



Comment on “Analysis of hospital traffic and search engine data in Wuhan China indicates early disease activity in the Fall of 2019” by Nsoesie et al.

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Comment on
*“Analysis of hospital traffic and search engine data in Wuhan
China indicates early disease activity in the Fall of 2019”*
by Nsoesie et al.

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Abstract

In a recent manuscript, Nsoesie et al. analysed vehicle counts in hospital parking lots and internet search trends, and suggested that the COVID-19 outbreak might have started in Wuhan, China as early as August 2019. This claim received widespread media coverage despite the lack of validation from peers. This review serves as a pre-publication evaluation of the study. We identify several problems, even questionable research practices, including but not limited to: inappropriate and insufficient data, misuse and misinterpretation of statistical methods, and cherry-picking internet search terms. We also reflect on scientific publishing in a time of public emergency.

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If you torture the data long enough, it will confess to anything.

Ronald H. Coase

1 Background

The manuscript under review [1] applies digital epidemiology to determine the time of the initial outbreak of the ongoing COVID-19 pandemic caused by a novel coronavirus, SARS-CoV-2. The authors obtained vehicle counts extracted from satellite images of hospital parking lots and Baidu search trends of two symptoms related to COVID-19. In both datasets, they observe an increase in August 2019, leading the authors to suggest an outbreak of COVID-19 much earlier than the first documented case on 1 December 2019 [2].

The study is posted to DASH, a repository for researchers related to Harvard University.¹At the time of preparing this review, this manuscript is featured at the top of “trending works” of DASH. Indeed, the study attracted widespread media coverage (e.g. [3]), even political attention, partly thanks to the self-promotion of some of the authors through social media.

There is no doubt that the manuscript has gained its popularity, and its authority might never be questioned outside the academic community. However, the merit of an academic paper can only be established through peer reviews, that is, careful evaluations by people with related expertise.

With our expertise in mathematics, statistics, and medical sciences, we consider it our duty to prepare the following review for the methods and results of the manuscript. This would hardly affect the popularity of the study, but we seek to leave a record in the literature for future reference.

Our review may overlap with some remarks made in social media and mainstream media (e.g. [4]). We did consult the media and participated in discussions on social media. But in this review, we only include arguments that can be solidified to meet the academic standard. On the other hand, our original analysis involves advanced statistics. We make effort to simplify our explanation to reach a broader audience.

¹The full record once contained the entry “dc.description.version: Accepted Manuscript”. It is later updated to “Author’s original”.

2 Satellite imagery

The authors selected six hospitals for their study. They claim to have excluded “sub-specialty hospitals” such as Wuhan Asias Heart. But they curiously included “Hubei Women and Children’s Hospital” (湖北省妇女儿童医院), better known as “Hubei Maternity and Child Health Care Hospital” (湖北省妇幼保健院). This hospital is specialized in gynecology, obstetrics, and pediatrics, but has no pneumology for adults. It is not a logical choice for patients who develop COVID-19 related symptoms. The traffic volume at its parking lot might be more sensitive to seasonal children diseases, such as children diarrhea caused by rotavirus in the peak seasons of autumn and winter [5].

Satellite images of the hospitals were obtained from the company Remote Sensing Metrics (RS Metrics). The company also delineated parking lots and streets by automated feature extraction, then identified and counted the cars. The authors claim that (word by word)

“Images with tree cover, building shadow, construction and other factors that present difficulties in defining the contours were excluded since this could lead to over- or under-counting of the number of vehicles.”

The authors did not publish the original images and data, apart from five figures as examples. This makes it impossible to check their counts. But this is understandable, as the amount of data could be very large.

A problem arises, however, from the media coverage of the study. The news report of the American Broadcasting Company (ABC) [3] uses several images with tree covers, building shadows, and constructions; see Figure 1. These images, also bearing the logo of RS Metrics, should have been excluded by the authors. In fact, the flawed images only exemplify how these elements could lead to extremely inaccurate counts, as the authors warn in the manuscript. Even worse, the photos are clearly taken from different angles. Some invisible areas in the 2018 photos become visible in the 2019 photos, making the count even more misleading. The captions of the flawed images make it clear that they were “provided to ABC”. It is not clear if they were provided by the authors or by RS Metric.

We suggest the authors clarify that the images were not provided by them and are not used in their analysis. In particular, they need to explain how they handled the parking lot of “Wuhan Women and Children’s Hospital” that was under construction near the end of 2018, as annotated on the left of the top panel of Figure 1.

For the sake of this review, we assume no wrongdoing on the part of the authors.



Figure 1: Images used in the ABC coverage of the study [3]. One clearly sees tree covers, building shadows, and even a construction site (annotated on the left of the top panel). They should have been excluded from the study, as the authors claim. Many areas covered by obstacles in the 2018 photos become visible in the 2019 photos, leading to inaccurate and misleading counts.

3 Analysis of vehicle count

The dataset of vehicle counts is of very poor quality. In a period of more than two years, from January 2018 to early April 2020, we count 7, 8, 10, 23, 24, and 37 data points, respectively, for the six hospitals from Figure 2(a) of the paper. Note that “Hubei Women and Children’s Hospital”, a specialty hospital not quite related to COVID-19, contributes 24 data points. The data points are not uniformly distributed, not only among the hospitals, but also in time. About 30 data points accumulate after April 2020, as shown in Figure 2a.

Nevertheless, the authors decide to draw a smooth curve from the scatterplot using a local regression (LOESS), which usually requires a large, densely sampled dataset to produce good results. They then observe “a steep increase in volume starting in August 2019 and culminating with a peak in December 2019” from the LOESS curve.

Validation and tests are essential for statistical analysis, as should have been taught to everyone who deals with data. The authors claim to have used “high traffic areas including the Huanan Seafood Market and two railway stations (Wuchang and Hankou) for validation”, but did not give any detail.

To illustrate the problem of the authors’ practice, let us make the following observation on the LOESS curve: There is a very steep decrease in volume starting in December 2019 and culminating with a valley in February 2020. Following the analysis of the authors, we may suggest that there has been a trend of social distancing starting as early as 1st December 2019. See Figure 2a.

This, however, does not match reality. The outbreak went unnoticed until the end of December 2019 [6], and a new coronavirus was identified as the cause only in early January 2020 [7]. The local government did not implement the public health lockdown until 23 January 2020 [8]. In fact, before smoothing, the data points clearly show a sudden drop in traffic volume on this date; see Figure 2a.

The problem here is the use of the smoothing method and the interpretation of the smoothed curve.

LOESS [9] is one of many methods that generate a smooth curve from scattered data. It is a non-parametric regression, as one does not need to specify a function of any form to fit the data. This is both an advantage and a disadvantage, depending on the situation. On the bright side, LOESS is very flexible when there is no theoretical model. However, LOESS may distort the data in several ways. In the case of a peak or valley, for example, a LOESS smoothing will decrease its height or depth but increase its width. This phenomenon is

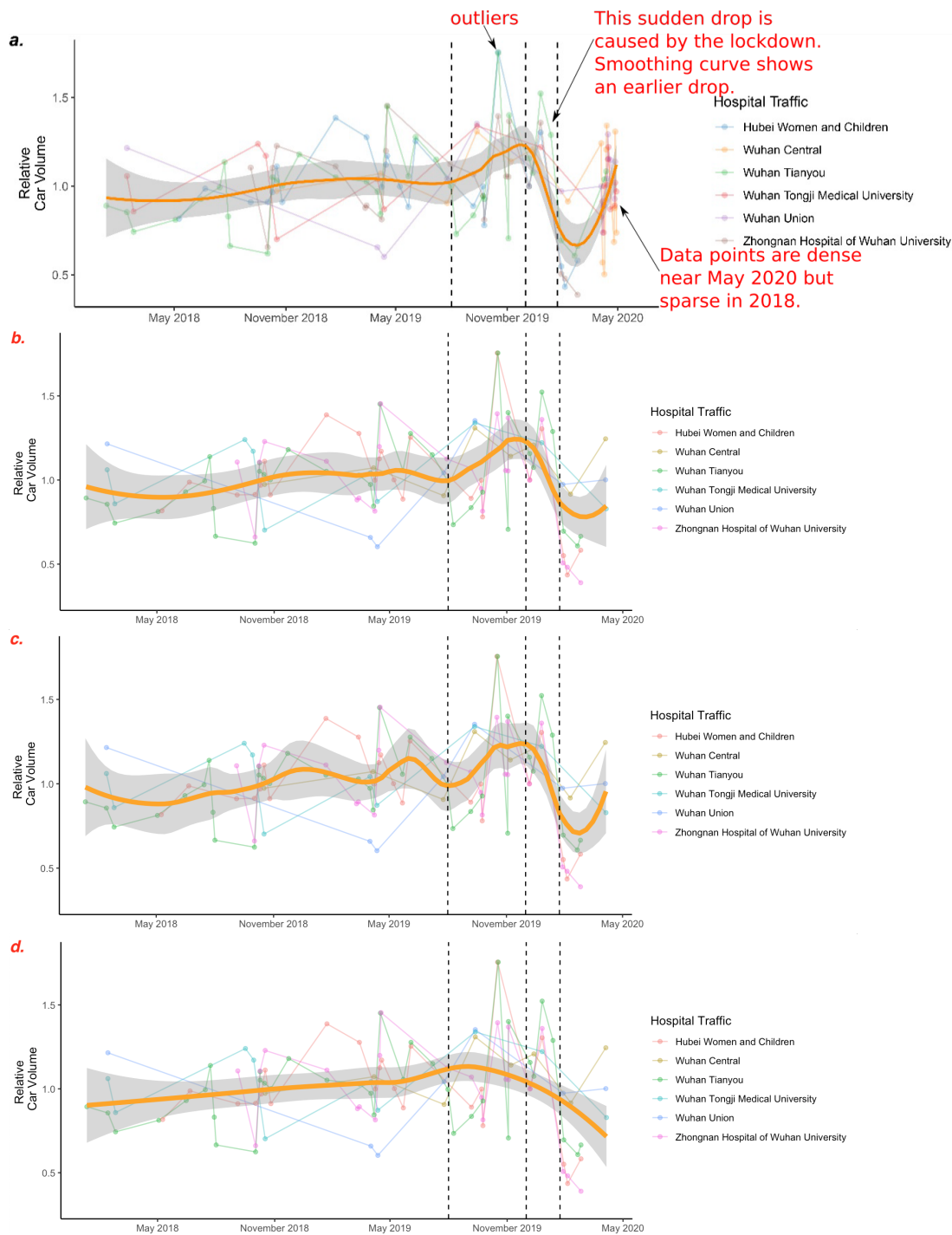


Figure 2: LOESS smoothing results. **a.** The LOESS curve ($\alpha = 40\%$) given in the manuscript. We point out that the data is not uniform in time, that the LOESS curve suggests an earlier decrease of volume that does not match reality, and that there are outliers to which the LOESS method is sensible. **b.** Reproduction of the curve using extracted data points. **c.** LOESS curve with $\alpha = 30\%$ reveals two more peaks. **d.** LOESS curve with $\alpha = 80\%$, default value for the `geom_smooth` function in the `ggplot2` package, has no peak at the end of 2019.

demonstrated above by the lockdown valley. Moreover, the LOESS curve is very sensitive to outliers. This is the case in the dataset under discussion (see Figure 2a). Note that one outlier is contributed by “Hubei Women and Children’s Hospital”, possibly caused by a seasonal children disease. Thus, the LOESS smoothed curve is merely an indicator of a trend, but never a measurement of the starting point of a peak or valley, as the authors seem to believe.

The LOESS method has two parameters: The degree of the polynomial used to locally fit the data, and the span parameter α , which can be understood as the size of the window within which the curve is locally estimated. Tuning these parameters is crucial for the quality of analysis: If the degree is small or the span parameter is too big, the data will be over-smoothed and important features will be erased. If the degree is too big or the span parameter is too small, the curve will not be smooth enough to reveal any trend. The authors used a span parameter $\alpha = 40\%$ and appear to have used degree 1.

To check the authors’ analysis, we use WebPlotDigitizer [10], a tool also used by the authors, to extract data from Figure 2a of the manuscript. The extraction is successful for data until early April 2020; data points afterward are too dense to distinguish from each other. The extracted data allow us to reproduce Figure 2a of the manuscript using the `geom_smooth` function in the `ggplot2` package of R [11]; see Figure 2b. We conjecture that the authors used the same function in the same package.

However, if we change the span parameter, the smoothing curve becomes very different. With $\alpha = 30\%$ (see Figure 2c), we observe two new peaks, one at the end of 2018, the other in the middle of 2019. They make the peak at the end of 2019 much less significant. These two peaks were not present in the LOESS curve with $\alpha = 40\%$, as the window is just large enough to smooth them out. With $\alpha = 80\%$ (see Figure 2d), apparently the default span value of `geom_smooth`, the peak at the end of 2019 is also smoothed out. We thus think that the authors are obliged to justify their choice of 40% span over other values, if not for their convenience.

In conclusion, the authors chose a smoothing method without justification, selected smoothing parameters without justification, misused the method on data of insufficient quantity and quality, and then over-interpreted the smoothing curve without any validation.

4 Baidu search trends

The authors obtained search volumes of the terms “cough” and “diarrhea” from the database of Baidu (<http://index.baidu.com>), the primary search engine in China, and observed “elevated levels of Baidu search queries” for these keywords. The search trend for the keyword “cough” coincides with yearly influenza seasons; hence the authors emphasize the keyword “diarrhea” which, according to the authors, is “a more COVID-19 specific symptom”. The plot shows that the search trend for “diarrhea” is elevated since August 2019.

We failed to reproduce these data from Baidu’s database using the Chinese words 腹泻 or 拉肚子, both translate to “diarrhea”. In response to our inquiry, the authors revealed that the actual Chinese term they used was 腹泻的症状, which translates to “symptom of diarrhea”.

This should raise an alarm for several reasons.

- The authors did not report the exact Chinese keywords they used for the search trend. As a search term, “symptom of diarrhea” sounds strange to the ear of native Chinese speakers. Baidu’s search trends also confirm that “diarrhea” is *usually* a much more used keyword; see Figure 3 (top).
- The most common symptoms of COVID-19 reported from China were fever (88.7% during hospitalization) and cough (67.8%), while diarrhea was uncommon (3.8%) [12]. According to a large-scale study in the UK [13], diarrhea is only the 7th most common symptom of COVID-19, behind cough, fever, shortness of breath, fatigue, confusion and cough (sputum).
- The observation of the authors cannot be reproduced by usual Chinese words for “diarrhea” (see Figure 3 top), nor by other terms such as “short of breath” or “difficulty breathing” (see Figure 3 middle, also [4]).
- Unfortunately, even the search term “symptom of diarrhea” does not support the authors’ claim. The elevation in August 2019 is not unique for Wuhan but nationwide observed in China. See Figure 3 (bottom).

In conclusion, the authors failed to justify their choice of the keyword “diarrhea”, did not use the correct Chinese translation, and did not check more keywords, nor the nationwide trend, to validate their claim. This can only be described as cherry-picking.

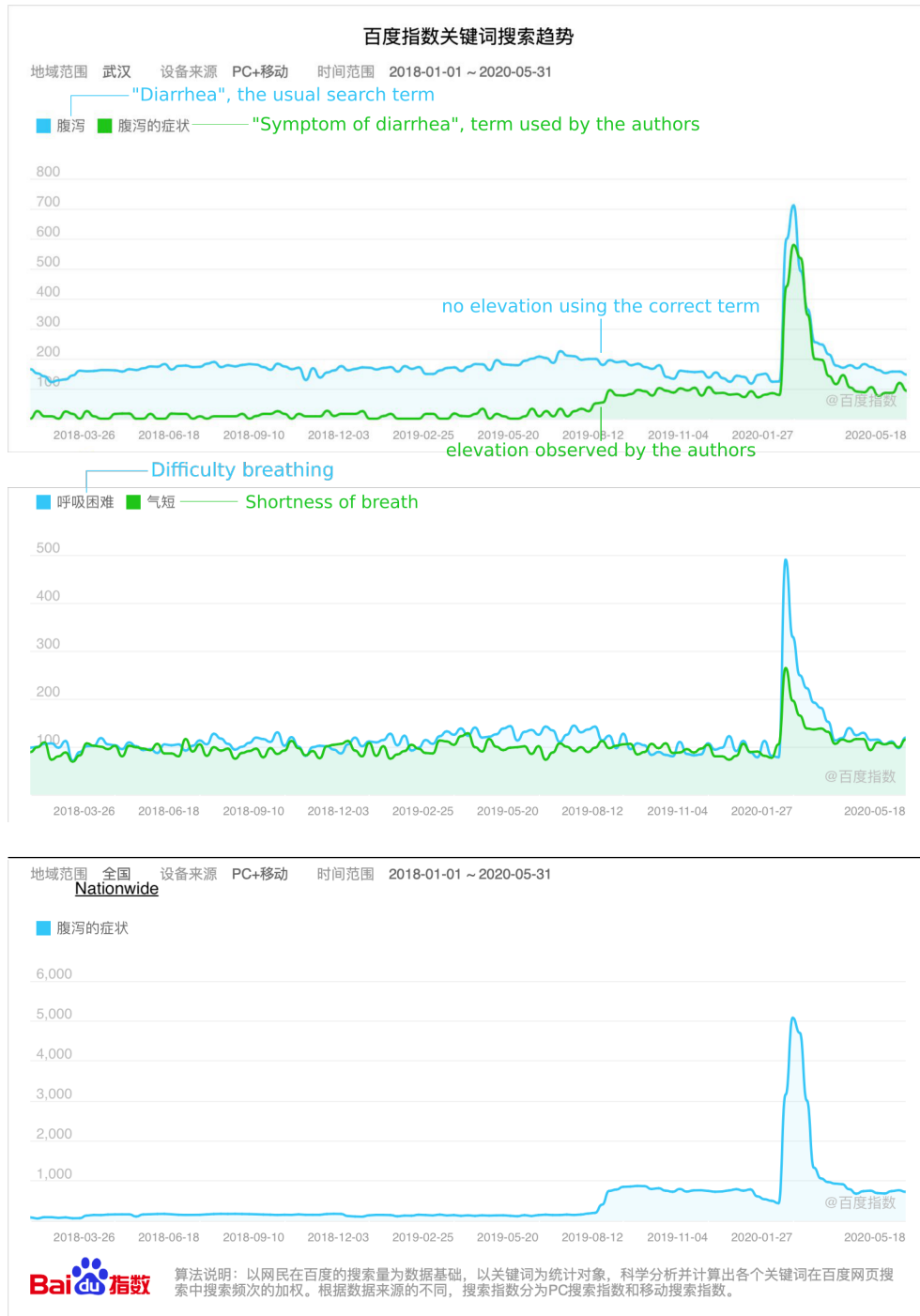


Figure 3: Baidu search trends. Top: The usual translation for “diarrhea”, 腹泻, shows no elevation as claimed by the authors. It turns out that the authors used the keyword 腹泻的症状, which translates to “symptom of diarrhea”. Middle: No elevation is observed before January 2020 in the trend of 呼吸困难 (difficulty breathing) or 气短 (shortness of breath). Bottom: The elevation in the trend of 腹泻的症状 (symptom of diarrhea) is more visible in the nationwide trend, showing that the trend is not Wuhan-specific.

5 Internet epidemiology done right

The idea of using internet search trends to monitor infectious diseases is certainly interesting and deserves more attention. In fact, there has been a successful application of digital epidemiology in the COVID-19 pandemic [14]: A recent study by Wang et al. used WeChat, the largest social media in China, to detect and track the COVID-19 outbreak in China. Instead of a few cherry-picked terms, Wang et al. made an extensive list of keywords related to the COVID-19 disease, including “SARS”, “Feidian” (非典, abbreviated Chinese word for SARS), “novel coronavirus”, “coronavirus”, “fever”, “cough”, “shortness of breath”, “fatigue”, “diarrhea”, “runny nose”, “infection”. For each of these terms, the trends were obtained from an index of posts from the platform of WeChat, as well as an index of searches of Baidu. The data were then analyzed and reported.

Wang et al. crosschecked their findings with the earliest reported dates of symptom onset and confirmed cases of COVID-19 in December 2019. It was found that the spikes in WeChat Index closely followed the symptom onset dates for confirmed cases. In particular, the WeChat trend for “SARS”, typically used by physicians more alerted to the situation, spiked in the first three days of December, in coincidence with the symptom onset of the first confirmed COVID-19 cases [2]. The trend of “Feidian”, typically used by the public, began to rise on December 15 and stayed at a relatively high level until December 29, in coincidence with 33 cases confirmed from 15 to 27 December 2019. These terms are more sensitive than the symptoms of COVID-19 used in the Harvard study because, in the very early stage of the outbreak, people did not understand the disease beyond the fact that it is similar to SARS. There is no noticeable spike in the trend of COVID-19 related terms in November.

In the manuscript under review, the authors argue that “diarrhea” is a “more COVID-19 specific symptom” as its trend “was neither seen in previous flu seasons (n)or mirrored in the cough search data”. This is a very weak justification for their choice of the search term.

We now hypothesize that “shortness of breath” is a much better predictor for COVID-19 deaths. First of all, “shortness of breath” is a much more common symptom than “diarrhea” [13]. We obtain Google Trends for “shortness of breath” from 1 March to 15 May 2020, and observe a unique trend that was neither seen in previous flu seasons nor mirrored in the “cough” or “diarrhea” search data.

To further test our hypothesis, we obtain the smoothed COVID-19 deaths data from the Institute for Health Metrics and Evaluation (IHME), a research institute at the University

of Washington working in the area of global health statistics and impact evaluation. It was found that Google Trends for “shortness of breath”, when adjusted for the 28-day time lag, was highly correlated with the daily COVID-19 deaths in the United States, with Pearson’s $R=0.96$; see Figure 4. This significant association may help guide clinical management decisions.

We might have convinced many readers that our hypothesis sounds reasonable. However, careful statistical analysis and validation are necessary to ensure academic rigour. As we have no intention to extend our argument any longer in this review, we stop here and refrain from making any premature claim.

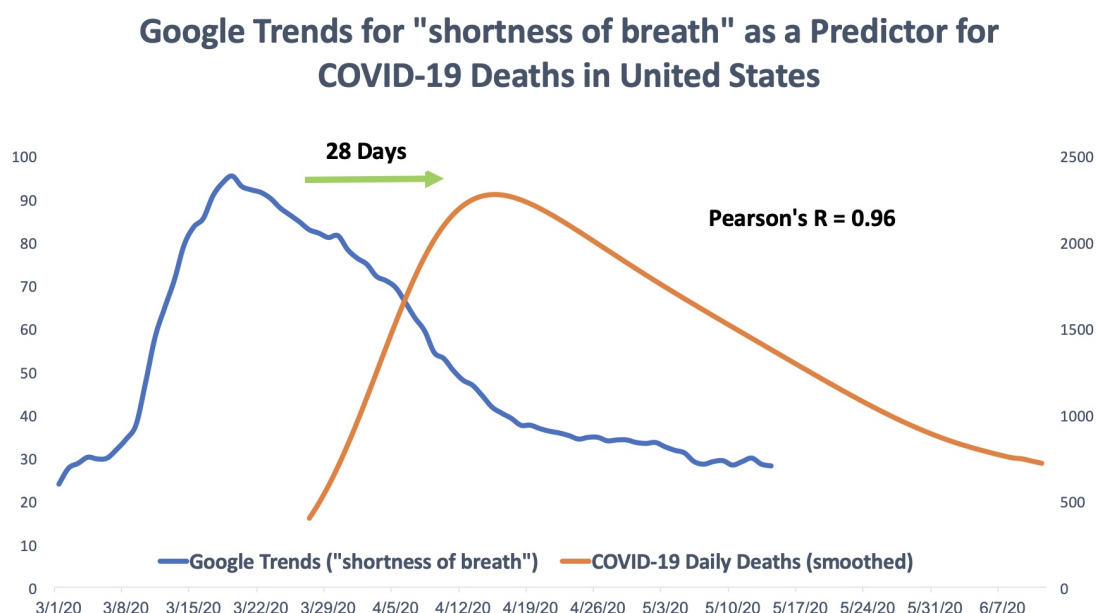


Figure 4

6 Reflections

The ongoing COVID-19 pandemic caused by the SARS-CoV-2 virus is presenting an unprecedented challenge to the scientific community. While researchers around the world strive to analyze and understand the disease, fast dissemination and circulation of research results become critical to an effective response to the public health emergency.

Many scientific journals have expedited publications of coronavirus-related submissions, but can hardly accommodate the demand. As a consequence, many scientific manuscripts

are made public as “preprints” without formal peer reviews [15]. This practice certainly accelerates the exchange of knowledge among researchers, as has been observed in disciplines that are long accustomed to preprints (e.g. mathematics and physics).

However, insufficient quality control facilitates studies of poor quality to sneak into the public sphere [16]. At the time of preparing this review, Retraction Watch records more than 20 retracted papers about COVID-19 [17]. These studies, intentionally or not, often become the source of misinformation and conspiracies that harm the global effort to battle the pandemic.

Authors of the manuscript include renowned pioneers in the new field of digital epidemiology, the use of “non-traditional” data streams such as satellite images and internet search trends for early detection of epidemics. They cited some previous works, including two perspectives [18, 19] and a feasibility study [20], to support the validity of their method.

The study under review is a bold move to use digital epidemiology to claim an event undetected by traditional surveillance. Unfortunately, it fails to maintain academic rigour nor academic integrity. The authors misused statistical tools on insufficient data and misinterpreted the result, leading to premature claims that only bring media popularity but harm academic reputation. It is a pity that a field at such an early stage already gets plagued by statistical fallacies. Moreover, the cherry-picking of search keywords for internet trends is a very questionable research practice [21]. We understand that digital epidemiology suffers from insufficient data, as the authors admit in the manuscript. This does not justify the abuse of statistical methods and the suppression of evidence.

Before ending this review, we would like to express the following opinions in view of the current crisis of scientific publishing:

- Preprint repositories should all implement basic moderation.

Either before or in the early stage of the COVID-19 outbreak, many repositories (arXiv, medRxiv, ChemRxiv, etc.) implemented basic screening for plagiarisms, non-scientific contents, and papers that potentially endangers public health [15]. ArXiv also removes “papers in need of significant review and revision”. But this does not seem to be the case for DASH, an institutional repository of Harvard that hosts the manuscript under review.

- Peer-review should be possible to all manuscripts at every stage of publishing.

Traditionally, peer reviews are organized by journal editors after receiving the submission. This begins to change in recent years; services like PubPeer (<https://pubpeer.com/>):

//pubpeer.com/) enable peer reviews before submission or after publication. However, the manuscript under review does not have a DOI nor an arXiv ID, hence not indexed by PubPeer. This leaves us with no other option but to write a separate paper. It would be nice if PubPeer and similar services could cover more manuscripts, including those posted to institutional repositories or personal websites.

- News media should stop reporting preprints as established studies.

The purpose of preprint is to gather opinions from peers, not to draw attention from new media. Nevertheless, more and more studies are prematurely made public through media coverage. Many preprint repositories warn that preprints “should not be reported in news media as established information”. We think that news media should follow this warning instead of ignore it. Moreover, media have the duty to pass on this warning to their readers when reporting preprints.

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