Received: 8 November 2020 | Revised: 13 December 2020 | Accepted: 4 January 2021
DOI: 10.1002/ima.22552

RESEARCH ARTICLE

WILEY

Future IoT tools for COVID-19 contact tracing and prediction: A review of the state-of-the-science

Vicnesh Jahmunah[1] | **Vidya K. Sudarshan**[2] | **Shu Lih Oh**[1] | **Raj Gururajan**[3] | **Rashmi Gururajan**[4] | **Xujuan Zhou**[3] | **Xiaohui Tao**[5] | **Oliver Faust**[6] | **Edward J. Ciaccio**[7] | **Kwan Hoong Ng**[8,9] | **U. Rajendra Acharya**[1,2,3,10,11]

[1]School of Engineering, Ngee Ann Polytechnic, Singapore, Singapore
[2]Biomedical Engineering, School of Social Science and Technology, Singapore University of Social Sciences, Singapore, Singapore
[3]School of Management and Enterprise, University of Southern Queensland, Toowoomba, Queensland, Australia
[4]Royal Brisbane and Women's Hospital, Herston, Queensland, Australia
[5]Faculty of Health, Engineering and Sciences, University of Queensland, Brisbane, Australia
[6]Department of Engineering and Mathematics, Sheffield Hallam University, Sheffield, United Kingdom
[7]Department of Medicine – Cardiology, Columbia University, New York, New York
[8]Department of Biomedical Imaging, University of Malaya, Kuala Lumpur, Malaysia
[9]Department of Medical Imaging and Radiological Sciences, College of Health Sciences, Kaohsiung Medical University, Kaohsiung, Taiwan
[10]International Research Organization for Advanced Science and Technology (IROAST), Kumamoto University, Kumamoto, Japan
[11]Department Bioinformatics and Medical Engineering, Asia University, Wufeng, Taiwan

Correspondence
U. Rajendra Acharya, School of Engineering, Ngee Ann Polytechnic, Singapore 599489.
Email: aru@np.edu.sg

Abstract

In 2020 the world is facing unprecedented challenges due to COVID-19. To address these challenges, many digital tools are being explored and developed to contain the spread of the disease. With the lack of availability of vaccines, there is an urgent need to avert resurgence of infections by putting some measures, such as contact tracing, in place. While digital tools, such as phone applications are advantageous, they also pose challenges and have limitations (eg, wireless coverage could be an issue in some cases). On the other hand, wearable devices, when coupled with the Internet of Things (IoT), are expected to influence lifestyle and healthcare directly, and they may be useful for health monitoring during the global pandemic and beyond. In this work, we conduct a literature review of contact tracing methods and applications. Based on the literature review, we found limitations in gathering health data, such as insufficient network coverage. To address these shortcomings, we propose a novel intelligent tool that will be useful for contact tracing and prediction of COVID-19 clusters. The solution comprises a phone application combined with a wearable device, infused with unique intelligent IoT features (complex data analysis and intelligent data visualization) embedded within the system to aid in COVID-19 analysis. Contact tracing applications must establish data collection and data interpretation. Intelligent data interpretation can assist epidemiological scientists in anticipating clusters, and can enable them to take necessary action in improving public health management. Our proposed tool could also be used to curb disease incidence in future global health crises.

KEYWORDS

contact tracing, coronavirus disease, COVID-19, deep learning, digital tools, intelligent internet of things, wearable devices

1 | INTRODUCTION

The World Health Organization (WHO) continues to report elevated numbers of COVID-19 confirmed cases and deaths in countries across the globe: Africa, the Americas, Eastern Mediterranean, Europe, South-East Asia and the Western Pacific. Figure 1 provides statistics on the number of COVID-19 cases and the number of COVID-19 related deaths globally, from the World Health Organization, as on June 18, 2020.[2] It is apparent that there are about 8 242 258 and 445 522 infected cases and deaths, respectively, from COVID 19, with the Americas being the most affected, accounting for ~50% of the cases and deaths. The WHO has also corroborated that while progress is seen in many countries, the pandemic continues to escalate globally.[3] With current vaccines being exploratory or in preclinical stages,[4] pharmaceutical treatments for COVID-19 are not yet available,[5] and therefore a successful intervention to prevent the pandemic spread is a challenging task.[6] COVID-19 has been reported to spread mainly through droplet transmission, which can disperse to anyone within a distance of 1 m.[1] Hence, to curb the virus spread and to inhibit resurgence of infections, social and technological measures have been implemented worldwide. One of these technological measures that has been utilized in many countries is contact tracing based on internet of things (IoT) Technology.

IoT has been employed in the medical, industrial, transportation, and environmental domains,[7] displaying several advantages over systems which lack internet connection. In the tracking of COVID-19 cases, it is particularly useful as a monitoring system, enabling early disease detection, which leads to less invasive treatment, efficient control of spread, improved accuracy in diagnosis, limited financial expenditure and burden, and reduced likelihood of error.[8] These advantages have to be balanced with the inherent challenges and complications of the technology. IoT systems face security and privacy threats[7] from cyber-attacks, stemming from inadequate authorization and verification, weak web interface protection, or lack of encryption.[9] Interoperability is another challenge wherein the exchange of information among different IoT systems might be problematic due to the contrasting nature of these systems.[7] Another challenge comes from a possible interruption to some services and/or the availability of resources as a result of varying transmission speed of data communication channels.[10] Quality of service parameters, such as reliability, readiness, security, service time, and energy consumption may be compromised in an IoT device, posing another challenge.[11]

The main challenge for contact tracing is to capture the dynamic nature of the pandemic. Perfect measurements are impossible, because the available data fails to cover both geographical and temporal extent of the sample space. However, an abstract interpretation of contact tracing data is possible. This abstract interpretation must be based on knowledge which is acquired through expert guidance. Despite the impossibility of representing the sample space in its entirety, it is generally agreed that a higher data volume increases the available information and thereby improves the decision support quality of

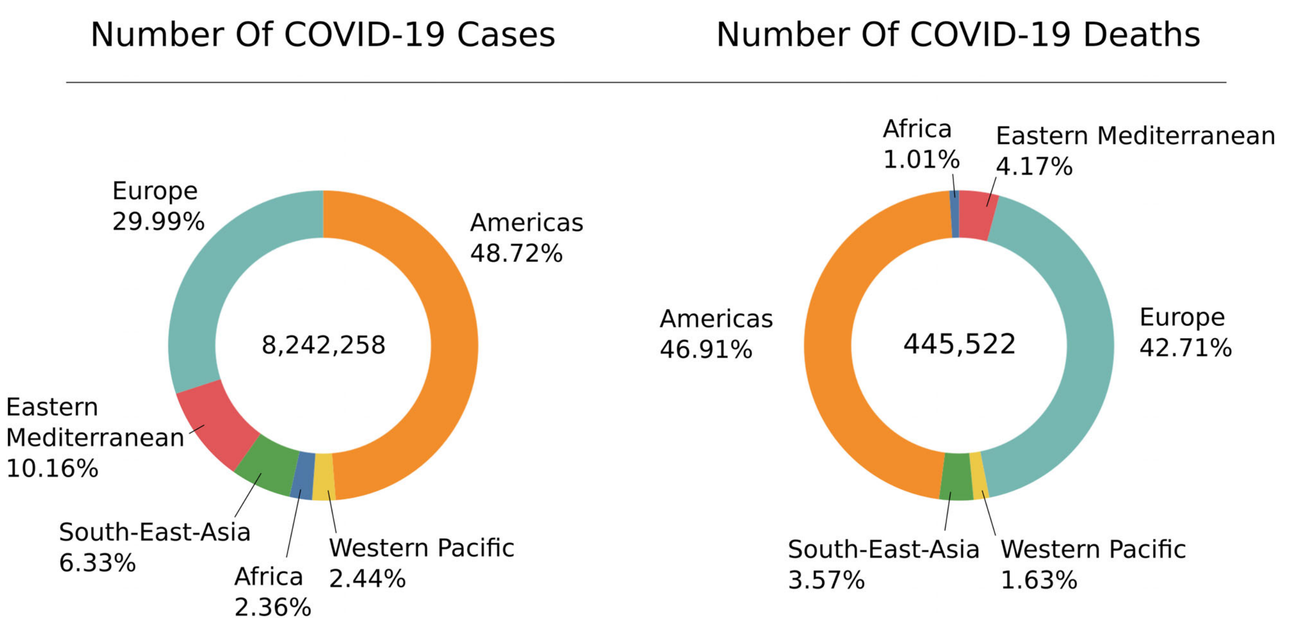

FIGURE 1 A, Number of COVID-19 cases and, B, number of COVID-19 deaths globally[1] [Color figure can be viewed at wileyonlinelibrary.com]

contact tracing applications. Indeed, both data volume and data rate exceed, by far, the neurological capabilities of a single human being. Therefore, expert guidance can only happen on a methodological level where groups of experts work cooperatively on methods for data interpretation. Once the data interpretation methods have been established, the next task is to construct learning systems that capture the algorithms which underpin these methods and the knowledge involved in the method development. In this paper, we describe our first tentative steps toward the construction of an AI system which can improve the interpretation of contact tracing data.

To support our thesis, we have structured the remainder of the manuscript as follows. The next section provides some background on COVID-19 and on "social distancing" (also known as physical distancing), as well as technological measures that have been implemented to reduce the spread of the disease. Section 3 details a literature review of contact tracing which helps us to identify research gaps and potential future directions for contact tracing. In the subsequent sections, we evaluate and refine these thoughts by focusing on the role of artificial intelligence in contact tracing. Concluding remarks are provided in Section 8.

1.1 | Background of coronavirus disease

In 2020, the world has experienced novel coronavirus, otherwise known as COVID-19. The protein spikes on the outside of the virus molecule resemble a crown, known as *corona* in Latin. The first symptoms of the disease came to light in Wuhan, Hubei province of China, on December 1, 2019.[12] Assimilating this information, the term COVID-19 was coined by the WHO in February 2020 to describe the disease.[12] The virus itself was termed severe acute respiratory syndrome coronavirus 2 (SARS-COV-2) by the International Committee on Taxonomy of Viruses, due to its phylogenetic properties.[13] Bats are suspected to harbor alpha and beta coronaviruses.[14] Animal coronavirus is believed to have become endowed with the ability to transmit to humans,[12] possibly via pangolins, which may be the intermediate host between bats and humans.[12] Some clinical representations of COVID-19 include dry cough, sore throat, fever, and/or experiencing breathlessness.[15] Since the reporting of the first case, the virus spread across China within 30 days.[16] As the virus evolved over the following 4 months, it rapidly spread to many countries across the globe, posing a global health threat, and forcing the WHO to declare COVID-19 a pandemic on March 11, 2020.[12] As COVID-19 is quite contagious, it can spread rapidly, and continues to advance within the human population.[12] Since the outbreak, a range of social and technological measures has been implemented with the aim to slow the spared of COVID-19. The next sections introduce some of these measures with a clear focus on contact tracing.

1.1.1 | Social distancing

Social distancing is defined as the maintenance of a safe distance of at least 1 m from others in open spaces, at any point in time, to minimize viral spread. The WHO advocates a minimum of 1 m apart,[17] but these guidelines vary around the world. In Singapore, France, and China, this is pegged at a distance of 1.5 m in Italy and Germany, 1.8 m in the US and 2 m in Canada.

1.1.2 | Quarantine

A contact is defined as any person who had a face-to-face or direct physical encounter with a suspected or confirmed COVID-19 case, within a distance of 1 m for more than 15 minutes, or who has cared for a COVID-19 patient without donning proper personal protective equipment (PPE).[1] Quarantine is defined as a separation of contacts in their homes or other isolated areas for a time period, often 14 days, to diminish the risk of potential transmission of the virus.[1]

1.1.3 | Contact tracing

Contact tracing can help to identify close contacts of positive cases, and can thereby allow the early potential detection of further cases. By doing so, contact tracing can reduce quarantine cases and control an epidemic within a country.[3,6] Technology is used to identify individuals who have had close contact with those infected, so that they may be quarantined to avert further infections. This process is comprised of four stages: (a) contact identification, wherein close contacts of an individual since the onset of illness are identified, (b) contact listing wherein these identified individuals are listed as contacts and are provided with information about prevention of the disease as well as isolating high risk contacts at home or in hospitals, (c) contact follow-up whereby regular follow-ups are conducted with all contacts to monitor symptoms and test for possible infection, and (d) contact discharge which involves omitting contacts from the follow-up list when the follow-up period is over or when the contact is reclassified as a case, noncontact, or noncase subsequently.[1] Hence, an efficient and expedient contact tracing tool is imperative to identify individuals

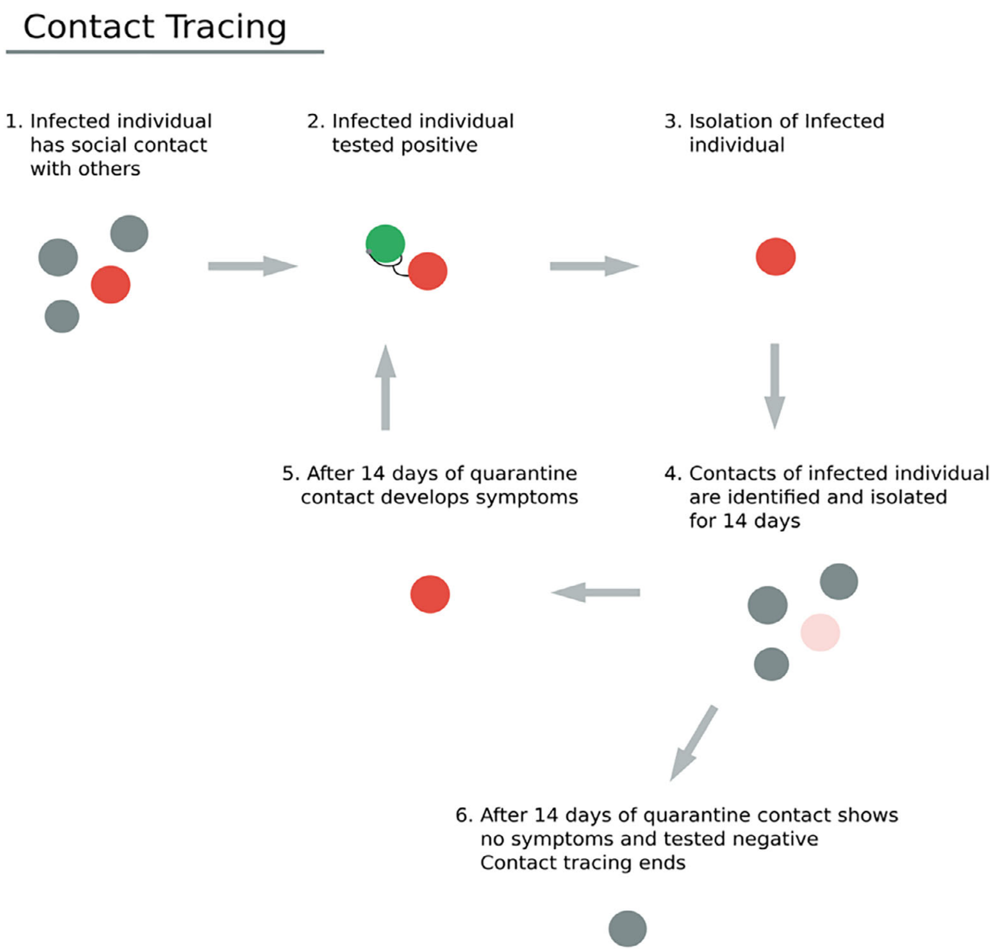

FIGURE 2 Summary of the contact tracing process [Color figure can be viewed at wileyonlinelibrary.com]

who have had close contact with those infected and to quarantine them to avert further infections. The process is summarized in Figure 2. The individuals, depicted as circles in the figure, move around freely, which implies that all contact tracing applications must be based on wireless technology. By far the most pervasive wireless technology in use today are mobile phones. Contact tracing depends on their widespread use, processing power, and wireless connectivity. These properties allow the implementation of IoT methods which can gather contact data. The next section provides an expert review of wireless IoT technology for contact tracing.

2 | BACKGROUND OF THE INTERNET

Back in 1999, the distinction was quite clear: there was an internet for humans and there were the beginnings of the IoT.[18] The idea was to distribute measurement and control data over the internet which flows to and from central servers. The server concept is not new, and indeed at the dawn of the computer age the processing technology was concentrated on mainframe servers. At this time, the reason for having the server concept came from resource constraints, that is, processing resources were expensive and it made sense to concentrate them at a few locations. Today, processing is not a challenging issue anymore; even a smartphone has more processing power than the old mainframe servers. Current justifications for the server concept revolve around data accessibility and, even more importantly, centralized control decisions. Big data holds the promise of providing an overview about a situation, such as the pandemic. It is very hard, if not impossible, to achieve that overview with local processing solutions. The central decision points which are needed get fed a large volume of data from a sensor network that is as extensive as possible. IoT technology can help to establish dynamic sensor networks almost without limitations in terms of sensor number and data volume. The next section provides an in depth review of IoT technology. Based on that review, we put forward challenges and shortcomings of that technology. Some of these shortcomings translate into challenges for COVID-19 contact tracing. Having established these challenges, we are in a position to propose an intelligent internet of things which could be the solution to such challenges.

2.1 | IoT

IoT refers to the physical devices that are connected to the Internet in order to support easy sharing and collection of data required for appropriate decision-making, without need for significant human intervention.[19] An IoT system is comprised of five layers, consisting of embedded systems like processors, sensors, and communication tools within web-based smart devices that aid in the collection and sharing of acquired data.[20] These layers include the perception, network, middleware, application, and business layers. The bottommost perception layer consists of physical devices, such as sensors or barcodes that collate information to be delivered to the network layer. The network layer enables information transmission from the perception layer to the information processing system using wired or wireless connections, such as mobile communication standards (4G, 5G), Bluetooth, or Wi-Fi. The subsequent middleware layer processes the gathered information and makes appropriate decisions based on the results obtained from omnipresent computing devices. The application layer utilizes the processed information to provide application- specific services to users. In the topmost business layer, the information and statistics acquired from the application layer are utilized for the planning of future goals and strategies.[7]

Figure 3 details the architecture of a typical IoT system. IoT applications range from simple smart watches or smartphones, to complex driverless cars. IoT devices share the collated data from sensors by linking them to an IoT gateway or other edge devices, wherein data are sent to the cloud for analysis (in rare cases it is locally analyzed). These devices actively correspond with other related systems and act on the information they receive from one another.[8] For COVID-19 quarantine and contact tracing purposes, IoT is advantageous due to its ability to track biometric measurements, such as the heart rate, blood pressure, and glucose levels of high-risk patients and trace infected patients, to enable timely information sharing and accurate detection of suspected/infected cases.[8] Furthermore recent studies have affirmed that tapping on IoT machinery is an effective and safe way of handling COVID-19.[8,21] Hence, tapping on IoT technology allows the collection of real-time data and crucial information concerning infections and infected cases.[22] The efficiency of contact tracing may be enhanced through app-based digital tracing,[23] a method that has been adopted by many countries recently.

2.2 | Challenges of IoT applications

An IoT system should include the following characteristics in order for it to be considered for use in contact tracing. It should have security components embedded at each layer of the architecture to inhibit security threats or attacks.[24] These security components might include protocols, such as Secure Socket Layer and Datagram Transport Layer Security. They should be implemented between transport and application layers for security solutions.[25] This helps to ensure privacy by supporting authentication within a secured network to ascertain communication with reliable parties,[26] and meeting "quality of service" metrics such as

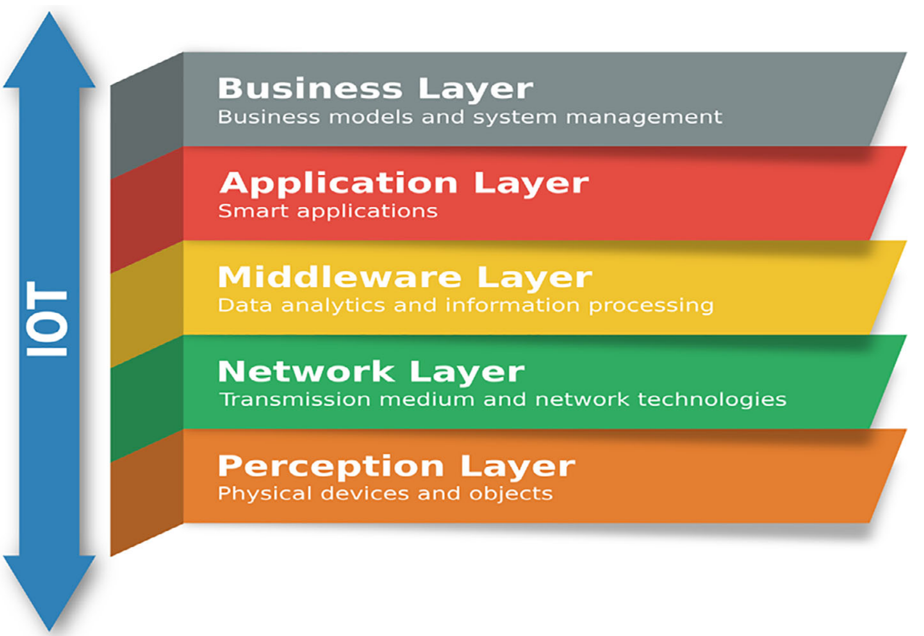

FIGURE 3 Architecture of an IoT system[7] [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Smartphone applications used by different countries for COVID-19

Countries	Tools (app/devices)	Features	Advantages	Limitations
Purpose: contact tracing				
Australia[27,28]	• COVID SAFE app for contact tracing.	BTS	-Privacy is not infringed. -Bluetooth signals work best in open spaces.	-Voluntary, so only a small fraction of population downloaded the app. -Data collected cannot be used yet as information sharing details have yet to be finalized and app appears to be interfering with continuous blood sugar monitoring.
Austria[28]	• Stopp Corona	BTS	-Close contacts are informed anonymously when a case is tested positive and instructed to self-isolate.	-Inaccuracy of app -Usage of app is voluntary/
Brazil[29]	• Coronavirus-SUS app	Geolocation tracking, location maps	-Location maps are much more accurate than GPS. -Privacy of individuals is protected as information is only collected in groups.	-Risk of privacy infringement
China[28]	• Ali pay and WeChat app	GPS tracker	-Usage of app is mandatory so data collected may be more reliable.	-Location is tracked so privacy is infringed. -Having to proof an individual is at low risk by scanning the QR health code before setting out to do any tasks.
Columbia[28]	• CoronApp	GPS tracker	-The app can be used without registering.	-Location of users is tracked so privacy is infringed. -Usage of app is voluntary.
Hawaii, USA[27]	• Questionnaires sent everyday through text and e-mail for at risk of infection	Online survey	-Health information sent to the department of health is encrypted, so privacy is protected. -Up to five times more contacts can be monitored.	-Individuals need to spend about 5 minutes to be surveyed daily.
Indonesia[30]	• PeduliLindun/Care Protect app	BTS	-Users' data will only be accessed if they are "at risk."	-Obtains permission for seven features from users (location, photos, camera etc.) intruding privacy. -Concerns of continuous surveillance by government.
India[28]	• Arogya Setu app	BTS, GPS tracker	-Usage of app is mandatory so information collated may be more reliable.	-Data security concerns. -Location tracking causes privacy concerns.

TABLE 1 (Continued)

Countries	Tools (app/devices)	Features	Advantages	Limitations
Israel[28]	• Track Virus app	BTS	-User is not identified with this app. -App allows user to check independently if they had crossed paths with any confirmed cases.	-Usage of app is voluntary.
Malaysia[30]	• My Trace app(android users) • My Sejahtera app(apple product users)	BTS	-More information can be collected as the apps are catered to different types of phone users.	-MyTrace app obtains permission for 7 features from users(location, photos) appearing to be intrusive.
Philippines[28,30]	• Stay Safe PH/We Trace app	GPS tracker	-Easy to use.	-Obtains permission for 7 features from users (location, photos, camera, etc.) intruding privacy.
Singapore[27]	• Trace Together app for contact tracing • Wearable device for contact tracing • Safe Entry app for contact tracing	BTS, QR code scanner	-Privacy is not infringed. -Easy to use	-Usage of app is voluntary, only about a fifth of the population had downloaded the app upon its launch. -False positives as signals can travel through walls
South Korea[28,31]	• Corona-100 m • Advanced information technology system (integrated IT system) for contact tracing	Infected cases data retrieved from mobile phones, police, immigrations, government agencies, insurance agencies and hospitals, credit card companies and public transit companies.	-Newly confirmed cases and deaths were reduced. -Data shared between medical professionals and within public sector helped to reduce COVID-19 cases, averting severe lockdowns.	-Undesirable invasion of privacy
Thailand[28,30]	• MorChana app	BTS, GPS tracker	-Collated data from app would be processed using epidemiology analysis and AI.	-Obtains permission for 9 features from users (location, photos, camera, etc.) intruding privacy. -Usage of app is voluntary.
USA[28]	• Safe Paths app	GPS tracking	-Individuals will be notified if they had crossed paths with a confirmed case.	-Usage of app is voluntary. -App is an open source, risk of infringement; reliability may be a concern.
Vietnam[30]	• Blue zone app	BTS	-Users can search for other users without revealing their identity.	-Obtains permission for six features from users (photos, camera, etc.) intruding privacy.
Purpose: tracking of quarantine cases				
China/Hong Kong/ Taiwan[27]	• Direct geolocalization	Wi-Fi/GPS	-Hong Kong and Taiwan managed to limit deaths despite being close to China.	-Privacy can be infringed.
Hong Kong[32]	• Stay Home Safe app • Wristband paired with app	Geofencing technology(phone app, QR code)	-Privacy is not infringed as location is not tracked.	-Wristbands have been under-used (only a third used). -Glitches and errors are reported.

Abbreviations: app, application; BTS, Bluetooth signals; GPS, global positioning system.

TABLE 2 Wearable devices used for COVID-19

	Smart devices	Purpose	Advantages	Disadvantages
Wearable devices	Thermometers,[3334]	• Measure/monitor temperature.	- Relatively cheap - User-friendly - Accurate	- Some devices have a short battery life while some cause concerns over security and privacy of data - IoT-Q-bands can be easily spoilt
	Glasses[35]	• Crowd monitoring/ identify people with higher temperature.	- Reduced human interactions. - Infrared sensors are in-built and allow around 200 people to be monitored at a time.	
	Helmets[36]	• Capture the location and image of a person.	- Reduced human interactions. - Detection of high temperature alerts health officials.	
	IoT-Q-bands[37]	• Track people who arrive at airports/ quarantined subjects.	- Relatively cheap tracking system.	
	Proximity tracing[38]	• Enables workers to maintain social distancing.	- Emits a loud sound when workers come into close contact.	
	Easy band[39]	• Monitors safe distancing	- Band beeps to alert people to keep a safe distance from each other. - Better results compared to smartphone applications. - Relatively cheap - People feel safer using this device.	

reliability, security, availability, and servicing time.[11] Table 1 discusses IoT tools and devices comprising smartphone applications mainly, utilized by some countries to address COVID-19 issues. Table 2 discusses wearable devices while Tables 3, 4, and 5 discuss drones, robots and IoT buttons, respectively.

2.3 | Challenges of implementing IoT in COVID-19 settings

There are challenges associated with the implementation of IoT to combat the pandemic. The first challenge involves scalability concerns, wherein a large number of IoT devices need to be used in healthcare settings for accurate reading and measurement of vital signs in COVID-19 patients, which would then be sent to the IoT cloud.[48] Thus, for this largely scaled setting, IoT devices would need to be used in large amounts with several sensor points. This results in a sizeable data population moving around tiny nodes. Furthermore, the energy requirements of these devices increase due to the scalability.[48]

Another challenge lies in the need for larger spectrum and bandwidth in IoT devices. With the demand for more IoT devices, there is a dire need for larger spectrum and bandwidth. For instance, the current use of Wi-Fi or 3G/4G networks will soon become less potent if needing to accommodate many devices. This may result in errors or delay the transfer of data from the devices to cloud or the desired body, potentially leading to a loss of lives through delayed tracing methods and algorithms.[48]

While security is a crucial concern, scalability and elevated energy requirements call for IoT security solutions to have more energy efficiency and less computational complexity to provide end-to-end protection of data, privacy of consumers and secured authentication.[49] Hence, another challenge is in successfully providing the necessary security solutions for IoT devices to be managed safely in the community without major breaches of privacy.

The large amounts of data transferred from IoT devices to cloud or an application program interface, pose the challenge of requiring large data centres to store such big data, without overloading of resources available.[48]

3 | IOT ROLE ACROSS COUNTRIES IN ADDRESSING THE PANDEMIC

3.1 | The use of smartphone applications

The use of smartphone applications and smartphone applications used by different countries are given in Table 1.

TABLE 3 Drones used for COVID-19

	Devices	Purpose	Advantages	Disadvantages
Drones	Delivery-based[40]	• Transfer medical supplies between labs and medical centres. • Deliver medical supplies to patients.	- Reduced human interactions. - Reduced visits to hospitals. - Increased access to medical support. - Rapider diagnosis	- Drones are not secured, poor quality of service and little connections.
	Disinfectant-based[41]	• Disinfect areas	- Reduce contaminations and infections through disinfections by drones.	
	Thermal imaging-based[42]	• Capture temperature in the crowd.	- Reduced human interactions.	
	Surveillance-based[43]	• Crowd/ social distancing monitoring.	- Able to announce crucial information from officials.	
	Multipurpose-based[44]	• Combination of four types of drones to carry out various tasks.	- Able to capture temperature, disinfect areas, monitor crowd and announce information.	
	Announcement-based[45]	• To make crucial announcements	- Can be used in locations with low internet accessibility	

TABLE 4 Robots used for COVID-19

	Devices	Purpose	Advantages	Disadvantages
Robots	Telerobots[46]	• Distant diagnosis/treatment/surgery • Deliver medical supplies to patients.	- No human interactions. - Reduced visits to hospitals. - Increased access to medical support. - Rapider diagnosis.	- Privacy concerns
	Social[46]	• Communicate with quarantined patients.	- Reduced mental health problems in quarantined patients.	
	Independent[46]	• Disinfect contaminated areas/asses respiratory signs of patients	- Reduced/no human interactions. - Reduced risk of infections.	
	Collaborative[46]	• Aids in preparing food/medication for quarantined patients.	- Prevents close contact between patients and healthcare workers.	
	Multipurpose drones[44]	• Combination of four types of drones to carry out various tasks.	- Able to capture temperature, disinfect areas, monitor crowd and announce information.	
	Announcement drones[45]	• To make crucial announcements	- Can be used in locations with low internet accessibility.	

TABLE 5 IoT buttons used for COVID-19

Devices	Purpose	Advantages	Disadvantages
IoT buttons[47]	• Alert family members/health care providers when isolated patients' condition exacerbates at home.	- Only a button needs to be pressed for alerts to be sent.	-

3.2 | The use of wearable devices

An array of IoT-based smart thermometers have been used to record body temperatures constantly. These thermometers are not only user-friendly, but are also relatively cheap and accurate (Table 2).

3.3 | The use of drones

The use of drones in COVID-19 is shown in Table 3.

3.4 | The use of robots

The use of robots in COVID-19 is shown in Table 4.

3.5 | The use of IoT buttons

The content of Table 1 indicates that the majority of countries, such as Singapore, Australia, and Hong Kong use phone applications to trace and contain COVID-19 cases, and to identify close contacts of positive cases. Among the Association of Southeast Asian Nations (ASEAN) countries, Singapore and Vietnam use safer apps that require the least user permissions for contact tracing. The apps in countries like Thailand, Philippines, Malaysia, and Indonesia require more user permissions. In general, granting these permissions allows the app to access personal data. Although privacy laws forbid the access of personal data, once permission has been granted there is no technological barrier anymore, and hence data could be accessed with a limited ability to detect any breaches of privacy law.[30] While Singapore and Hong Kong explore applications together with wearable devices, countries and districts such as Hawaii and South Korea, explore a varying range of tools, such as online surveys and integrated information technology (IT) systems. Singapore has developed a "Trace Together" application that works based on the Bluetooth communication standard. Similar applications are also being used by other ASEAN countries, including Australia, and the United Kingdom. Despite their usefulness, these applications may drain phone battery life and may encounter interoperability issues.[50]

Additionally, these applications have been reported to be under-used by the public, because use is voluntary rather than mandated by law. While some countries, such as Hong Kong, Taiwan and China, Ghana, Iceland, Israel, India, Norway, and many states in the United States have rolled out applications that rely on GPS to obtain location data from individuals, such methods are deemed to be an invasive of privacy, and they are unappreciated or condemned by members of the public. Furthermore, GPS data may not be sufficiently accurate, especially in crowded or high-rise areas.[50] South Korea is lauded by the WHO for containing COVID-19 well,[3] but its approach constitutes a significant invasion of privacy. Hawaii metes out daily online surveys, wherein completion may appear to be a hassle. Additionally, less IT savvy or less affluent people, who may not even have a computer at home, may be disadvantaged. In particular, the elderly, who are identified as a vulnerable group, are less likely to have the knowledge to manoeuvre these technologies, placing them at further disadvantage of developing serious health consequences as a result of infection spread.

Tables 2 to 5 discuss other IoT tools that are explored in the various stages of COVID-19, from contact tracing to monitoring of quarantined patients. While these tools exhibit various advantages, akin to smartphone applications, they also exhibit disadvantages. For example, the use of drones poses security issues, and robots pose privacy issues, while wearable devices pose both security and safety issues, among other concerns.

Predominantly two different types of wireless technologies, (a) Bluetooth Low Energy (BLE)[51] based and (b) Ultra-Wide Band (UWB)[52] based, are available for the task of contact tracing. The BLE based IoTs uses BLE protocols to detect the relative locations of two beacons which can be standalone BLE tags with inbuilt alert features (phones' inbuilt beacon). The two big players, Google and Apple, have developed BLE-based contact tracing solutions called exposure notification. Even though BLE beacon-based solutions are relatively cheap and easy to manage, studies have reported erroneous false positive results and serious privacy concerns. For instance, the Trace Together application used in Singapore is BLE-based and hence faces weak privacy.[53] In comparison to BLE beacon-based technologies, UWB based IoT technology was found to be an excellent solution for social distancing and contact tracing. UWB based IoTs use a low energy level for short-range, high-bandwidth communications over the radio spectrum, and can be used to determine spatial parameters (distance and location) with high accuracy and a low error margin of about 10 cm.[52] In addition, UWB has a smaller likelihood of noise interference, which makes it appropriate for indoor application, thus; suitable for an office or factory environment in social distancing and contact tracing. Table 6 summarizes BLE beacons and UWB based IoTs (apps or devices/tools).

3.6 | BLE and UWB-based IoT

Different BLE and UWB based IoTs developed by companies for contact tracing and social distancing are shown in Table 6.

4 | ADDRESSING SECURITY AND PRIVACY ISSUES IN IOT

Decentralization is one of the principal solutions to address cyber security issues in wireless technology.[54] In this setting, information obtained is split into bits and stored in different parts of a network instead of storing the chunk of information within a central server, such that none of the separate parts will contain the full information. As a result, decentralized architectures are favored to address security issues in IoT tools.[55] In particular, decentralization and privacy protection are promising characteristics for contact tracing purposes.[56] However, decentralization alone can maintain the privacy of users sufficiently. Together with decentralization, enhanced user privacy should be applied at the protocol level of the architecture.[57] Some user privacy techniques include a physical layer that hides certain measurements of users,[58] improved security keys that create temporary identifications[59] and differential privacy that adds noise to adjusted structures of data.[60]

5 | CHALLENGES IN CONTACT TRACING FOR COVID-19

Presently, traditional contact tracing methods, such as making phone calls, are being used in countries like the United States. For instance, the Penn COVID-19 contact tracing team from Pennsylvania reported achieving a 72% success rate for being able to follow up contact tracing cases, using numbers available in the electronic health records. While above 80% of these contacted cases managed to have their interviews completed, a significant number of cases were not reachable due to incorrect phone numbers or the lack of alternate means of contact.[61] Additionally, the physical contact tracing process is cumbersome due to: (1) incomplete identification of contacts, (2) inefficient paper-based reporting systems, (3) intricate data management requirements, and (4) process delays which prolongs the time from contact detection to quarantining of suspected cases.[62] Furthermore, this human-focused approach also has significant data security issues.

TABLE 6 Different BLE and UWB based IoTs developed by companies for contact tracing and social distancing

Company	Name of device (IoT)	Features	Cost (price)
BLE beacons based			
Kinexon	Kinexon safezone	Wearable sensor, works with Android/ iPhone	$100-200/tag
BluEpyc	BluEpyc BLE devices	Works with Android/iPhone or BluEpye gateway	$100-200/tag $450/gateway
Estimote	BLE beacons and wearable tag	Works with Android/iPhone	$99/tag
Apps with built-in BLE and GPS			
	Check-In	PWC App	$150/location/ month
IBM	Watson Works	Set of products that embeds Watson artificial intelligence (AI) models and applications	
Safer Me	Safer Me	Bluetooth App works well indoors	$5/user/month
ServiceNow	Safe Work Place Suit – ServiceNow Contact Tracing	Integrated with CISCO DNA Spaces, a powerful location-based services platform.	
Sign In	Smart Visitor	Contactless Sign In App	$100/location/ month
UWB based tags for contact tracing and/or social distancing			
Iterate Labs	COVID-safe	Accelerated contact tracing	$100/tag
ARIN Technologies Inc.	Social Distancer/ARIN Alert tag	App	$100-200/tag
Tsingoal	Local Sense	Contact tracking and trace back system	
Pozyx	Pozyx wearable tag	High accuracy and reliability	$200/tag
Fleetwood Electronics	Insta Trace Badges	Badges with high accuracy and privacy	$99/tag
TRX Systems	Neon Micro-Tracer	No phones, beacons, and Wi-Fi required. High accuracy contact tracing	$1999

These challenges can be alleviated with the use of digital tools that are assimilated into public health systems.[62] Application-based digital tools could be useful in enhancing contact tracing processes.[23] Some of these digital tools, such as the outbreak response, symptom tracking, and proximity tracing tools are already being used for contact tracing, as discussed in Table 1. While smartphone applications are advantageous, they do have limitations. Some members of the public, the elderly for instance, who may have limited access to these technologies, could be excluded[62]; hence data collected, using these applications, may be unreliable. Furthermore, smartphone applications work on a voluntary basis; hence, the data collected does not represent a truly random sampling of the population.[63] In some cases, individual privacy could be infringed—for example, when GPS trackers are integrated into the tools. In addition, some smartphone applications, such as the Trace Together application used in Singapore, may not be compatible with Apple devices and may halt Bluetooth scanning. Other IoT tools such as wearable devices, robots, and drones also face similar security and/or privacy issues. Hence, digital tools should be designed with careful consideration, and they should not be used as the sole solution for contact tracing.[62]

Presently, wearable technology is not only being used to combat COVID-19, but is also being used widely in the fitness and healthcare domains, and it is becoming more socially acceptable even outside of these domains.[64] Singapore is rolling out wearable tokens, while South Korea, Bulgaria, and Hong Kong are using wristbands. When these wearable devices are made mandatory, more reliable and representative contact tracing data can be collected from a population. Furthermore, when these devices only rely on Bluetooth, without tracking location with the GPS, individuals may be more willing to use them, because the potential for invasion of privacy is lower. Thus, an ideal contact tracing tool may encompass a wearable device, implemented in conjunction with a complementary digital tool like a smartphone application. The challenge of large data, generated by any such wearable devices and phone applications, may be converted to opportunities for research. These opportunities will be discussed in subsequent sections.

6 | INTELLIGENT INTERNET OF THINGS

In 2020, an estimated 25 to 50 billion devices are connected to the Internet. Predictions indicate that IoT tools will be the primary data sources on the Internet.[65] Data science is an inter-disciplinary field, comprising data mining and machine learning techniques among others, to better comprehend data.[52] Data science is anticipated to contribute significantly in making IoT applications more intelligent.[52,66] IoT tools that generate large amounts of real-time data face the challenges of big data, that exhibit one or multiple of the following properties: large amount of data, high data rate, large data variation.[67] This calls for the need to overcome the challenges by transforming such data into smart data, wherein useful information could be obtained for improved decision-making[68] through cost-effective and novel information processing methods.[52]

7 | PROPOSED NEXT GENERATION TOOLS AND DISCUSSION

7.1 | Deep learning

Recent technological innovations have brought about a change in our understanding of data. We are now living in the age of big data, wherein research in science and technology spawns sizeable data volumes.[69] Faced with unique challenges in analyzing and interpreting big data, there is a need to shift from traditional methodology to more advanced techniques of big data analysis.[69] One of these advanced techniques is deep learning, a new paradigm in artificial intelligence (AI). Conceptually, deep learning is a subfield of machine learning. However, unlike traditional approaches, a deep learning model is composed of many deep networking layers with the capacity of extracting knowledge from very large data quantities.[70] Having this ability avoids feature engineering, which is in essence an information reduction strategy.[71] Hence, deep learning algorithms are becoming established in many public health domains ranging from disease classification[72-75] to crowd monitoring.[76] Some deep learning models employed prevalently include physiological signal analysis and convolutional neural networks,[77] auto encoders,[78] deep belief networks,[79] long short-term memory networks,[80] and deep feedforward neural networks. AI- based models comprising conventional machine learning as well as advanced deep models have also been employed to manage or aid in the diagnosis of COVID-19.[81-83] Training deep learning models from scratch is computationally complex, and hence, it takes considerable processing resources to execute and to validate the training tasks within an acceptable time frame. To be specific, training a deep learning system scale well, means both faster and more processing resources in parallel will speed up the processing time. Hence, in a compute cluster environment, monetary resources translate directly into reduced processing time. The ability to execute training tasks in parallel is especially advantageous when it comes to hyper parameter tuning, because searching for these parameters is based on trial-and-error methods, and having that design strategy implies that testing more hyper parameters yields better results.[84] A transfer learning method could be beneficial, because that method incorporates a pretrained deep learning model from a related source field as a base for the training process.[85] This might enable cost-effective and effortless classification of tasks.[84]

7.2 | Next generation tools

Wearable devices that incorporate IoT technology are likely to profoundly influence healthcare and lifestyles in the future.[86] IoT, coupled with big data analytics, is anticipated to be a useful tool in converting conventional methodology to more advanced technology[87] wherein data generated by these devices can be analyzed using big data approaches for informed decision-making.[7] Thus, the large data created by wearable devices creates an opportunity for the application of AI techniques, such as deep learning, on these data in the future.[88] With the infusion of AI, intelligent IoT (IIoT) systems are created, augmenting existing IoT applications. Hence, future contact tracing tools could potentially include wearable devices, like a watch and phone applications, infused with IIoT, with special features, such as complex data analysis and intelligent data visualization integrated into the system.[89] For complex data analysis and intelligent data visualization, the Python language and deck.gl algorithms could be utilized, respectively, in the system. IIoT is also anticipated to benefit COVID-19 analysis by predicting impending disease-related events.[90] Thus, sizeable data obtained from the phone applications and wearable devices will be sent to integrated deep learning data analysis and data visualization systems, which will be maintained in the cloud server for training and identifying data patterns, respectively, so as to potentially predict COVID-19 clustering. This information could be made accessible to epidemiologists via secured web interfaces. To address safety and security concerns, the IIoT architecture will be decentralized with user privacy techniques applied at the protocol level in wireless system. Figure 4 shows our proposed next generation tool for contact tracing, maintained in a cloud computing setting. Our proposed tool exhibits some advantages and limitations, as compared to existing tools.

7.2.1 | Advantages

1. Existing tools are useful for contact tracing. The proposed tool is probably the only one useful for both contact tracing and prediction of COVID-19 clusters.
2. A wide range of sizeable population data would be available to train the deep models.
3. Security and privacy issues will be addressed.

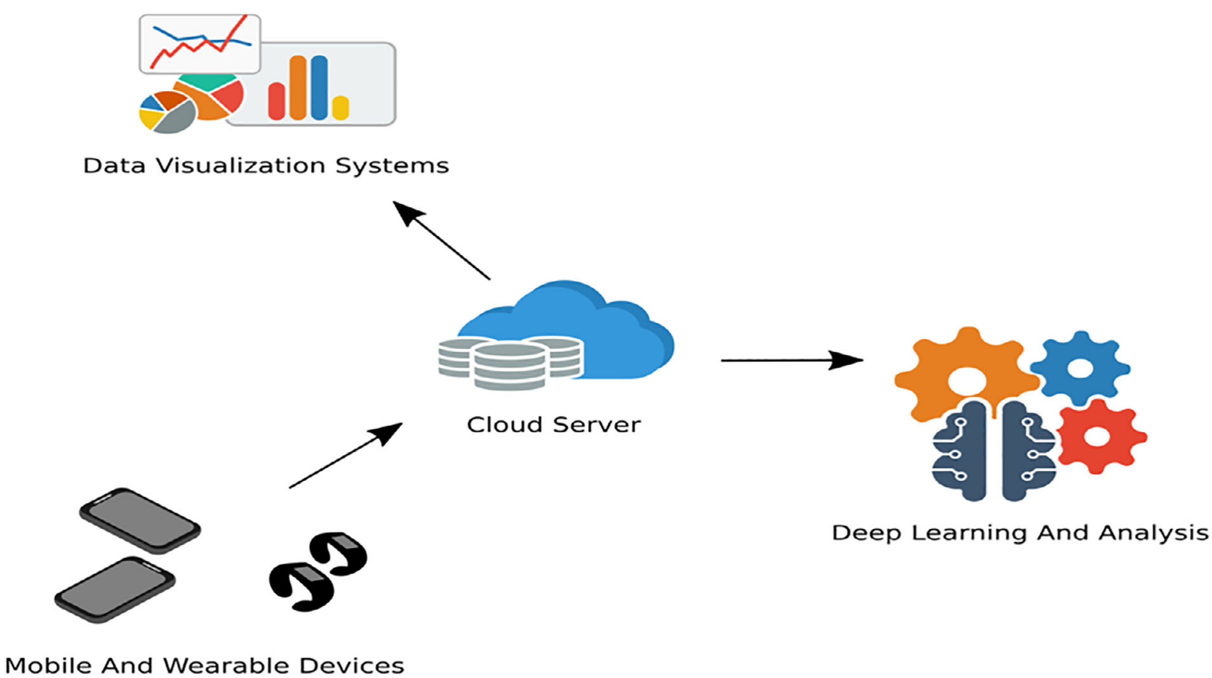

FIGURE 4 Proposed next generation tool for contact tracing [Color figure can be viewed at wileyonlinelibrary.com]

7.2.2 | Disadvantages

1. Most countries which are currently facing a financial crisis may not be able to provide such a tool to its citizens, for contact tracing.

8 | CONCLUSION AND FUTURE SCOPE

Countries around the globe have deployed digital tools to assist with understanding, tracing, and reducing COVID-19 infections. While many phone applications with GPS or Bluetooth technology are being explored in the process, these may invade privacy as well as generate an unacceptably large number of false positives cases. Wearable devices are gaining popularity and they are expected to be influential in shaping both healthcare and lifestyle applications in the future, especially when integrated with IoT systems. Although wearable devices with Bluetooth technology may have some limitations, these are outweighed by several systemic advantages. Large data, gathered by the wearable devices, creates the opportunity to develop intelligent IoT systems by incorporating AI based decision support structures.

The existing tools being used for contact tracing exhibit various limitations. The virus is still spreading in many countries as a robust system to predict COVID-19 clusters is not available, and hence efficient methods to contain the virus, are not in place as of yet. Thus in this work, we have proposed a futuristic cost-effective tool that can be utilized for contact tracing and prediction of COVID-19. The solution is based on a phone application combined with a wearable device, infused with special IIoT features—complex data analysis and intelligent data visualization—that is embedded within the system. Big data, such as location and identification details, obtained from both phone application and wearable device is sent to the integrated deep learning data analysis and data visualization systems, which will be kept in a cloud server and used for training and identifying patterns in data to predict COVID-19 clusters. This information should be accessible by epidemiologists to detect clustering so that necessary actions can be taken to better control the situation. The architecture would also be secure with privacy maintained. The proposed tool may also find use for contact tracing or large-scale monitoring in any future health crises.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

ETHICS STATEMENT

This research paper does not involve any study with human participants and/or animals performed by any of the authors.

DATA AVAILABILITY STATEMENT

Not applicable.

ORCID

Vicnesh Jahmunah https://orcid.org/0000-0002-0091-6049
Vidya K. Sudarshan https://orcid.org/0000-0003-4494-8226

REFERENCES

1. African Union, Africa Centres for Disease Control and Prevention. Guidance on Contact Tracing for COVID-19 Pandemic – Africa CDC. 2020. Available from https://africacdc.org/download/guidance-on-contact-tracing-for-covid-19-pandemic/
2. Coronavirus disease COVID-2019 - Situation report 150. World Heal Organ; 2020.
3. “No excuse” for countries that fail in contact tracing, says WHO chief Tedros. Reuters; 2020.
4. Thanh Le T, Andreadakis Z, Kumar A, et al. The COVID-19 vaccine development landscape. *Nat Rev Drug Discov*. 2020;19(5):305-306.
5. Kissler SM, Tedijanto C, Goldstein E, Grad YH, Lipsitch M. Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science*. 2020;368(6493):860-868.
6. Ferretti L, Wymant C, Kendall M, et al. Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science (80-)*. 2020;368(6491):1-8.
7. Kumar S, Tiwari P, Zymbler M. Internet of things is a revolutionary approach for future technology enhancement: a review. *J Big Data*. 2019;6:111. https://doi.org/10.1186/s40537-019-0268-2.
8. Pratap R, Javaid M, Haleem A, Suman R. Internet of things (IoT) applications to fight against COVID-19 pandemic. *Diabetes Metab Syndr Clin Res Rev*. 2020;14(January):521-524.
9. Hewlett Packard Enterprise. Internet of Things Research Study 2015 Report; 2015. Available from: http://fortifyprotect.com/HP_IoT_Research_Study.pdf
10. Wu Y, Kapitanova K, Li J, Stankovic JA, Son SH, Whitehouse K. Run time assurance of application-level requirements in wireless sensor networks. Paper presented at: Proceedings of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks, IPSN '10. 2010.
11. Huo L, Wang Z. Service composition instantiation based on cross-modified artificial bee colony algorithm. *China Commun*. 2016;13(10):233-244.
12. Liu YC, Kuo RL, Shih SR. COVID-19: the first documented coronavirus pandemic in history. *Biom J*. 2020;43(4):328-333.
13. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Rajendra AU. Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Comput Biol Med*. 2020;121:103792.

14. Tao Y, Shi M, Chommanard C, et al. Surveillance of bat coronaviruses in Kenya identifies relatives of human coronaviruses NL63 and 229E and their recombination history. *J Virol*. 2017;91(5):e01953-16.
15. Singhal T. A review of coronavirus Disease-2019 (COVID-19). *Indian J Pediatr*. 2020;87(4):281-286.
16. Wu Z, McGoogan JM. Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: summary of a report of 72314 cases from the Chinese Center for Disease Control and Prevention. *J Am Med Assoc*. 2020;323(13):1239-1242.
17. COVID-19: physical distancing World Health Organisation. 2020. Available from https://www.who.int/westernpacific/emergencies/covid-19/information/physical-distancing
18. Oriwoh E, Conrad M. "Things" in the Internet of things: towards a definition. *Int J Internet Things*. 2015;4(1):1-5.
19. Zheng S, Qian YL, Xiang ZP, Bo LH, Liu F, Sheng ZR. Recommendations and guidance for providing pharmaceutical care services during COVID-19 pandemic: a China perspective. *Res Soc Adm Pharm*. 2020;17(1):1819-1824.
20. Sfar AR, Chtourou Z, Challal Y. A systemic and cognitive vision for IoT security: a case study of military live simulation and security challenges. Paper presented at: 2017 International Conference on Smart, Monitored and Controlled Cities (SM2C). 2017. p. 101-105.
21. Peeri NC, Shrestha N, Rahman MS, et al. The SARS, MERS and novel coronavirus (COVID-19) epidemics, the newest and biggest global health threats: what lessons have we learned? *Int J Epidemiol*. 2020;49(3):717-726.
22. Dewey C, Hingle S, Goelz E, Linzer M. Supporting clinicians during the COVID-19 pandemic. *Ann Intern Med*. 2020;172 (11):752-753. https://doi.org/10.7326/M20-1033.
23. Kucharski AJ, Klepac P, Conlan A, et al. Effectiveness of isolation, testing, contact tracing and physical distancing on reducing transmission of SARS-CoV-2 in different settings. *medRxiv*. 2020;3099(20):20077024. http://medrxiv.org/content/early/2020/04/29/2020.04.23.20077024.abstract.
24. Yan Z, Zhang P, Vasilakos AV. A survey on trust management for Internet of things. *J Netw Comput Appl*. 2014;42:120-134.
25. Dierks T, Allen C. RFC 2246: The TLS Protocol. Network Working Group 1999.
26. Roman R, Najera P, Lopez J. Securing the Internet of things. Computer (Long Beach Calif); 2011.
27. Contact tracing apps: Which countries are doing what? From the economic times.
28. Office of the Privacy Commissioner: Overview of COVID-19 Contact Tracing Apps – 12 May 2020 Office of the Privacy Commissioner: Overview of COVID-19 Contact Tracing Apps 20201-10.
29. Gesley J. Regulating electronic means to fight the spread of COVID-19. *Libr Congr*. 2020;5080.
30. A Comparative Review of Contact Tracing Apps in ASEAN countries. Data Protection Excellence Network. 2020.
31. Ko H, Park S, Choi GJ. Information technology–based tracing strategy in response to COVID-19 in South Korea—privacy controversies. *JAMA*. 2020;323(21):2129-2130.
32. Hong Kong is using tracker wristbands to geofence people under coronavirus quarantine. Quartz. 2020.
33. Chamberlain S, Singh I, Ariza C, Daitch A, Philips P, Dalziel B. Real-time detection of COVID-19 epicenters within the United States using a network of smart thermometers. 2020;1-15.
34. Tamura T, Huang M, Togawa T. Current developments in wearable thermometers. *Adv Biomed Eng*. 2018;7(November):88-99.
35. Mohammed MN, Hazairin NA, Syamsudin H, et al. 2019 novel coronavirus disease (Covid-19): detection and diagnosis system using iot based smart glasses. *Int J Adv Sci Technol*. 2020;29(7 Special Issue):954-960.
36. Mohammed MN, Syamsudin H, Al-Zubaidi S, Sairah AK, Ramli R, Yusuf E. Novel covid-19 detection and diagnosis system using iot based smart helmet. *Int J Psychosoc Rehabil*. 2020;24(7):2296-2303.
37. Singh V, Chandna H, Kumar A, Kumar S, Upadhyay N, Utkarsh K. IoT-Q-band: a low cost internet of things based wearable band to detect and track absconding COVID-19 quarantine subjects. *EAI Endorsed Trans Internet Things*. 2020;6(21):163997.
38. Wearable technology in the time of COVID-19. 2020Accessed November 6, 2020.
39. Tripathy AK, Mohapatra AG, Mohanty SP, Kougianos E, Joshi AM, Das G. EasyBand: a wearable for safety-aware mobility during pandemic outbreak. *IEEE Consum Electron Mag*. 2020;9(5).
40. COVID-related Drone Delivery Soars Into Canadian First Nation. 2020.
41. Sharma M. How Drones Are Being Used to Combat COVID-19. 2020. https://dronelife.com/2020/06/10/ddc-drone-covid-drone-delivery/
42. Mohammed MN, Hazairin NA, Al-Zubaidi S, Sairah AK, Mustapha S, Yusuf E. Toward a novel design for coronavirus detection and diagnosis system using iot based drone technology. *Int J Psychosoc Rehabil*. 2020;24(7):2287-2295.
43. Marr B. Robots and drones are now used to fight COVID-19 [Internet]. 2020 Accessed November 6, 2020. https://www.forbes.com/sites/bernardmarr/2020/03/18/how-robots-and-drones-are-helping-to-fight-coronavirus/?sh=5044ff1e2a12
44. Delhi civic body begins thermal screening people on balconies with drones. 2020.
45. Drones to stop the COVID-19 epidemic. 2020. Available from: https://www.bbva.com/en/drones-to-stop-the-covid-19-epidemic/
46. Tavakoli M, Carriere J, Torabi A. Robotics, smart wearable technologies, and autonomous intelligent Systems for Healthcare during the COVID-19 pandemic: an analysis of the state of the art and future vision. *Adv Intell Syst*. 2020;2: 2000071.
47. IoT alert button finds new uses during coronavirus pandemic. 2020.
48. Kamal M, Aljohani A, Alanazi E. Iot Meets Covid-19: Status, Challenges, and Opportunities. arXiv; 2020.
49. Aman MN, Basheer MH, Sikdar B. Two-factor authentication for IoT with location information. *IEEE Internet Things J*. 2019; 6(2):3335-3351.
50. Maclean W. Factbox: the race to deploy COVID-19 contact tracing apps. *Reuters*. 2020. https://www.reuters.com/article/us-health-coronavirus-apps-factbox-idUSKBN22Q2KU.
51. Li J, Guo X. COVID-19 Contact-tracing Apps: a Survey on the Global Deployment and Challenges. 2020;(August). Available from: http://arxiv.org/abs/2005.03599

52. Mahdavinejad MS, Rezvan M, Barekatain M, Adibi P, Barnaghi P, Sheth AP. Machine learning for internet of things data analysis: a survey. *Digit Commun Networks*. 2018;4(3):161-175. https://doi.org/10.1016/j.dcan.2017.10.002.
53. Ding J, Nemati M, Ranaweera C, Choi J. IoT connectivity technologies and applications: a survey. *IEEE Access*. 2020.
54. Bansal P, Panchal R, Bassi S, Kumar A. Blockchain for Cybersecurity: A Comprehensive Survey. In: 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT). 2020. p. 260-265.
55. Valdivia LJ, Del-Valle-Soto C, Rodriguez J, Alcaraz M. Decentralization: the failed promise of Cryptocurrencies. *IT Prof*. 2019;21:33-40.
56. Coronavirus contact-tracing apps: can they slow the spread of COVID-19? Nature.
57. Shubina V, Holcer S, Gould M, Lohan ES. Survey of decentralized solutions with mobile devices for user location tracking, proximity detection, and contact tracing in the covid-19 era. *Datamation*. 2020;5(4):1-40.
58. Taha S, Shen X. A physical-layer location privacy-preserving scheme for mobile public hotspots in NEMO-based VANETs. IEEE Trans Intell Transp Syst; 2013.
59. Han J, Susilo W, Mu Y, Yan J. Privacy-preserving decentralized key-policy attribute-based encryption. IEEE Trans Parallel Distrib Syst; 2012.
60. NIU B, Chen Y, Wang Z, Li F, Wang B, Li H. Eclipse: preserving differential location privacy against long-term observation attacks. *IEEE Trans Mob Comput*. 2020;1.
61. Beidas RS, Buttenheim AM, Feuerstein-simon R, Kilaru AS, Asch DA, Volpp KG, et al. Optimizing and implementing contact tracing through behavioral economics; 2020.
62. Organization WH. Digital tools for COVID-19 contact tracing: annex: contact tracing in the context of COVID-19. *Geneva PP - Geneva: World Health Organization*. 2020. Available from: https://apps.who.int/iris/handle/10665/332265.
63. Drew DA, Nguyen LH, Steves CJ, et al. Rapid implementation of mobile technology for real-time epidemiology of COVID-19. *Science (80-)*. 2020;0473:eabc0473.
64. Kirk S. The wearables revolution: is standardization a help or a hindrance?: mainstream technology or just a passing phase? *IEEE Consum Electron Mag*. 2014;3(4):45-50.
65. Atzori L, Iera A, Morabito G. The Internet of things: a survey. *Comput Netw*. 2010;54(15):2787-2805. Available from:. http://www.sciencedirect.com/science/article/pii/S1389128610001568.
66. Firouzi F, Chakrabarty K, Nassif S, eds. *Intelligent Internet of Things [Electronic Resource]: from Device to Fog and Cloud / Edited by Farshad Firouzi, Krishnendu Chakrabarty, Sani Nassif. 1st Ed. 20*. Cham: Springer International Publishing; 2020.
67. Manyika J, Chui Brown M, Bughin J, Dobbs R, Roxburgh C, Hung Byers A. *Big data: The Next Frontier for Innovation, Competition and Productivity. McKinsey Glob Inst*. McKinsey & Company; 2011.
68. Sheth A. Transforming big data into smart data: deriving value via harnessing volume, variety, and velocity using semantic techniques and technologies. Paper presented at: 2014 IEEE 30th International Conference on Data Engineering. 2014. p. 2.
69. Emmert-Streib F, Yang Z, Feng H, Tripathi S, Dehmer M. An introductory review of deep learning for prediction models with big data. *Front Artif Intelligen*. 2020;3:4.
70. Goodfellow I, Bengio Y. Courville A-deep learning-MIT. *Deep Learning*. Cambridge, Massachusett: MIT Press; 2016;800.
71. Faust O, Hagiwara Y, Hong TJ, Lih OS, Acharya UR. Deep learning for healthcare applications based on physiological signals: a review. *Comput Methods Prog Biomed*. 2018;161:1-13. http://linkinghub.elsevier.com/retrieve/pii/S0169260718301226.
72. Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. *Comput Biol Med*. 2018;100:270-278. https://doi.org/10.1016/j.compbiomed.2017.09.017.
73. Lih OS, Jahmunah V, San TR, et al. Comprehensive electrocardiographic diagnosis based on deep learning. *Artif Intell Med*. 2020;103:101789. Available from: http://www.sciencedirect.com/science/article/pii/S0933365719309030.
74. Acharya UR, Fujita H, Oh SL, et al. Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network. *Futur Gener Comput Syst*. 2018;79:952-959.
75. Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H, Subha DP. Automated EEG-based screening of depression using deep convolutional neural network. *Comput Methods Prog Biomed*. 2018;161:103-113. https://doi.org/10.1016/j.cmpb.2018.04.012.
76. Cheong KH, Poeschmann S, Lai JW, et al. Practical automated video analytics for crowd monitoring and counting. *IEEE Access*. 2019;7:183252-183261.
77. Indolia S, Goswami AK, Mishra SP, Asopa P. Conceptual understanding of convolutional Neural network- a deep learning approach. *Procedia Comput Sci*. 2018;132:679-688.
78. Lu X, Tsao Y, Matsuda S, Hori C. Speech enhancement based on deep denoising autoencoder. Per presented at the Proceedings of the Annual Conference of the International Speech Communication Association, Interspeech. 2013.
79. Hua Y, Guo J, Zhao H. Deep belief networks and deep learning. Paper presented at the Proceedings of 2015 International Conference on Intelligent Computing and Internet of Things, ICIT 2015. 2015.
80. Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Comput*. 1997;9(8):1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735.
81. Abbasian Ardakani A, Acharya UR, Habibollahi S, Mohammadi A. COVIDiag: a clinical CAD system to diagnose COVID-19 pneumonia based on CT findings. *Eur Radiol*. 2020;31(1).
82. Ardakani AA, Kanafi AR, Acharya UR, Khadem N, Mohammadi A. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: results of 10 convolutional neural networks. *Comput Biol Med*. 2020;121:103795.
83. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Acharya UR. Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Comput Biol Med*. 2020;121:103792.
84. Huang SJ, Zhao JW, Liu ZY. Cost-effective training of deep CNNs with active model adaptation. *Proc ACM SIGKDD Int Conf Knowl Discov Data min*. 2018;8:1580-1588.
85. Pan SJ, Yang Q. A survey on transfer learning. *IEEE Trans Knowl Data Eng*. 2010;22:1345-1359.

86. Tresp V, Overhage JM, Bundschus M, Rabizadeh S, Fasching PA, Yu S. Going digital: a survey on digitalization and large-scale data analytics in healthcare. *Proc IEEE*. 2016; 104(11):2180-2206.
87. Mourtzis D, Vlachou E, Milas N. Industrial big data as a result of IoT adoption in manufacturing. In: Procedia CIRP. 2016.
88. Wu M, Luo J. Wearable technology applications in healthcare: a literature review. *Online J Nurs Informatics Contrib*. 2019.
89. Patel KK, Patel SM, Scholar PG. Internet of things-IOT: definition, characteristics, architecture, enabling technologies, application & future challenges. *Int J Eng Sci Comput*. 2016;6(5):1-10. Available from: http://ijesc.org/.
90. Pratap R, Javaid M, Haleem A, Suman R. Internet of things-IOT: definition, characteristics, architecture, enabling technologies, application & future challenges. *Diabetes Metab Syndr Clin Res Rev*. 2020;14(January):521-524.

How to cite this article: Jahmunah V, Sudarshan VK, Oh SL, et al. Future IoT tools for COVID-19 contact tracing and prediction: A review of the state-of-the-science. *Int J Imaging Syst Technol*. 2021;31:455–471. https://doi.org/10.1002/ima.22552