Linking human behaviors and infectious diseases

Nita Bharti[a,b,1]

Human behaviors determine outbreak trajectories of infectious diseases. This fundamental relationship underlies why broad behavioral interventions (BIs) are effective tools in outbreak management. BIs target an overall reduction in contacts and behaviors that enable pathogen transmission as a nonspecific solution for preventing new infections. Despite that, there is a lot that remains unknown about the interactions between human behavior and infectious diseases. These gaps limit targeted outbreak management and prevention. In PNAS, Vigfusson et al. (1) narrow this gap by exploring multiple ways to assess behavioral changes in infectious hosts using existing data sources. By linking mobile-phone call detail records (CDRs) with health records of clinically confirmed influenza, they measure deviations in routine behaviors during illness compared to pre- and postillness behaviors.

Background: Behavior and Epidemiology

There are many well-studied links between human behavior and infectious diseases. The concept of the behavioral immune system posits that susceptible individuals exercise preventative behaviors when faced with the threat of infection (2). Disease avoidance saves the immune system from the costly process of reacting to the invasion of a pathogen. These behaviors include reactions like disgust and avoidance of infectious hosts. Other individual behaviors linked to epidemiological outcomes are correlated with exposure and infection. For example, higher social activity is linked to an increased likelihood of influenza infection during outbreaks (3). At larger scales, synchronized movements among susceptible individuals that increase population density and contacts can drive population-wide disease outbreaks (4, 5).

Human behaviors linked to active infections have been more difficult to characterize. Asymptomatic or mildly symptomatic individuals can be central to superspreading events because behaviors do not change during a period of infectiousness (6, 7). For symptomatic infections in humans, disease modelers and policy makers often assume that hosts have fewer contacts or move less than healthy hosts (5), but data explicitly showing this phenomenon have been limited.

CDRs and Epidemiology

Mobile-phone data have been a central data source for measuring human behavior and more specifically, movement. The findings of González et al. (8) in 2008 first demonstrated the use of anonymized mobile-phone data in tracking detailed human movements through space and time. As phone usership and prevalence grew, CDRs became a favored source of passive surveillance data for human mobility and were quickly linked to studies ranging from natural disaster relief (9) to infectious disease dynamics (10). CDRs make it possible to retrospectively track the movement of phone users in areas with phone coverage while they are using their devices. These mobility traces have been used to explain the observed spatial spread of pathogens, including the novel coronavirus (11). Measuring connectivity between locations helps estimate the likelihood of introduction events. Similarly, movements within locations are used to estimate contact rates and transmission potential during outbreaks (12). The findings of Vigfusson et al. (1) demonstrate deviations in the movements of influenza-infected members of the population that will likely impact disease transmission. This indicates that transmission predictions based on healthy or preinfection movement patterns may be misleading for disease models.

Same Data, Different Information

Since 2008, the use of mobile-phone data for epidemiology and public health has grown in quantity but stagnated in breadth. CDRs are used exhaustively to measure movement, and although movement is an excellent proxy for contacts and subsequent pathogen transmission potential, it is not the only behavior that can change during an outbreak. CDRs have also been used to reconstruct virtual and physical contact

[a]Department of Biology, The Pennsylvania State University, University Park, PA 16802; and [b]Center for Infectious Disease Dynamics, The Pennsylvania State University, University Park, PA 16802

Author contributions: N.B. wrote the paper.

The author declares no competing interest.

See companion article, "Cell-phone traces reveal infection-associated behavioral change," 10.1073/pnas.2005241118.

[1]Email: nita@psu.edu.

Published February 23, 2021.

networks to assess local pathogen transmission risk (13). With a much-needed fresh perspective, Vigfusson et al. (1) move the field of phone data measurably forward by analyzing existing data in a different way. In addition to measures of movement, they also consider other behaviors around phone use and find deviations in patterns of call frequency and duration during illness. By establishing baseline behavior patterns before and after a confirmed influenza diagnosis, they can detect departures from individual patterns during times of illness. They link phone usage and health records and compare geographically paired, clinically confirmed influenza diagnoses with people who did not receive an influenza diagnosis. Their approach does not require app download, opt in, symptom reporting, or factors that can impose additional biases on participants.

Bias and Inequities in Mobile Phone-Derived Data

In areas of high inequities in access to either healthcare or technology, the digital divide between rich and poor and between rural and urban creates the potential for solutions based on mobile phone-derived data to magnify disparities without addressing underlying conditions (14). Vigfusson et al. (1) wisely focused their proof of concept study on a population that they describe as largely homogenous, or at least significantly less heterogeneous than most populations, when measured across a number of critical factors. Throughout Iceland, phone ownership is high and phone network coverage is high in areas of human occupation. Residents of Iceland enjoy universal healthcare, resulting in relatively equitable access to influenza diagnostics, and sick leave. Disparities in access to these services and social goods give rise to behaviors that determine the surveillance and trajectory of outbreaks, as seen in the United States for influenza (15) as well as COVID-19 (16).

In most settings, health inequities prevent some people from being able to afford medical attention when ill, travel to healthcare centers (17), or missing work while symptomatic (18). They are less likely to be clinically diagnosed with an influenza infection, and they may not be able to change their movement patterns while infected. A critical element of the study by Vigfusson et al. (1) shows that phone call patterns change when people are ill, both in frequency and duration. These are behaviors that individuals without access to healthcare or sick leave have control over. Changes in movement may be biased by privilege, but changes in phone usage are less likely to be influenced by the same inequities.

While there will be persistent resource disparities, digital divides, and issues of usership bias, data representation, and privacy, this paper shows that if some of these disparities are reduced, symptomatic infections can elicit deviations in patterns of behavior that may reduce transmission. Symptomatic infections may also produce behavioral changes that may be detectable despite resource inequities.

Transferrable Technology

One strength of the study design lies in identifying a homogenous population. Conversely, this indicates that the methodology applied to that population may not be ideal in locations where it may be most necessary due to health inequities. However, the framework presented in the paper allows for exploration of applications within this approach. The behavioral features that deviate during illness and the ways in which they change will likely be different in various populations, but they may still be detectable. For example, in hard to reach or resource-limited settings, healthcare-seeking behavior during illness may actually lead to an increase in movement and number of contacts (17).

Vigfusson et al. demonstrate deviations in the movements of influenza-infected members of the population that will likely impact disease transmission.

The behavioral features of interest will also change over time. Device capabilities and primary uses have changed significantly since 2009, when the CDRs used in the study by Vigfusson et al. (1) were collected. The authors point out that today, changes in data usage may be more effective for detecting behavioral deviations during illness than voice calls, which are not as common as they once were. The behavioral features that can be explored with this approach will change with device capability and social norms.

While considering broader applications of this study, important issues arise regarding data security and anonymity (19). Pairing CDRs with health records should be considered cautiously, especially in markets where these links could lead to litigation or the denial of basic rights, such as healthcare and sick leave. It is easy to imagine health insurance companies in the United States denying coverage to patients based on behaviors they can glean from CDRs. The authors propose a few solutions for how this type of passive surveillance may be executed securely and anonymously in real time. Their solutions rely on a neutral third party that accepts data from the mobile-phone operators and government health officials. This approach may be more successful in some locations than others, depending on the balance between government oversight and the stringency of data privacy laws. Linking CDRs with health records may also highlight different behaviors that deviate during illness between populations based on variable access to universal healthcare, paid sick leave, and mobile devices.

In the study, Vigfusson et al. (1) point out, "Notably, the diagnosed group displays significant changes in mobility, even prior to seeking healthcare and receiving a diagnosis." In the absence of behavioral restrictions, formal guidance, or confirmed diagnoses, when given the agency to alter individual behavior in response to feeling ill, symptomatic illness can induce behavioral changes that reduce disease transmission.

With this approach, disease models may not have to rely on assumptions about the behaviors of infectious individuals that impact pathogen transmission. Human behaviors play a critical role in the transmission of infectious diseases, and knowing exactly how behaviors change can greatly improve model predictions and outbreak management.

Public health and epidemiology lean toward interdisciplinary approaches, urging natural scientists and social scientists to work together to push progress at the interface of disciplines. Identifying links between human behaviors and infectious diseases demonstrates clear societal benefits to successfully integrating natural and social sciences.

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