The hopes and hazards of using personal health technologies in the diagnosis and prognosis of infections

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Work from numerous groups has shown the potential of using data from wearable devices to characterise each individual’s unique baseline, identify deviations from that baseline suggestive of a viral infection, and to aggregate that data to better inform population surveillance trends. With a growing global population of connected wearable users, this could potentially help improve the earlier diagnosis and management of infectious individuals and improve timeliness and precision of tracking infectious disease outbreaks. However, despite these possibilities, there are important considerations when interpreting wearable data, including generalisability of user populations, sensor accuracy and comparability, and overfitting of models. Additionally, before deploying such tools as a global health solution, the proactive integration of community engagement through a user-centred design is, at a minimum, required to begin mitigating the risk of digital health illiteracy, structural inequality, and social marginality. Regional frameworks establishing transparent standards for participant data protection as data privacy, data use, and data rights are required to truly protect participant’s rights, empower participants, and minimise risk of harm. As these sensors continue to evolve, standardised data and reporting, as well as collaboration and data sharing across study and technology groups will also be necessary.

Personal health technologies—technologies (consumer or medical grade) used by an individual that generate data from that individual—offer an unprecedented opportunity to completely alter how we currently detect and manage infectious diseases at an individual as well as population level. Currently, management decisions in the setting of possible infection are made based on symptoms and objective physiological measurements, whether the person primarily making those decisions is the patient or a health-care provider. Because symptoms are often non-specific, the recognition of abnormalities in physiological parameters have an important role in diagnosing and guiding therapeutic interventions. However, abnormality has historically been defined by what is normal for a healthy population, rather than what is normal for an individual. For example, an elevated temperature, which has been recognised as a hallmark of infection since the beginning of recorded history, is commonly (but not consistently) classified as a temperature of 38°C or higher. Similarly, a respiratory rate of more than 20 breaths per min or a heart rate of more than 100 beats per min in an adult would also be considered abnormal and might indicate a person who requires expedited, or a higher level of care. However, what is actually a person’s “normal” varies substantially between individuals. For oral temperature, that range falls between 35.7°C and 37.4°C,1 respiratory rate between 12 and 20 breaths per min,1 and resting pulse rate between 40 and 109 beats per min. Therefore, these broad population ranges are imprecise when applied to a specific individual, especially for identifying an early change in their physiological status. Individuals experience daily, weekly, and seasonal fluctuations unique to them in a range of physiological parameters and activities.4 Only by knowing what is normal for an individual when they are well is it possible to identify the earliest possible deviations from that normal. This is what personal health technologies make possible, in the real world outside of a health-care setting, and in a nearly passive manner.

Because of the emergence of COVID-19, numerous studies examining personal sensor data have found digital signals supporting the potential benefit of using these technologies to identify and track viral illness. Continuously evolving personal health technologies can be harnessed to collect unique baseline data on individuals and populations, which allows for earlier and more precise detection of viral illness; but for these tools to be successful, biases related to health inequity, loss to follow-up, an absence of data harmonisation, and others need to be addressed.

Usability of personal health technologies

It is relatively recent that personal health technologies have become available that enable investigators to even consider addressing the potential value of identifying individual changes in physiological parameters in large populations. Wearable sensors available to individuals can now track not only activity, but also body position, heart rate and rhythm, skin temperature, oxygen saturation, an electrocardiogram, and electrodermal activity and sound (figure 1). From these metrics respiratory rate, heart rate variability, heart arrhythmias, sleep, and sleep stages are derived. Other medical-grade wearables, not yet designed for a large consumer market, can also continuously track blood pressure as well as derive systemic vascular resistance and cardiac output.4

Wearable sensor technologies are available in a wide range of form factors beyond the most commonly used wrist-worn sensors. There are options for rings, arm bands, earbuds, adhesive patches, and clothing that all are capable of tracking multiple physiological parameters. Each offers certain advantages and disadvantages, but the most effective will be the one that provides the most reliable information that the intended user will be willing
and able to use as frequently and for as long as needed. There are little data available on long-term use of any of these wearables, with one survey in Canada finding that of people who purchased their own activity tracker, just 55% were still using it, but those that were still wearing it wore it an average of 23 days in the previous month. In another study that gave participants a wrist wearable, approximately 25% wore the sensor for the majority of the 4-month requested monitoring period. A study of nearly 4.5 million insurance plan members who were offered financial incentives for achieving activity goals found that only 1–2% activated a device, but of those that did, 80% were still using the device at 6 months. A meta-analysis found that median participant retention across eight studies was only 5.5 days, and that most studies did not include a population representative of the ethnicities and diversity of the USA.

For many, a non-wearable, passive multiparametric sensor can provide the best option for longitudinal data. For example, under-mattress pads that can monitor heart rate, respiratory rate, and various sleep parameters have been found in preliminary work to identify early physiological decompensation. A wide range of contactless sensors for in-home use that use computer-vision, infrared thermography, radar, and audio can track individual vital signs, as well as cough frequency and quality, in some cases, even when in different rooms.

As remarkable as progress has been over the last several years in the availability of consumer technologies that monitor and report physiological variables, it is important to recognise that the accuracy of the information provided is variable and should not be considered clinically dependable unless appropriate validation evidence exists, and ideally regulatory agency approval. For example, there have been recent concerns raised of the accuracy of oxygen saturation determined not only from the wrist with consumer sensors, but also from hospital-based finger-tip devices due to skin pigmentation differences. To aggregate findings from multiple sensors it will also be important to understand how sensor-specific and usually proprietary algorithms for calculating metrics such as daily resting heart rate and respiration rate can differ across devices.

**Studies of personal health technologies in infectious diseases**

There is typically a delay from the time someone gets sick to when they develop symptoms, seek care, get tested, and finally receive a test result for COVID-19 and other viral infections. It then takes an additional 1–3 weeks before test results are collected and aggregated into a central surveillance system, which often relies on outdated reporting methods such as fax machines. When wearable data is aggregated for a population, it is possible to so-called nowcast or track viral activity in real time. Previous studies have shown that identifying resting heart rate and sleep data outside of an individual’s normal levels, can be used to improve real-time predictions for influenza-like illness at the state level. Similarly, models to predict COVID-19 anomalies in China and south-central Europe using wearable data from 1.3 million users who wore Huami smartwatches (Hefei, China) also showed promise (table 1). The Robert Koch institute, Berlin, Germany, has launched a similar fever trend tracker based on resting heart rate and activity data from more than 500,000 participants. Kinsa smart thermometers (San Francisco, CA, USA) have also shown utility in predicting influenza-like illness activity and potentially COVID-19. Novel data streams from sensors can offer key insight into trends, timing of outbreaks, and identifying specific geographical hotspots of infection. They might prove especially useful when integrated with both traditional clinical and laboratory surveillance and other novel surveillance data, including those from wastewater, internet search terms, social media, and mobility data (figure 2).

Individual-level diagnosis using continuously collected data from wearables has many benefits, including improved COVID-19 screening, especially when routine diagnostic tests are not readily available at scale. During infections, continuously collected heart rate data has shown that an individual’s heart rate tends to increase about 8–10 beats per min for every 1°C rise in fever, and data from animal models suggested that changes in diurnal heart rate can be detected 4 days before fever. Wearables have also shown early promise to improve models to differentiate symptomatic individuals who have COVID-19 versus those who have other infections. App-based collection of self-reported symptom data has identified key symptoms predictive of COVID-19.
compared with other infections, with loss of smell and taste as the main predictor.\textsuperscript{24} The addition of wearable data into these models has shown potential to further improve the discriminative ability of these models, with an area under the curve increasing from 0·71 (95% CI 0·63–0·79; considering symptoms only) to 0·80 (0·73–0·86; using also wearable data; table 1).\textsuperscript{21}

Individual sensor data also has shown promise to identify positive individuals.\textsuperscript{26} For COVID-19 positive individuals than for influenza symptoms and physiological changes are more severe to 0·80 (0·73–0·86; using also wearable data; table 1).\textsuperscript{21}

Physiological data could predict illness on a specific day with an AUC of 0·77

As new metrics are added to sensors, substantially greater research is needed to better understand wearable changes for different infections, asymptomatic infections, non-infectious insults, and tracking long-term consequences, such as with post-acute sequelae of SARS-CoV-2 infection. Identifying early signs of decompensation can be especially useful for early initiation of antivirals, monoclonal antibodies, supportive care, and closer individual monitoring. Additionally, as vaccines are rolled out, sensor-based monitoring might prove useful for identifying immune response to vaccination, and potential side-effects and improve our ability to track infections and quantify vaccine effectiveness.

**Prediction models**

The true value of the growing availability of personal, multiparametric, continuous sensor technologies is dependent on the development of meaningful detection or prediction models, which should follow existing standards before being implemented in the clinic\textsuperscript{26} to ensure their reproducibility.\textsuperscript{26,68} Experience with early

| Parameters analysed | Wearable sensors included | Study population | Key finding |
|---------------------|---------------------------|------------------|-------------|
| Total participants, N | COVID-19 positive participants, n |                  |             |

**Table 1: Observational studies of wearables in the prediction of viral illnesses**

AUC=area under the curve. Some data not available because specific numbers of COVID-19 positive individuals were not reported. Studies needed to have a peer-reviewed, preprint article or post supporting data on their website. *As of Jan 2, 2020.

- Table 1: Observational studies of wearables in the prediction of viral illnesses

- Population-level studies

- Scripps' Fitbit study\textsuperscript{24} Resting heart rate and sleep Fitbit 47249 \textsuperscript{} Inclusion of Fitbit data significantly improved Centers for Disease Control and Prevention models of current influenza-like illness

- Kinsa\textsuperscript{30} Temperature Kinsa smart thermometers 1321 counties \textsuperscript{} Fever anomalies are significantly correlated (r=0.54–0.55) with COVID-19 case counts at the county and state level, respectively, and with national influenza-like illness activity (r=0.95) in the USA

- Corona Data Donation App\textsuperscript{29} Resting heart rate, physical activity Wearable fitness sensors 535298\textsuperscript{*} Sensor data might predict fever anomalies in Germany

- Huami users\textsuperscript{30} Resting heart rate, sleep Huami wearables 1.3 million \textsuperscript{} Physiological anomaly rate correlates with COVID-19 case counts in Chinese cities (average p=0.68)
diagnostic and prognostic models in COVID-19 suspected or confirmed individuals has highlighted several challenges and limitations. Most importantly, they are at high risk of bias, due to (1) bias on the participant domain, when the participants enrolled might not be representative of the general population; (2) bias in the predictor domain, when the predictors are not available at the intended time and can be influenced by the measurement outcome; (3) bias in the outcome measurement, when it is measured subjectively; and (4) bias in the analysis domain (overfitting) due to small sample size and complex modelling strategies, which can be avoided only with a strict separation between training, validation, and test sets (table 2). There are often issues in reporting important parameters such as the length of the follow-up or the concurrent prevalence of COVID-19 and other viral infections such as influenza in the considered population, although different models report performance with different statistical measures, making it more difficult to compare them for the same prediction task. Among the studies overviewed in the work of Wynants and colleagues, all reported moderate to excellent prediction performance, but because of the high risk of bias due to both poor reporting and methodological issues, the results could be overly optimistic and not represent reality. This bias is a serious issue which was underscored in analyses after the publication of a mortality prediction model for COVID-19 patients that was based on several blood sample biomarkers and found a very high predictive accuracy of 90%. Subsequent studies and perspectives highlighted a number of limitations, including the limited clinical use and applicability of this model, the difficulty in reproducing the results in a different dataset, the potential bias due to different sources of the predictor biomarkers, and the interpretability of the model.

Although wearable sensors might offer a convenient means of individual data collection and model development that can potentially enable the detection for COVID-19 and other viral infections, there are best practices that must be followed in the analysis of these data and multiple limitations to this approach. Obtaining sufficiently large data to provide the needed specificity for the identification of a given disease could be challenging and is dependent on individuals obtaining and then self-reporting if they test positive. Furthermore, individuals owning a smartwatch and participating in these studies are probably not representative of the broader population; therefore, the results might not be generalisable to the whole population. In the future, these models will need to address these limitations, taking into account other more technical issues related to the prediction of rare events, the model complexity that could drive to overfitting, and the fact that data from wearables are particularly affected by artifacts.

Health inequities
The rapid proliferation of digital health innovations to address the COVID-19 pandemic could be especially valuable as a means to improve health delivery for vulnerable or typically hard to reach populations. However, many of the social, environmental, economic, and cultural
determinants of health that already contribute to these populations being underserved in existing systems of care (eg, race and ethnicities bias, economic and educational disadvantages, health illiteracy, inadequate healthcare access and quality, and complexity of individual behaviour) are compounded when digital technologies are expected to be incorporated organically. In fact, additional disparities in digital technology access, digital engagement, and digital health literacy can layer on additional inequality. Even worse, the race of the person using the technology can influence its accuracy. The historical scarcity of culturally contexted interventions has contributed to poor uptake and scalability of digital health technologies, which risks increasing disparities. Designing solutions with (rather than for) the intended end users, alongside providing the infrastructure needed to assure universal access, and the digital health education frameworks necessary are what is needed for digital technologies to serve as vital public health tools that help minimise disparities rather than contribute to them.

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Meaningful community engagement such as with religious leaders, local authorities, and other community leaders at early stages of study inception is fundamental to understand the communities' needs to address the inequity and action gaps experienced at a community level. Empowering communities through participation and advocacy of digital health implementation and research establishes community trust, addresses and resolves hesitancies, helps effectively communicate the importance of research findings, ensures successful digital health implementation, and ultimately increases representation of historically marginalised communities. Additionally, providing educational opportunities for community members on the use of the digital tools in general, and for specific health conditions, through easy-access, free, and culturally tailored educational tools for all digital and health literacy population levels.

The large and growing proportion of the world’s population with a cell phone and internet access, can layer on additional inequality. Even worse, the race of the person using the technology can influence its accuracy. The impact this can have on health outcomes was highlighted in a study involving nearly 10,000 hospitalised patients in which Black patients had nearly three times the frequency in a study involving nearly 10,000 hospitalised patients in which Black patients had nearly three times the frequency of occult hypoxaemia not detected by pulse oximetry.

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to participants is crucial to ensure consumer trust and adoption.57

The COVID pandemic has highlighted unacceptable major gaps in care that exist due to long-standing disparities. However, some responses to addressing COVID-19 have provided examples of how digital health tools can help to minimise disparities. For example, WHO partnered with instant messaging platforms WhatsApp (with over 2 billion active users in 180 countries) and Viber (1·2 billion users in 190 countries) to create a dedicated coronavirus informational service, with plans to be available in over 20 languages.58 Further, existing digital platforms that had been specifically designed for underserved communities were able to be rapidly modified to address COVID-19 care needs. For example, an app created in 2018 for the Syrian refugee population in Turkey was adapted for COVID-19 to assess symptoms, disseminate health information, and support prevention efforts.59 Before the pandemic, digital health tools have provided the opportunity to extend access to health research and adoption.57

The value of remote monitoring of individuals to help maintain health is in its earliest stages of exploration. The COVID-19 pandemic has rapidly accelerated the work needed to move that field of research forward. The desire to address an unprecedented health need motivated investigators, funders, and many individuals worldwide to support a large number of studies made possible through the use of personal health technologies. The findings from these studies will inform future work with ever-improving sensor technologies, enhanced user experiences, and more sophisticated analytics to provide unique solutions to support individual and public health needs. However, the pandemic has also exposed long enduring gaps in inequities in existing systems of care that can only be addressed through their thoughtful, collaborative, and user-centric implementation.

There remains much to learn. Ongoing studies will provide valuable lessons that will guide future use of personal health technologies to improve the diagnosis and treatment of infectious diseases in a more individualised, safer, and equitable manner. Such efforts could provide the opportunity to establish coherent policies and frameworks that keep up with the advancement of technologies and will require multi-stakeholders from government, science, technology, innovation, and civil society to develop sustainable solutions.

**Contributors**
All authors were equally involved in original drafting, writing, reviewing, and editing of the manuscript. JMR and SRS contributed to the conceptualisation of the manuscript.

**Declaration of interests**
SRS is a part-time employee of physIQ, Chicago, Illinois, USA. All other authors declare no competing interests.

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