Understanding the Epidemic Course in Order to Improve Epidemic Forecasting

Peng Jia1,2

1Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hong Kong, China, 2International Institute of Spatial Lifecourse Epidemiology (ISLE), Hong Kong, China

Abstract The epidemic course of the severe acute respiratory syndrome (SARS) has been differently divided according to its transmission pattern and the infection and mortality status. Unfortunately, such efforts for the coronavirus disease 2019 (COVID-19) have been lacking. Does every epidemic have a unique epidemic course? Can we coordinate two arbitrary courses into an integrated course, which could better reflect a common real-world progression pattern of the epidemics? To what degree can such arbitrary divisions help predict future trends of the COVID-19 pandemic and future epidemics? Spatial lifecourse epidemiology provides a new perspective to understand the course of epidemics, especially pandemics, and a new toolkit to predict the course of future epidemics on the basis of big data. In the present data-driven era, data should be integrated to inform us how the epidemic is transmitting at the present moment, how it will transmit at the next moment, and which interventions would be most cost-effective to curb the epidemic. Both national and international legislations are needed to facilitate the integration of relevant policies of data sharing and confidentiality protection into the current pandemic preparedness guidelines.

Plain Language Summary The period of the severe acute respiratory syndrome (SARS) epidemic has been divided according to its transmission pattern and the infection and mortality status. Unfortunately, such efforts for the coronavirus disease 2019 (COVID-19) have been lacking. Does every epidemic have a unique pattern? Can we find a common real-world progression pattern of the epidemics? To what degree can such arbitrary divisions help predict future trends of the COVID-19 pandemic and future epidemics? The advanced spatial and digital technologies provide a new perspective to understand the transmission patterns of epidemics, especially pandemics, and a new toolkit to predict the progress of future epidemics on the basis of big data. In the present data-driven era, data should be integrated to inform us how the epidemic is transmitting at the present moment, how it will transmit at the next moment, and which interventions would be most cost-effective to curb the epidemic. Both national and international legislations are needed to facilitate the integration of relevant policies of data sharing and confidentiality protection into the current pandemic preparedness guidelines.

The “life” course of an epidemic starts from the human-ecology interaction and can develop into a pandemic, such as coronavirus disease 2019 (COVID-19). Think about the four periods the course of the severe acute respiratory syndrome (SARS) epidemic has been divided into, according to its transmission patterns: from wildlife to humans (December 2002 to early January 2003), humans to humans in the epicenter (January to February 2003), epicenter to other regions (early February to mid-March 2003), and humans to humans in other regions (mid-March to May 2003). However, according to the infection and mortality status, the SARS epidemic course has been differently divided into four periods: portent and incubation (December 2002 to February 2003), outbreak and spread (February to early May), fastigium and stability (May), and recession and recovery (June) (Zhong, 2011). These different arbitrary divisions, while confusing us and being susceptible to the Modifiable Temporal Unit Problem (MTUP) whereby the resulting epidemic trend may vary by time windows selected in the analyses (Tao et al., 2014), can also open a window of opportunity for reflection on is every epidemic a unique “individual” with a unique life course? Can we coordinate different arbitrary courses into an integrated course, which could be less subject to MTUP and better reflect a common real-world progression pattern of the epidemics? More importantly, since people are still experiencing the COVID-19 pandemic or facing the risk for COVID-19 reemergence in many regions, we have to ask to what degree such arbitrary divisions can help to predict the future trends of the COVID-19 pandemic and the future epidemics?
COVID-19 has visited many countries, and most, if not all, of them have not prepared for or even realized the risk of COVID-19 until it landed on their territory. This could be understood to some extent. After all, any emergency response is at the economic expense of society with side effects in many aspects (Nussbaumer-Streit et al., 2020). There is generally a lack of data-sharing mechanisms and infrastructures (e.g., data-sharing protocols, intersystem interfaces, and confidentiality protection mechanisms) for most countries to make robust place-specific prediction of risk and further generate evidence-based measures of emergency response ahead (Kummittha, 2020). Therefore, efforts of understanding the COVID-19 epidemic course have been lacking.

It has been mentioned that understanding transmissibility of the COVID-19 epidemic is crucial for predicting the course of the epidemic and the likelihood of sustained transmission (Lipsitch et al., 2020). However, very few, if not none, of mathematical models that consider factors including the infection’s transmissibility to predict the impact of the COVID-19 epidemic have been useful to the real-time epidemic control on the ground (Jia & Yang, 2020a). An important reason for this uselessness is that, without the support of spatial real-time data and models, we have largely or fully lost spatial features of the epidemic and can only see a limited number of snapshots over the full, continuous spectrum of the epidemic (Jia et al., 2020). For example, the spatial relationships among humans and cities (i.e., the First Law of Geography that everything is related to everything else, but near things are more related than distant things) have been significantly downplayed in most, if not all, prediction models for COVID-19 (Shi et al., 2020). The life course of an epidemic or pandemic is even more spatial than that of an endemic or hyperendemic: The accumulation of risk and infection converts an endemic into a hyperendemic, which has shown its clear “life” course; after being upgraded to an epidemics and even further pandemic, its spatial life course is just too clear to neglect. Human movement at all scales, from local routine activities to global air travel, has further complicated the epidemic course, which could not be fully understood by clinical course data and mathematical models. Fully understanding in order to be able to forecast the course of the COVID-19 epidemic can be treated as elucidating the “exposome” (i.e., the totality of all exposures, originally in the context of environmental exposures and chronic diseases) of the COVID-19 epidemic, which requires a systematic framework and a combination of advanced data and methods (Bradley et al., 2020). The next-generation national disease surveillance and reporting system would link a wide array of data sources together, including multiscale human movement data, to enable the construction of the epidemic course (Jia & Yang, 2020b).

Spatial lifecourse epidemiology is an emerging discipline that stems from chronic disease research fields for tackling the “exposome” (Jia, 2019) and has been prospectively adapted to infectious disease and epidemic research areas to characterize the epidemiologic triad at every moment as a snapshot over a lifecourse process (Jia et al., 2020). A family of spatial, location-aware, big data, citizen science (i.e., crowdsourcing), and artificial intelligence tools can implement multifactorial, dynamic monitoring of one’s exposure over the life course in a high dimension and resolution (Jia & Yang, 2020c). For example, remote sensing at different prediction models and achieve a data-driven epidemic course of the COVID-19 in China (Kummittha, 2020). Therefore, efforts of understanding the COVID-19 epidemic course have been lacking.

Spatial lifecourse epidemiology is an emerging discipline that stems from chronic disease research fields for tackling the “exposome” (Jia, 2019) and has been prospectively adapted to infectious disease and epidemic research areas to characterize the epidemiologic triad at every moment as a snapshot over a lifecourse process (Jia et al., 2020). A family of spatial, location-aware, big data, citizen science (i.e., crowdsourcing), and artificial intelligence tools can implement multifactorial, dynamic monitoring of one’s exposure over the life course in a high dimension and resolution (Jia & Yang, 2020c). For example, remote sensing at different prediction models and achieve a data-driven epidemic course of the COVID-19 in China (Kummittha, 2020). Therefore, efforts of understanding the COVID-19 epidemic course have been lacking.

Transparent, anonymous reporting of travel and contact history of a relatively large number of COVID-19 cases has been realized in China for the first time in the history of pandemics, thus opening a new avenue in the era of big data for more advanced, transdisciplinary approaches to refine results from mathematical prediction models and achieve a data-driven epidemic course of the COVID-19 in China (Kummittha, 2020). However, again, the COVID-19 pandemic is still ongoing. The worldwide spatial data are needed to be shared in a collaborative, secure way for weaving a spatial life course of the COVID-19 across the globe, which holds unprecedented potential to further convert the current retrospective analyses into prospective forecasting. Although such cross-disciplinary data sharing has been locally realized when responding to the COVID-19 epidemic, many of them are just temporary solutions that could not be adopted for early
warning. To improve pandemic response and prediction, both national and international legislation are needed to facilitate the integration of relevant policies of data sharing and confidentiality protection into the current pandemic preparedness guidelines. Third-party (governmental) agencies at national and international levels should also be identified for implementation of these visions, for example, a department of big data management at municipal, provincial, and/or national levels, and the World Health Organization at the global level.

We are now in the data-driven era, also called the Fourth Paradigm, where established theories are insufficient to fully guide data collection in a rapidly changing context, especially when we are facing increasingly frequent and impactful epidemics (Bedford et al., 2019). Instead, data should be used to enrich and calibrate theories. Scientific discovery is becoming increasingly impossible without the support of intensive data. It would not be sufficient and timely to arbitrarily define the periods of the epidemic on the basis of what we have observed. Big data should be integrated and speak for themselves, informing us how the epidemic is transmitting at the present moment, how it will transmit at the next moment, and which interventions would be most cost-effective to curb the epidemic. Rather than defining the epidemic course arbitrarily, we should be informed by data and then prepare for the epidemic proactively.

Conflict of Interest
The author declares no conflict of interest relevant to this study.

Data Availability Statement
All data are available from the cited references. No more data are used in this policy article.

References
Bedford, J., Farrar, J., Ihekweazu, C., Kang, G., Koopmans, M., & Nkengasong, J. (2019). A new twenty-first century science for effective epidemic response. *Nature*, 575(7781), 130–136. https://doi.org/10.1038/s41586-019-1717-y
Bradley, D. T., Mansouri, M. A., Kee, F., & Garcia, L. M. T. (2020). A systems approach to preventing and responding to COVID-19. *EClinicalMedicine*, 100325. https://doi.org/10.1016/j.eclinm.2020.100325
Jia, P. (2019). Spatial lifecourse epidemiology. *Spatial Lifecourse Epidemiology, 1* (3), e57–e59. https://doi.org/10.1016/s2542-5196(18)30245-6
Jia, P., Dong, W., Yang, S., Zhan, Z., Yu, L., & Lai, S. (2020). Spatial lifecourse epidemiology and infectious disease research. *Trends in Parasitology*, 36(3), 235–238. https://doi.org/10.1016/j.pt.2019.12.012
Jia, P., & Yang, S. (2020a). Time to spatialise epidemiology in China. The *Lancet Global Health, 8*(6), e764–e765. https://doi.org/10.1016/S2214-109X(20)30120-0
Jia, P., & Yang, S. (2020b). China needs a national intelligent syndromic surveillance system. *Nature Medicine*, 26(7), 990. https://doi.org/10.1038/s41591-020-0921-5
Jia, P., & Yang, S. (2020c). Are we ready for a new era of high-impact and high-frequency epidemics? *Nature*, 580(7803), 321–321. https://doi.org/10.1038/d41586-020-01079-0
Kummu, K., & R. K. (2020). Smart technologies for fighting pandemics: The techno- and human-driven approaches in controlling the virus transmission. *Government Information Quarterly, 37*(3), 10481. https://doi.org/10.1016/j.giq.2020.101481
Lipsitch, M., Swerdlow, D. L., & Finelli, L. (2020). Defining the epidemiology of Covid-19—Studies needed. *The New England Journal of Medicine*, 382(13), 1194–1196. https://doi.org/10.1056/NEJMp2002125
Nussbaumer-Streit, B., Mayr, V., Dobrescu, A. I., Chapman, A., Persad, E., Klerings, I., et al. (2020). Quarantine alone or in combination with other public health measures to control COVID-19: A rapid review. *The Cochrane Database of Systematic Reviews, 4*, CD013574. https://doi.org/10.1002/14651858.CD013574
Shi, W., Tong, C., Zhang, A., Wang, B., Shi, Z., Yao, Y., & Jia, P. (2020). Forecasting COVID-19 onset risk and evaluating spatiotemporal variations of the lockdown effect in China. Durham, NC: Research Square. Available at https://doi.org/10.21203/rs.3.rs.28675/v1
Tao, C., Monsuru, A., & Tobias, P. (2014). Modifiable Temporal Unit Problem (MTUP) and its effect on space-time cluster detection. *PLoS ONE, 9*, e100465.
Zhong, K. (2011). In E.-K. Olsson & L. Xue (Eds.), *SARS from east to west* (pp. 24–26). New York City: Lexington Books.

Acknowledgments
I thank the International Institute of Spatial Lifecourse Epidemiology (ISLE) for the research support.