findings on the monkeypox exposure mitigation strategies employed by men who have sex with men and transgender women in the United States. *Arch Sex Behav*. 2022;51:3653-3658.
43. Atarodi A, Dastani M, Ghorbani M, Atarodi A. The role of mass media and social media in developing awareness of self-care behavior against the outbreak of Covid-19. *Libr Philos Pract*. 2021;4848:1-12.
44. Nuti SV, Wayda B, Ranasinghe I, et al. The use of google trends in health care research: a systematic review. *PLoS One*. 2014;9(10):e109583.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Yan W, Du M, Qin C, et al. Association between public attention and monkeypox epidemic: a global lag-correlation analysis. *J Med Virol*. 2022;e28382. doi:10.1002/jmv.28382