Fitbit-informed influenza forecasts

Over the past two decades, widespread adoption of mobile phone technology has facilitated the real-time acquisition of individual-level data on human behaviour. Mobile technologies have helped to improve geographical navigation, facilitated the exchange of goods and money, accelerated information transfer, and strengthened predictions for the spread of infectious diseases. The rise of portable health-monitoring devices has also allowed individuals to track their vital signs and sleep patterns, generating a trove of information to monitor population health.

In The Lancet Digital Health, Jennifer Radin and colleagues analyse data obtained from 47,249 Fitbit wearable device users to forecast influenza-like illness (ILI) activity. Previous work has shown that an individual’s resting heart rate tends to spike during infectious episodes, which can be accurately captured by Fitbit devices. An increase in the proportion of Fitbit users experiencing elevated resting heart rate might signal the occurrence of an infectious disease outbreak. The innovative study by Radin and colleagues is the first to use wearable device data to study influenza outbreaks.

The authors report positive correlations between historical patterns in Fitbit-derived resting heart rate data and weekly surveillance time series for ILI in five US states in 2016–18. Peaks in aggregated resting heart rate were well defined and generally coincided with ILI outbreaks, lending support to the use of these data in capturing short-term changes in population health. The authors also developed short-term prediction models for ILI activity using resting heart rate indicators and autoregressive terms as covariates. In their final model, they report high correlation between observed and predicted incidence in all five states (range 0·84–0·97).

The study by Radin and colleagues is a promising first step towards integrating wearable device measurements in predictive models of infectious diseases. Inspired by published literature on the subject,6–9 we can make a few recommendations for methodological improvements. The authors built a baseline null predictive model that only uses historical ILI activity as input—a so-called autoregressive approach. They showed that the prediction accuracy of the baseline model is improved by the addition of Fitbit resting heart rate data. However, the baseline model is limited by its use of ILI activity from 3 weeks earlier as input. Influenza dynamics are complex and involve longer-lived processes such as the influence of seasonal factors and immunity from past seasons.10 The addition of autoregressive terms beyond 3 weeks, and up to 52 weeks, would improve model performance and provide a more realistic assessment of the contribution of Fitbit resting heart rate data to influenza forecasts.

As an illustration, we found that the prediction errors of the model presented by Radin and colleagues, one that combines Fitbit data with historical ILI activity, are larger than those obtained using historical influenza information from the past 52 weeks as inputs (appendix). Model performance can be further improved by considering external covariates, including influenza-related Google searches, Tweets, and electronic health records (appendix). It is worth noting that Radin and colleagues’ approach performs relatively well in California compared with existing models. Geographical differences in prediction accuracy between states, possibly due to differences in Fitbit coverage or influenza dynamics, could explain this finding.

Moving forwards, further evaluation of the use of Fitbit data by considering alternative forecasting approaches would be beneficial. We anticipate that Fitbit data could be used as one of several external covariates in predictive models for influenza, along with other health, digital, and social media indicators. Further validation would also benefit from analysis of Fitbit data over periods longer than 2 years. Large interannual variability exists in the intensity and timing of influenza epidemics, due to the complex evolutionary dynamics of the influenza virus, which cannot be fully captured over a short study period. However, analysis of additional years of data would require a long-term research agreement with the company that markets Fitbit devices.

Analysis of repeated individual biological measurements, such as those provided by Fitbit devices, is an enticing way to monitor population health, because measurements are passive, high volume, and non-invasive. The study by Radin and colleagues is an encouraging proof of concept in this direction. We welcome more health-related research involving Fitbit users, including studies that directly connect influenza sickness status with changes in resting heart rate.
Such work could help to identify specific thresholds (and durations) of spikes in resting heart rate that are predictive of influenza and other infections.

A possible limitation of using Fitbit data for epidemiological purposes is the particular age profile of wearable device users, which makes monitoring of children’s health difficult. Although Fitbit studies might work well for seasonal influenza viruses that affect adults, they might be less relevant for pandemic situations, in which infections are more concentrated among children. A similar caveat applies to other digital data streams that are primarily informed by adult behaviour.3

In conclusion, we anticipate that the large amount of real-time data generated by Fitbit and other personal devices will continue to prove useful for public health and augment traditional surveillance systems. The ever-expanding big data revolution offers unique opportunities to mine new data streams, identify epidemiologically relevant patterns, and enrich infectious disease forecasts.

We declare no competing interests. This article does not necessarily represent the views of the NIH or the US government.

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