JJEE
Jordan Journal of Electrical Engineering

Volume 8, Number 2, June 2022
Pages 133-150

ISSN (Print): 2409-9600, ISSN (Online): 2409-9619

# A Review on Wireless Fidelity Co-Location Technology Adopted Indoors for Technology-Based Contact Tracing

**Agburu O. Adikpe[1*], Matthew Iyobhebhe[2], Caleb A. Amlabu[3], Ishaya C. Botson[4], Bankole A. Omojola[5], James G. Bashayi[6], Chukwudi Ezugwu[7]**

[1] Electronics and Telecommunications Engineering Department, Ahmadu Bello University, Zaria, Kaduna, Nigeria
E-mail: agburuadikpe@gmail.com
[2, 3, 4, 5, 6, 7] Department of Electrical/Electronics Engineering Technology, School of Engineering Technology, Federal Polytechnic of Nasarawa, Nasarawa, Nigeria

*Received: November 03, 2021* *Revised: December 10, 2021* *Accepted: December 20, 2021*

***Abstract—*** As the number of casualties and confirmed cases of the Coronavirus disease 2019 (COVID-19) gradually decreases, several countries across the globe are gradually trying to ease their society to some semblance of normalcy. However, to avoid systems that restrict social interactions in indoor environments, it is necessary to adopt solutions that redefine the ethos of social interactions within indoor environments. To achieve this, technology-based contact tracing (TCT) has been adopted as one of the systems used to mitigate the spread of the outbreak. On this premise, this review discusses co-location technologies suitable for indoor environments, with a specific focus on co-location solutions whose implementation costs are affordable, scalable, and whose access conditions utilize existing infrastructures that are available in off-the-shelf user equipment. This review focuses on wireless fidelity (WiFi) as a co-location technology adopted for TCT. On this premise, the limitations around adoption and recommendations, which highlight improvements, are compactly discussed around WiFi. In this context, a future research direction - on which this review is based - is compactly discussed.

***Keywords—*** Technology-based contact tracing; Contact tracing; COVID-19; WiFi; Indoor co-location technology.

## 1. INTRODUCTION

While the mode of infection varies with the diverse outbreaks that have plagued humanity, a consistent theme attributed to how individuals within the same space are infected is largely tied to the time frame an infected person spends in a location with other individuals. In cases where the mode of infection is airborne, the likelihood of the latter getting infected increases exponentially [1]. Considering indoor infrastructures such as healthcare facilities, restaurants, campuses, religious buildings and ubiquitous indoor spaces - where people gather for lengthy periods - the consequence of an outbreak could be terrible if not curbed on time. The ongoing Coronavirus disease 2019 (COVID-19) came as a shock and its ripples are still felt globally. To curb the spread of the pandemic, preventive measures such as social distancing, quarantine and contact tracing (CT) came to the fore in order to flatten-the-curve of the outbreak [2]. Among these measures, CT was adopted by medical personnel and other relevant entities such as the government to curb the spread of the outbreak. This CT process aided the involved entities to locate and isolate the infected individual and those with whom the infected individual had any interactions. Although CT is not new as it had been adopted in curbing the spread of past epidemics and pandemics, the CT process adopted at the time was manual and did not scale well in addressing outbreaks that are airborne. This process required training medical personnel and individuals - with little to no medical background - to identify individuals that are infected, and using the information obtained

* Corresponding author
Article's DOI: 10.5455/jjee.204-1635982606

from the infected individual to identify individuals who may be latent carriers of the disease. However, failing to locate the infected and latent carriers can cause the disease to silently spread [3]. On this premise, technology-based contact tracing (TCT) was introduced. TCT systems are not necessarily pharmaceutical interventions, but they play a significant role in curbing the spread of an outbreak [4]. The introduction of the TCT process was implemented not as an alternative to the manual CT process, but to argument it. Though, TCT has been discussed in literature before COVID-19 [5-7], the COVID-19 outbreak was what thrust the intervention into the limelight. This enabled private and government entities to engage researchers and designers, who went on to develop several TCT solutions, most of which utilized technologies such as ultra-wideband (UWB), Bluetooth Low Energy (BLE), cell towers, global positioning systems (GPS), wireless fidelity (WiFi), and ultrasound. Based on the assumption that mobile phones are ubiquitous [7, 8], most of the widely adopted solutions were built atop wireless communication features embedded in smartphones [2]. For the intervention to be effective, individual involvement in adopting the TCT interventions and cooperation in providing relevant information when necessary is crucial. To achieve this, several infrastructures (some of which were already in use and some novel) were utilized to gather information. The existing infrastructures, which include WiFi access points (APs), GPS, cell towers, etc., require a far lower cost of application in implementing TCT interventions than novel interventions, most of which require new infrastructure for implementation. If an outbreak is airborne, a prompt and affordable response is crucial in localizing an infected individual, which is at the core of CT. On this premise, implementing novel solutions that require new infrastructures - to be adopted en masse - usually drives up application cost [9], which limits implementation of TCT in flattening the curve of the outbreak.

To sustain the ongoing social interactions and avoid additional waves of lockdown - which restrict infrastructures that require the physical presence of individuals to thrive - it is necessary to utilize co-location wireless communication technologies. As an available option among others, TCT interventions built atop co-location based wireless communication technologies, enable the relevant entities to easily identify individuals who are infected as well as individuals who are potential contact risks. This supporting infrastructure reduces the need to add to the waves of lockdown that have negatively impacted multiple infrastructures. On this premise, this review discusses existing co-location based wireless communication solutions with focus on the attractiveness of utilizing the existing WiFi infrastructure in indoor environments, since a large number of WiFi-enabled user equipment (UE) are already in use.

### 1.1. Contribution of This Work

The core focus of this review is on WiFi co-location wireless communication technologies. Due to the already existing WiFi infrastructure and large number of WiFi enabled UE in use, it is expected that the implementation cost of utilizing the already established WiFi network as a TCT intervention would be affordable, scalable and flexible to adopt. The papers considered in this review ubiquitously reported on a number of indoor location-based inference wireless communication technologies that are adopted as TCT solutions. Publications that focus on privacy protocols and ethical concerns from a conceptual perspective were excluded in this work, although the concept of privacy and ethics was mentioned. In the same vein, this work touches on the adoption rate of TCT solutions but does not focus on the user adoption ratio as regards the implemented TCT solutions; rather, a fundamental area of this work discusses the potential of WiFi co-location based applications as TCT solutions in indoor environments.

Concerning the rest of this paper, section 2 compactly discusses wireless communication systems that are adopted as co-location based technologies. This is followed in section 3 by a discussion on a selected number of key metrics that are considered in selecting a co-location based technology for indoor spaces. Section 4 discusses WiFi as a TCT tool and a state-of-the-art review on standalone and hybrid WiFi based TCT solutions. Section 5 discusses the role of 5G and its applications within the expanding ecosystem of TCT. Section 6 discusses the limitations of using WiFi co-location technologies as TCT solutions. A compact overview of recommendations in utilizing WiFi as TCT solutions are discussed in section 7. Based on this review, section 8 highlights an ongoing research work carried out to develop a WiFi co-location solution that utilizes the existing WiFi infrastructure to track and locate UEs. Finally, this paper is concluded in section 9.

## 2. LOCATION-BASED TECHNOLOGIES

The exponential rate of innovation in the area of wireless communication has spawned a wave of novel applications that are embedded in UE adopted by users globally. The attention garnered as a result of its widespread deployment and adoption by researchers and industry is tending more to location-based services to users [9, 10]. The accuracy of these positioning technologies is of interest for a range of applications, especially in indoor environments, such as the campus of tertiary institutions, hospitals, government and private offices, shopping malls, etc. [8]. In the following subsections, we discuss a number of these location-based wireless communication technologies adopted as positioning tools.

### 2.1. Wireless Fidelity

Various variants of WiFi have been introduced since its inception. These variants are tagged with IEEE 802.11 followed by a letter or two, which represents the characteristics of the WiFi variant. For example, IEEE 802.11a/b/g/n/ac/ad are incremental standards concerned with the enhancement of communication speed [10 - 12]. As regards security, Wi-Fi has also undergone several improvements starting from wired equivalent privacy (WEP) to WiFi protected access (WPA), WPA2, WPA2-pre-shared Key (PSK), WPA2-enterprise (802.1X), IEEE 802.11i, and now the management frames are protected using IEEE 802.11w [12]. As regards location estimation services, researchers have focused on the IEEE 802.11a/b/g. Nevertheless, the extra features of standards such as IEEE 802.11n/ac/i/v are also vital in enhancing the localization-based services offered by these standards [10]. WiFi 6, which is based on 802.11ax technology, is the latest version of the Wi-Fi standards which provides high-throughput and reliable communications [13].

Nowadays, WiFi access is almost ubiquitous in key environments such as the campus of tertiary institutions, government and private offices, cafe’s, shopping malls, etc. [8]. This is due to benefits such as high flexibility, low access condition and its wide distribution in comparison to other wireless communication features in the expanding ecosystem of WiFi to the internet of things (IoT). On this premise, users are more likely to enter these environments with the WiFi on their UEs turned on rather than other wireless features such as BLE and GPS. This ubiquity makes WiFi sensing a widely adopted approach for addressing a range of analytic tasks [8]. As delineated in Table 1, WiFi sensing can be done over the network or via the user's UE. In literature [8, 9, 14, 15], WiFi sensing - done using a users' UE, also known as client-side sensing - can be performed using triangulation via time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength indicator (RSSI) to multiple WiFi access points and localize a UE's position. Network-side sensing on the other hand uses the network to view the UEs connected through the WiFi access point. The information obtained is used to perform analytics. This approach has been used for monitoring the mobility of WiFi enabled UEs by analyzing the sequence of the access points that see the same UE over a period of time [8].

### 2.2. GPS

The GPS system provides location and time information to UEs equipped with GPS transceivers through a mesh of GPS radio navigation satellites. The co-location feature of this technology provides means to track and localize UEs within proximity within a time frame. Although this premise is promising as a TCT solution - since its usage is practically ubiquitous in devices that are GPS-enabled - its co-location feature is limited in indoor environments especially in high rising structures such as skyscrapers. This affects the scalability of this technology even if it functions indoors. It has been observed in literature [2, 16, 17] that its accuracy in localizing UEs falls within the margin of error, which is about 10 m. This limitation makes it inefficient as a positioning tool in indoor environments. In ideal conditions - not impeded by limitations such as atmospheric attenuation and other factors that lead to fading of the wireless communication channel - the GPS system functions well outdoors as a co-location technology. However, humans tend to spend most of their time indoors. An error of 10 m will increase the rate of false positive and false negative recorded by the system.

### 2.3. UWB

UWB is a wireless communication technology, which emits short UWB pulses (2 ns each) to track and locate a UE equipped with the UWB feature [18]. This technology transmits data across a wide bandwidth of 500 MHz without interference from the conventional narrowband and carrier wave transmission in the same frequency band. Once a UWB enabled device is within the range of another, the devices start "ranging." Ranging is used by the UWB enabled devices to determine time of flight (TOF) of transmission at diverse frequencies. These characteristics enable it to combat multipath fading [19]. TOF is the time taken for a signal transmitted from a UE to travel to another UE. Once the TOF is obtained, the range of separation between the UEs can be calculated based on the TOF and the known propagation speed of the signal [10]. Additional UWB approaches that are adopted for the positioning of UEs are delineated in [20]. The positioning process tracks the UE in real-time. In addition, it offers greater accuracy in line-of-sight (LoS) and strong localization in non-line-of-sight (nLOS) settings [18].

### 2.4. BLE

BLE is a short-range, low power wireless communication technology that operates in the 2.4 GHz industrial, scientific, and medical (ISM) band. BLE, which is a variant of Bluetooth was released in 2010 as part of the Bluetooth 4 radio specifications. BLE utilizes only 40 channels rather than 80 as used in Bluetooth. As a result, all channels which in this case covers twice the width compensates for lower transmission power and the accompanying interference problems found in the legacy Bluetooth. Out of the 40 available channels, three channels are reserved as advertising channels, which are used to initiate connection, while the remaining 37 channels are reserved for data transmission. A key advantage of BLE is that it consumes less energy than the legacy Bluetooth [21]. Energy-efficient (EE) communication is crucial for a viable IoT system powered by batteries. Also, the more sensing technologies become ubiquitous, the higher the maintenance cost of recharging or replacing the batteries [22]. Although energy harvesting has been considered as an alternative to batteries [23, 24], it has been observed that in most cases, the energy harvested is very little [25]. Therefore, EE communication remains a crucial part of the system design [26]. On this premise, BLE was designed to function as an EE system, which expands the effectiveness of BLE to the ecosystem of IoT. BLE sensing done using a users' UE can be performed using RSSI to multiple UEs. This can be used to estimate the proximity of a UE to another as well as localize a UE.

### 2.5. Radio Frequency Identification

Radio frequency identification (RFID) refers to a wireless communication system that is comprised of two elements. These elements are referred to as readers and tags. The reader is a device with one or more transceivers, which transmit and receive radio signals. On the other hand, tags are elements that have certain information embedded into them. They ubiquitously communicate this information to nearby readers. There are two types of tags: i) passive tags that have no batteries, but are powered by the signals transmitted at them and ii) active RFID tags, which contain batteries [27]. However, the return signal of the tag may still cause interference. Simultaneous transmission for multiple tags leads to the collision as the readers and the tags normally use the same channel. Three primary collisions occur. These are reader-to-reader collision, reader-to-tag collision and tag-to-tag collision [28].

### 2.6. Quick Response Code

Quick response code (usually abbreviated as QR code), is a machine-readable two-dimensional barcode [29]. The data enclosed in the QR code enable this feature to function as an identifier, tracker and locator [30]. QR codes are tolerant to dirt and damage and are readable from any angle [31]. Like the other technologies discussed, the designed functions of QR codes have diverse applications, the use of which is featured in functions such as loading a URL, obtaining a phone number, for geolocation purposes, etc. The information obtained from QR codes can be captured in real-time [29, 31]. At the earlier stage of the COVID-19 outbreak, countries like China adopted QR codes as one of the technologies adopted in curbing the spread of the outbreak [32]. The major challenge with this approach is that it required users to use their UEs to actively read the QR code attached at a location or to scan and exchange location-based information with other users. This limited its application because when compared to other technologies - that passively exchange information with users - using QR codes, although effective, might not always be utilized. Additional co-location technologies applied in indoor spaces as positioning systems are acoustic signals [33], infrared and mm-wave radar [34], cellular network [35, 36] and Zigbee [37].

## 3. KEY METRICS IN SELECTING INDOOR CO-LOCATION BASED TECHNOLOGIES

The exponential development of wireless communication technologies has drawn the attention of users to location-based wireless communication services. These services have practical application in areas such as navigation, location identification, and other services to meet positioning demands required by several professionals and infrastructures [9]. While outdoor services of these approaches are crucial, the ongoing COVID-19 outbreak has drawn research attention to TCT systems that would effectively and efficiently curb the spread of an outbreak in indoor scenarios. On this premise, researchers and designers consider several key metrics in selecting wireless communication technologies that would suffice to effectively and efficiently flatten the curve of the outbreak. Discussed below are a few of these metrics.

### 3.1. Accuracy

This key metric generally utilizes functions that track and localize UEs. These functions are observed in two services, namely proximity accuracy and location accuracy. The results obtained from both services are at its core one of the fundamental services that is crucial in TCT. The results obtained from these are crucial in employing other non-pharmaceutical, but supportive processes such as quarantine, social distancing, etc. While various wireless communication solutions are adopted by researchers and designers, it has been observed in literature that TCT systems - which utilize features such as GPS and cell towers - are not efficient in accurately sensing and tracking UEs indoors, as GPS is known to have an accuracy of about 10 m [16] and that of cell towers is extremely low [8]. To address this challenge, technologies such as WiFi, BLE, QR codes, RFID and UWB are largely preferred as indoor technologies to curb the spread of an outbreak. Depending on the design, solutions - built atop these technologies or adopting the services offered by these technologies - are found to have a higher degree of accuracy. Nonetheless, there exist variations in the performance accuracy of these wireless communication technologies. For example, factors such as the complexity of the indoor environment and UE heterogeneity affect the proximity and location accuracy of these technologies differently. The proximity and location accuracy of the selected indoor co-location based technologies are summarized in Table 1.

The information delineated in Table 1, ubiquitously present results that were consistent across several literatures. However, the information garnered in relation to the key metrics considered may still vary, since some works may introduce techniques that increase or decrease the benefit criteria of the metrics considered.

 

Table 1. Comparison of co-location based technologies used for TCT.

| Key metrics | BLE | GPS | WiFi | UWB | RFID | QR Codes |
|---|---|---|---|---|---|---|
| Location sensing | GPS [8]/ BLE Beacons [41] | SMart Integrated localization extension [10] | AP-level [8] | UE [10] | Reader utilizes TDOA [10, 42] | GPS coordinates on data obtained from QR Code [32] |
| Proximity sensing | Bluetooth [8] | - | AP-level [8] | UE [10] | Tag [20] | Device-to-device or device-to-infrastructure [32] |
| Location/ Proximity accuracy | Outdoors (<2m)/ indoors (<2m) [3] | Outdoors (~10m)/ indoors (extremely low) [16] | Outdoors (depending on APs)/ indoors (<1m) [3] | Outdoors (depending on UWB transmitters)/ indoors (<0.5m) [3] | Outdoors (-)/ indoors (~3m) | Outdoors (building level)/ indoors (room/floor level) [3] |
| Data collection | UE [8] | Network [42] | Network [8] | UE | UE | UE |
| Architecture | Client-based [8] | Network-based [43] | Network-based [8] | Client-based | Client-based | Client-based [32] |
| Scalability (Outdoor/ Indoors) | Yes, Yes [16] | Yes, No | Yes, Yes [44] | No, Yes | No, Yes | No, Yes |
| Application cost | Low [14] | Low [7] | Low [14] | - | Low [14] | Low [30, 32] |
| Real-time performance | No [8] | Yes | Yes [43] | Yes [18] | No | Yes [30, 31] |

### 3.2. Application Cost and Scalability

In this review, these two key metrics are considered together, since both are mutually inclusive [9, 14]. In addition, the co-joining of these metrics is motivated by the argument in the work of [38] regarding the degree of readiness of technology-based solutions deployed to address the ongoing pandemic. Branching out from their view, this work discusses these metrics in line with the view discussed in the introduction of this review. As discussed in the introduction, TCT solutions built atop technologies with existing infrastructure such as WiFi APs, cell towers, GPS, etc., would require lower implementation cost than novel interventions, which require new infrastructure for their operations. In essence, the application cost generally varies with the availability of supporting infrastructure. If an outbreak is airborne, a prompt and affordable response is crucial in localizing an infected individual and those who are in potential risk contact. On this premise, implementing novel solutions that require new infrastructures to be adopted en masse usually drives up the application cost [9], which limits implementation in flattening the curve of the outbreak.

### 3.3. Data Collection and Architecture

Earlier roll-outs of the TCT solutions were observed to privilege usage over privacy [39]. In order to tackle this challenge and increase adoption rates of users' involvement in using CT apps, diverse architectures that utilize diverse data collection techniques were adopted. As regards TCT system architecture, solutions were generally considered as either a network-based approach or a client-based approach. In most cases, solutions developed using the network-based approach do not require clients involvement, although client involvement is necessary for the client-based approach [40]. This disparity determined whether the information garnered from either approach could be gathered and handled by a central authority or stored in the user's UE for upload at the user's judgment. Concerning indoor location-based technologies, technologies such as BLE, UWB, RFID, and QR codes are generally technologies that can be utilized as client-centric systems, which store their information of the UE. On the other hand, technologies such as WiFi and GPS are generally adopted as network-centric systems which generally store the data collected by UEs in the network.

### 3.4. Real-Time Performance

This key metric is largely influenced by the factors discussed in subsection 3.3. In addition to the TCT system architecture and data collected, an additional factor considered to the latter is the user's willingness to disclose the data collected. The information garnered from this could be used to map a UE trajectory over a period of time. When an infected user - for example, a user infected with COVID-19 - refuses to disclose information on his or her status, it becomes difficult to utilize the TCT system to map out the individual's trajectory and promptly identify potential risk contacts who may have interacted with the infected user over a period of time.

## 4. WIRELESS FIDELITY AS A TCT TOOL

WiFi is another wireless communication technology that is identified as an effective CT tool [45]. In most uses cases, this solution works with the assumption that universities, corporate offices, and other locations where a high density of individuals tend to spend their day have access to WiFi. On this premise, WiFi based CT could be done from either the device or the network, and in other case they are used to characterize and model the movement of users. In comparison to WiFi, Bluetooth - which has garnered much attention as a CT tool - lacks range (typically 5-10 m) and so it requires a high density of deployed nodes to function effectively. UWB has less noise interference, which makes it a suitable TCT approach for indoor applications [46], although it is not widely available in off-the-shelf UEs. WiFi positioning is particularly attractive due to a large number of WiFi-enabled UEs already in use. A pragmatic approach would be the exploitation of the existing fixed WiFi infrastructure for the purpose of accurate positioning with no hardware modification and without time-consuming manual RF mapping of the positioning space. This would open the way to near ubiquitous indoor positioning at a low cost.

Following the COVID-19 outbreak, various entities have proposed standalone WiFi based TCT approaches or some hybrid TCT approaches that work with WiFi. Table 2 summarizes a number of these approaches.

Table 2. Comparison of WiFi co-location approaches for TCT.

| Reference | Year | Standalone or hybrid approach | Range based positioning technique | Addresses privacy concerns | Passive or active WiFi sensing | Architecture |
|---|---|---|---|---|---|---|
| [6] | 2017 | Standalone | RSSI | Yes | Active sensing | Client-based |
| [7] | 2018 | Hybrid | RSSI | Yes | Active sensing | Client-side |
| [8] | 2020 | Standalone | Time-evolving graphs | Yes | Passive sensing | Network-side |
| [47] | 2020 | Standalone | - | Yes | Passive sensing | Client-side |
| [48] | 2020 | Hybrid | Geodata from positioning service providers | Yes | Active sensing | Client-side |
| [44] | 2020 | Standalone | String-matching operation | Yes | Passive sensing | Network-side |
| [49] | 2021 | Standalone | RSSI | Yes | Passive sensing | Client-side |
| [40] | 2021 | Standalone | Duration of occupancy at an AP | Yes | Passive sensing | Network-side |

The authors in [6] proposed a co-location based technique abbreviated as ENACT. This system uses two approaches: i) the decentralized approach, which gave liberty to infected users to inform others if they were possible contact risks and ii) the extended approach that was proposed to secure the identity of infected users who offered their data for CT purposes. To achieve this, an extended technique varied what the authors termed an "event tag" to prevent malicious users from mapping the entire campus and determining a user's trajectory.

The work of [7] proposed a hybrid solution that utilized BLE and WiFi to obtain data that can be used for CT. The authors termed "the privacy-preserving technique" proposed for CT as efficient privacy-preserving contact tracing for infection detection (EPIC). This applied matching techniques over encrypted content and enhanced its accuracy by using a weight-based matrix that includes data from a large number of short-range wireless communication systems.

The work of [8] proposed a network-side technology-based CT approach that involves passive WiFi sensing and excludes client-side involvement. The proposed approach exploits WiFi network logs gathered by enterprise networks for performance and security monitoring and utilizes them for reconstructing UE trajectories for contact tracing. The range-based positioning technique used a graph-based algorithm affected on time-evolving graphs.

The work of [47] proposed a hotspot duty cycle that enabled a UE that was not actively using its WiFi as either an active hotspot or WiFi receiver. This approach generally worked in scenarios where WiFi APs were unavailable. According to [47], the function does not interfere with the signals from WiFi access points. The approach works by having a UE scan, and stores nearby AP information to perform proximity sensing. The concept of positioning adopted was based on the measured distance from the AP. Although, how the values measured could be used to triangulate a UE was not delineated. In addition, the implementation of this approach was only possible on Android UEs as the application programming interface (API) was not uncovered on iOS UEs.

In the work of [48], the authors proposed a hybrid TCT system that utilized GPS, Bluetooth, cellular network and WiFi to curb the spread of an outbreak. The approach adopted a blockchain-enabled privacy-preserving CT scheme termed BeepTrace. The proposed BeepTrace solution can provide a timely framework for relevant entities to fast develop and deploy effective digital CT applications to curb the spread of the outbreak.

Since privacy is a serious concern using WiFi, the work of [44] proposes a solution that utilizes the data obtained from the WiFi TCT infrastructure in a passive and privacy-preserving manner. The approach dubbed QUEST incorporates computationally and information theoretically-secure protocols to prevent adversaries from gaining knowledge of an individual's location history. It includes support for accurately identifying users who were in the vicinity of a confirmed patient and then informing them via opt-in mechanisms. The authors deployed their technique on a campus-scale data set of over 50 million tuples in order to validate the utility of the technique as a TCT solution.

In [49], the authors proposed a client-side CT approach - which enabled users to utilize the "exposure data collection" app - to obtain information from scanned WiFi APs. A data processing approach and signal similarity metric were used for proximity sensing. Simulation results showed good performance as a TCT app in urban and suburban environments.

The work of [40] proposes a WiFi TCT infrastructure that probed if the location data obtained over WiFi networks could be used to show the spectrum in crowd change when related policies in respect to the COVID-19 outbreak are enacted over time. This infrastructure was implemented on three campuses. The supporting conjecture of the proposed WiFi infrastructure delineated that regardless of the coarse-grain distance sensing capability of WiFi, as long as the public health guidelines are adhered to in indoor spaces, WiFi data could sufficiently suffice in stating UE occupancy in a location. Although, the work discussed the mobility of users and delineated how individuals reacted towards the policies enacted to curb the spread of the outbreak, the method of inferring the user's position was primarily based on the user's duration of occupancy at an AP.

## 5. EXPECTED ROLE OF 5G AND ITS APPLICATIONS WITHIN THE EXPANDING ECOSYSTEM OF TCT

As governments, educational institutions, industries and several sectors of society attempt to return to some form of normalcy in its operation, the alternating spikes and drops of COVID-19 cases and its variant, has continually affected the operations of these sectors [50, 51]. In order for these diverse sectors of society and its people to progress beyond this point, it is imperative for all related entities to properly manage and utilize the full potential of technology-based interventions to not only protect, but also benefit people's lives and improve the economy [50].

Most mobile apps based TCT interventions are developed with the intent to address issues such as localization and proximity accuracy, privacy, UE heterogeneity, limited deployment and in some cases data governance in a post-COVID-19 world. While several literatures have proposed some form of solution to address these needs, it has not necessarily improved the rate of adoption [32, 52].

The cellular network space has had a tested and dependable system, which fills in the need required for a reliable TCT system. Although standardized bodies such as the third generation partnership project (3GPP) has not conducted any work in relation to TCT solutions [52], the 3GPP system architecture for 5G is prime to meet the need for localization and analytics in CT. Though 5G coverage is limited at the moment, it is expected to scale up in subsequent years [53]. Maximizing its potential for localization and its analytics would enable a swift and efficient response to future outbreaks. A compact discussion on its localization and analytics potential are discussed hereunder.

### 5.1. Localization

As delineated earlier on in this literature, localization is crucial in TCT (see subsection 3.1) and considering the impact of this factor in legacy cellular networks, it has been observed that its accuracy is not optimal especially in indoor scenarios [3, 16]. However, the deployment of 5G, especially at millimeter wave (mmWave) frequency largely improves it. At mmWave frequencies, highly directional beams are used for communication between the serving base station and the UE. These provide a highly beamformed gain that overcomes large isotopic path loss, improves link quality and reduces interference [54]. The localization accuracy of 5G deployment at mmWave frequencies falls within the ranging error of 0.61 m, which alongside its localization algorithms highly improves the accuracy of localizing 5G enabled UEs [52].

The 3GPP supports location services via the enhanced location service (eLCS) architecture. This architecture contains two elements that can be leveraged for TCT. These are the location management function (LMF) and the LCS client [52]. The LMF interacts with the access and mobility function (AMF) and entry point in the control plane for radio access networks (RANs). The AMF handles location management in the 5G network [55]. The LMF initiates the localization of UE and exploits the densification of the network brought about as a result of the adoption of mmWave frequencies and massive multiple input multiple output (mMIMO) to further increase positioning accuracy [52].

On the other hand, the LCS client serves as the entity that sends a request to the LCS server, called gateway mobile location center (GMLC) in the 3GPP architecture, in order to access location data of the mobile. The LCS client can be external to the 3GPP architecture or internal. The authors in [52] proposed that the LCS client inside the network provider may have an internal anonymization layer applied to the location data before being shared outwards with any other client/service, which is necessary for CT. 5G has continued to extend the location functionalities. In 5G, location information can be also accessed by an internal or external application function (AF) (which provides application services to the subscriber), or to a control function (CF) internal to the network. These functions can be seen as LCS clients as well [52].

### 5.2. Analytics

3GPP's network data analytics function (NWDAF) is a 5G Core network function (NF) that collects data from other NFs of the 5G core (5GC). NWDAF is network-aware and can interface with various control or data plan NFs to obtain information of interest for analysis [56]. The work of [52] expounded on the potential of NWDAF to utilize the information extracted for CT analytics. In [52], it was delineated that the unified data repository of the NWDAF could be used to store location information of UEs, while the unstructured data storage function could be used to support the storage and retrieval of related CT and mobility data. Although the CT data are unstructured, since it is not currently defined by 3GPP, the full potential of NWDAF, which is beyond the scope of this paper, provides information that aids the TCT procedure [52]. For further reading on NWDAF, readers could refer to [52, 56, 57].

## 6. CHALLENGES OF USING WIFI CO-LOCATION TECHNOLOGIES AS TCT SOLUTIONS

Despite the significant potential of WiFi co-location-based wireless communication technology as a TCT approach, it is not without its challenges when it comes to implementation. Some of these challenges which have largely contributed to the stagnant or dwindling TCT adoption rates are:

### 6.1. Positioning Accuracy

A major challenge using WiFi as a localization system for TCT concerns the position estimates at the granularity of AP location. As delineated in the works of [8, 40], this granularity has been identified as coarse grain. Obtaining precise location from this can be challenging because multiple users can connect to the same APs from separate rooms. Since estimates are primarily based on timestamps of devices connected to an AP, uninfected individuals could receive false risk alerts, which could cause unnecessary panic.

### 6.2. UE Heterogeneity

While the WiFi co-location approach is useful in TCT solution in curbing the spread of the outbreak, it ubiquitously works on the assumption that off-the-shelf UEs are utilized by individuals within indoor environments. However, this is not necessarily the case. According to [58], about 67% of the world's population owns a mobile phone, and according to [3], 56% of these mobile devices are smartphones. The remaining 44%, though wildly distributed in terms of functionality, may be present in indoor environments with WiFi users. Since the volume of the remaining 44% in indoor spaces cannot be ascertained by the WiFi infrastructure, the data obtained from either the network side or the client-side, would have some degree of uncertainty. This limits the application of this approach.

### 6.3. Unconnected UEs

Within closed environments, such as the campuses of tertiary institutions and hotels, most of these environments have their WiFi services inaccessible to user's UEs that are visitors or not residents of the space. Although these users may not be able to connect to the

WiFi network, their devices still remain visible in the WiFi network as unconnected devices. In addition, the media access control (MAC) addresses of the UEs are registered as unconnected UEs. The anonymity created by the unregistered UEs makes precise monitoring challenging [40].

### 6.4. Complexity of Users

The complexity of humans is a factor that is quite difficult to model. This non-deterministic characteristic is bound to introduce some form of error into TCT approaches designed atop the location-based technologies discussed. Considering the WiFi interventions proposed as TCT solutions (most of which ubiquitously use the WiFi data obtained through passive WiFi sensing), it is crucial to consider that not all UEs connected to the WiFi infrastructure would be mobile. For example, a student or staffs who use their laptop to connect to the internet through a WiFi AP may temporarily leave to attend to something else before returning to continue using his or her device. This introduces some uncertainty into the data set obtained. Therefore, this vagueness needed to be taken into account when the WiFi data set obtained is analyzed. This can lead to a false sense of security.

### 6.5. Limited 5G Coverage

TCT solutions built atop wireless communication technologies embedded in IoT devices are pragmatic only if the 5G connections are widespread. Although, a number of network operators are gradually expanding the deployment of 5G, its coverage is still limited [57].

## 7. RECOMMENDATIONS

The ongoing COVID-19 pandemic has enabled humanity to learn so much as regards our level of preparedness in tackling epidemic or pandemic outbreaks. Concerns around the degree of readiness in the implementation of these approaches vary in indoor and outdoor environments. It is necessary to design and establish an infrastructure that is scalable and flexible for use by off-the-shelf UEs. On this premise, this work discusses possible recommendations that can be considered by researchers, designers, and government entities in designing a TCT solution.

### 7.1. Increased Adoption Rate

One of the primary reasons behind the low adoption rate of TCT systems is tied to the privacy and ethical concerns surrounding the usage of the developed systems. To mitigate this concern surrounding the adoption of these systems, it is necessary to develop solutions that require no active user data collection, that is, the private data of the user as privacy is a major concern. To achieve this, it is crucial that government entities and related bodies design and utilize TCT systems that (in a non-intrusive sense) passively sense and obtain data for mapping out user's trajectory when necessary. The work of [8] proposes a network-centric approach that works along these lines, although scaling it to work with other wireless communication technologies or adapting other TCT systems to utilize this approach could scale the TCT system, which in turn increases its effectiveness outside key environments such as the campuses of tertiary institutions, government and private offices and shopping malls.

### 7.2. Optimizing Power and Signaling Overhead

TCT is largely dependent on accurately pinpointing the location of a client. Concerning accuracy, this is widely influenced by performance requirements such as location sensing and proximity sensing. However, the trade-off in obtaining high accuracy indoors influences other performance requirements such as application cost. In addition, more resources like power and signaling are wasted in most cases. It is, therefore, crucial to moderate these performance factors to match the demands of the indoor space where these solutions are implemented. This would likely increase the adoption rate of TCT solutions.

### 7.3. Expediting 5G Deployment

Though there are plethora of technical and non-technical factors that need to be addressed to increase the feasibility of 5G deployments, such as the soon to be industry standard for networks to evolve, optimize and expand; it is crucial that network operators work with adaptive polices that would enable them to meet the need of 5G and beyond networks. To achieve this, network operators could work with entities (e.g., Ericsson) that would enable them meet the standards required for 5G and beyond networks. This in turn would enable network operators to accommodate future demands of massive traffic to massive-connected UEs [57].

## 8. DISCUSSION AND ONGOING RESEARCH WORK

It is expected of 5G and future wireless networks to support exceptional services and UEs which make up the expanding ecosystem of the IoT. Regardless of the UE volume expected to be connected to the network, it has been observed across various generations of wireless networks that early adopters of these technologies have been within developed countries. This information may not necessarily account for the long-playing rate of adoption within developing countries. However, to make up for this lopsided-disparity, it is crucial to create TCT solutions that are built atop existing infrastructures to curb the spread of outbreaks. Based on this reality, our work considers the challenges and recommendation delineated in sections 6 and 7, respectively to develop a WiFi co-location solution that utilizes the existing WiFi infrastructure to track and locate UEs.

As regards positioning, our work considers the signal strength of the standard WiFi infrastructure since it performs better than time-based methods [9], which in terms of application cost is more expensive. It is expected that this approach would minimize the challenge of positioning accuracy. Furthermore, it is also expected that the implementation cost of this approach would be affordable, scalable and flexible for use by off-the-shelf UEs equipped with WiFi.

As identified in subsections 6.3 and 6.4, not all users may be present with their UEs when it is connected to a WiFi AP and in addition, some users may ephemeral. It is necessary to identify users in these categories and consider an acceptable error margin that accounts for this vagueness. To achieve this, our research intends to model this to match different environmental scenarios indoors. This would consider techniques such as weight-based matching score and fuzzy set theory to account for vagueness and expand the flexibility of the approach to account for additional variables. This is in order to design TCT system that utilizes the existing WiFi infrastructure to effectively and efficiently curb the spread of outbreaks.

## 9. CONCLUSIONS

This review does not reject the concept of developed and implemented novel TCT concepts that utilizes novel infrastructure, rather it delineates the need to use existing infrastructures to develop TCT solutions that would enable a prompt and affordable response to mitigating the spread of an outbreak. On this premise, this work discussed the attractiveness of utilizing the existing WiFi infrastructure as an indoor co-location based wireless communication technologies to be adopted as a TCT solution. In this regard, this review discussed state-of-the-art TCT solutions that utilized WiFi. In addition, other wireless communication technologies upon which TCT solutions are designed were discussed considering key metrics such as location sensing, proximity sensing, data collection, architecture, access condition, application cost and real-time performance. Furthermore, this review compactly discussed an ongoing research based on the challenges identified in this review.

## REFERENCES

[1] D. Lewis, "Why indoor spaces are still prime COVID hotspots," *Nature*, vol. 592, no. 7852, pp. 22-25, 2021.

[2] V. Chamola, V. Hassija, V. Gupta, M. Guizani, "A comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, blockchain, and 5G in managing its impact," *IEEE Access*, vol. 8, pp. 90225-90265, 2020.

[3] G. Grekousis, Y. Liu, "Digital contact tracing, community uptake, and proximity awareness technology to fight COVID-19: a systematic review," *Sustainable Cities and Society*, vol. 71, pp. 102995, 2021.

[4] A. Leung, X. Ding, S. Huang, R. Rabbany, "Contact graph epidemic modelling of covid-19 for transmission and intervention strategies," *ArXiv Preprint ArXiv:2010.03081*, 2020.

[5] K. Farrahi, R. Emonet, M. Cebrian, "Epidemic contact tracing via communication traces" *PloS One*, vol. 9, no. 5, pp. e95133, 2014.

[6] A. Prasad, D. Kotz, "ENACT: encounter-based architecture for contact tracing," *In Proceedings of the 4th International on Workshop on Physical Analytics*, pp. 37-42, 2017.

[7] T. Altuwaiyan, M. Hadian, X. Liang, "EPIC: efficient privacy-preserving contact tracing for infection detection," *In 2018 IEEE International Conference on Communications*, pp. 1-6, 2013.

[8] A. Trivedi, C. Zakaria, R. Balan, A. Becker, G. Corey, P. Shenoy, "WiFiTrace: network-based contact tracing for infectious diseases using passive WiFi sensing," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 5, no. 1, pp. 1-26, 2021.

[9] F. Liu, J. Liu, Y. Yin, W. Wang, D. Hu, P. Chen, Q. Niu, "Survey on WiFi-based indoor positioning techniques," *IET Communications*, vol. 14, no. 9, pp. 1372-1383, 2020.

[10] A. Makki, A. Siddig, M. Saad, C. Bleakley, "Survey of WiFi positioning using time-based techniques," *Computer Networks*, vol. 88, pp. 218-233, 2015.

[11] F. Evennou, F. Marx, "Advanced integration of WiFi and inertial navigation systems for indoor mobile positioning," *Eurasip Journal on Applied Signal Processing*, vol. 2006, pp. 1-11, 2006.

[12] P. Singh, R. Singh, S. Nandi, K. Ghafoor, S. Nandi, "Seamless v2i communication in hetnet: state-of-the-art and future research directions," *In Connected Vehicles in the Internet of Things,* pp. 37-83, 2020.

[13] Wi-Fi Alliance, *Wi-Fi Certified 6*, 2018. <https://www.wi-fi.org/discover-wi-fi/wi-fi-certified-6>

[14] N. Pirzada, M. Nayan, F. Subhan, M. Hassan, M. Khan, "Comparative analysis of active and passive indoor localization systems," *AASRI Procedia*, vol. 5, pp. 92-97, 2013.

[15] G. Deak, K. Curran, J. Condell, "A survey of active and passive indoor localisation systems," *Computer Communications*, vol. 35, no. 16, pp. 1939-1954, 2012.

[16] J. Bay, J. Kek, A. Tan, C. Hau, L. Yongquan, J. Tan, T. Quy, "BlueTrace: a privacy-preserving protocol for community-driven contact tracing across borders," *Government Technology Agency-Singapore, Tech. Rep*, vol. 18, 2020.

[17] A. Trivedi, D. Vasisht, "Digital contact tracing: technologies, shortcomings, and the path forward," *ACM SIGCOMM Computer Communication Review*, vol. 50, no. 4, pp. 75-81, 2020.

[18] S. Mark, "What is ultra-wideband, and how it work?" *Insights*, 2018. <https://insights.samsung.com/2021/08/25/what-is-ultra-wideband-and-how-does-it-work-3>

[19] M. Aftanas, J. Rovnakova, M. Drutarovsky, D. Kocur, "Efficient method of TOA estimation for through wall imaging by UWB radar," *IEEE International Conference on Ultra-Wideband,* vol. 2, pp. 101-104, 2008.

[20] R. Dagher, F. Molina, A. Abadie, N. Mitton, F. Baccelli, "An open experimental platform for ranging, proximity and contact event tracking using ultra-wide-band and bluetooth low-energy," *In CNERT 2021-IEEE INFOCOM Workshop on Computer and Networking Experimental Research using Testbeds*, pp. 1-6, 2021.

[21] M. Cunche, A. Boutet, C. Castelluccia, C. Lauradoux, V. Roca, *On Using Bluetooth-Low-Energy for Contact Tracing*, Doctoral Dissertation, Inria Grenoble Rhône-Alpes, INSA de Lyon, 2020.

[22] X. Fafoutis, E. Tsimbalo, W. Zhao, H. Chen, E. Mellios, W. Harwin, R. Piechocki, I. Craddock, "BLE or IEEE 802.15. 4: which home IoT communication solution is more energy-efficient?" *EAI Endorsed Transactions on Internet of Things*, vol. 2, no. 5, pp. 1-8, 2016.

[23] M. Gorlatova, A. Wallwater, G. Zussman, "Networking low-power energy harvesting devices: measurements and algorithms," *IEEE International Conference on Computer Communications,* pp. 1602–1610, 2011.

[24] M. Gorlatova, J. Sarik, G. Grebla, M. Cong, I. Kymissis, G. Zussman, "Movers and shakers: kinetic energy harvesting for the internet of things," *ACM International Conference on Measurement and Modeling of Computer Systems,* pp. 407–419, 2014.

[25] W. Seah, Z. Eu, H. Tan, "Wireless sensor networks powered by ambient energy harvesting (WSN-HEAP) - survey and challenges," *2009 1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace and Electronic Systems Technology*, pp. 1–5, 2009.

[26] X. Fafoutis, A. Di Mauro, C. Orfanidis, N. Dragoni, "Energy-efficient medium access control for energy harvesting communications," *IEEE Transaction On Consumer Electronics,* vol. 61, no. 4, pp. 402–410, 2015.

[27] *Radio Frequency Identification (RFID)*, 2018. <https://www.fda.gov/radiation-emitting-products/electromagnetic-compatibility-emc/radio-frequency-identification-rfid>

[28] F. Nawaz, V. Jeoti, "NFRA-C, neighbor friendly reader to reader anti-collision protocol with counters for dense reader environments," *Journal of Network and Computer Applications*, vol. 49, pp. 60-67, 2015.

[29] *History of QR Code*, 2012. <www.qrcode.com/en/history/>

[30] *QR code*, 2021. <http://www.wikipedia.com/wiki/QR_code>

[31] T. Ramdav, N. Harinarain, "The use and benefits of quick response codes for construction materials in South Africa," *Acta Structilia*, vol. 25, no. 2, pp. 94-114, 2018.

[32] M. Shahroz, F. Ahmad, M. Younis, N. Ahmad, M. Boulos, R. Vinuesa, J. Qadir, "COVID-19 digital contact tracing applications and techniques: a review post initial deployments," *Transportation Engineering*, pp. 100072, 2021.

[33] Y. Luo, C. Zhang, Y. Zhang, C. Zuo, D. Xuan, Z. Lin, A. Champion, N. Shroff, "Acoustic-turf: Acoustic-based privacy-preserving covid-19 contact tracing," *arXiv preprint arXiv:2006.13362*, 2020.

[34] M. Canil, J. Pegoraro, M. Rossi, "MilliTRACE-IR: contact tracing and temperature screening via mm-wave and infrared sensing," *arXiv preprint arXiv:2110.03979*, 2021.

[35] A. Alsaeedy, E. Chong, "Detecting regions at risk for spreading covid-19 using existing cellular wireless network functionalities," *IEEE Open Journal of Engineering in Medicine and Biology*, vol. 1, pp. 187-189, 2020.

[36] N. Ayan, N. Damasceno, S. Chaskar, P. de Sousa, A. Ramesh, A. Seetharam, A. Antonio, "Characterizing human mobility patterns during covid-19 using cellular network data," *IEEE 46th Conference on Local Computer Networks,* pp. 471-478, 2021.

[37] S. Bartoletti, A. Conti, M. Win, "Device-free counting via wideband signals," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 5, pp. 1163–1174, 2017.

[38] J. Hoepman, "Hansel and gretel and the virus: privacy conscious contact tracing," *arXiv preprint arXiv:2101.03241*, 2021.

[39] S. Banerjee, B. Raman, S. Sharma, "Apps for COVID: to do or not to do," *Indian Institute of Technology Delhi,* pp. 1-3, 2020.

[40] C. Zakaria, A. Trivedi, E. Cecchet, M. Chee, P. Shenoy, R. Balan, "Analyzing the impact of covid-19 control policies on campus occupancy and mobility via passive wifi sensing," *arXiv preprint arXiv:2005.12050*, 2021.

[41] P. Tedeschi, S. Bakiras, R. Di Pietro, "Iotrace: a flexible, efficient, and privacy-preserving IoT-enabled architecture for contact tracing," *arXiv preprint arXiv:2007.11928*, 2020.

[42] Y. Zhang, M. Amin, S. Kaushik, "Localization and tracking of passive RFID tags based on direction estimation," *International Journal of Antennas and Propagation*, vol. 2007, pp. 1-10, 2007.

[43] F. Cicala, W. Wang, T. Wang, N. Li, E. Bertino, F. Liang, Y. Yang, "PURE: a framework for analyzing proximity-based contact tracing protocols," *arXiv preprint arXiv:2012.09520*, 2020.

[44] P. Gupta, S. Mehrotra, N. Panwar, S. Sharma, N. Venkatasubramanian, G. Wang, "Quest: practical and oblivious mitigation strategies for COVID-19 using WiFi datasets," *arXiv preprint arXiv:2005.02510,* 2020.

[45] M. Jhanwar, S. Sarkar, "PHyCT: privacy preserving hybrid contact tracing," *IACR Cryptology ePrint Arch*ive, pp. 1-10, 2020.

[46] V. Jahmunah, V. Sudarshan, S. Oh, R. Gururajan, R. Gururajan, X. Zhou, X. Tao, O. Faust, E. Ciaccio, K. Ng, U. Acharya, "Future IoT tools for COVID-19 contact tracing and prediction: a review of the state-of-the-science," *International Journal of Imaging Systems and Technology*, vol. 31, no. 2, pp. 455-471, 2021.

[47] M. Dmitrienko, A. Singh, P. Erichsen, R. Raskar, "Proximity inference with Wifi-colocation during the COVID-19 pandemic," *arXiv preprint arXiv:2009.12699*, 2020.

[48] H. Xu, L. Zhang, O. Onireti, Y. Fang, W. Buchanan, M. Imran, "Beeptrace: blockchain-enabled privacy-preserving contact tracing for covid-19 pandemic and beyond," *IEEE Internet of Things Journal*, vol. 8, no. 5, pp. 3915-3929, 2020.

[49] G. Li, S. Hu, S. Zhong, W. Tsui, S. Chan, "VContact: private WiFi-based IoT contact tracing with virus lifespan," *IEEE Internet of Things Journal,* 2021.

[50] Y. Siriwardhana, C. De Alwis, G. Gür, M. Ylianttila, M. Liyanage, "The fight against the COVID-19 pandemic with 5G technologies," *IEEE Engineering Management Review*, vol. 48, no. 3, pp. 72-84, 2020.

[51] G. James, "Covid: Omicron study suggests major wave in January," *BBC News,* 2021. <https://www.bbc.com/news/uk-59621029>

[52] D. Giustiniano, G. Bianchi, A. Conti, S. Bartoletti, N. Melazzi, "5G and beyond for contact tracing," *IEEE Communications Magazine*, vol. 59, no. 9, pp. 36-41, 2021.

[53] U. Cisco, "Cisco annual internet report (2018–2023)," White Paper, 2020. <https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.html>

[54] M. Agiwal, N. Saxena, A. Roy, "Mobile assisted directional paging for 5G communications," *Transactions on Emerging Telecommunications Technologies*, vol. 29, no. 2, pp. 1–23, 2018.

[55] 3GPP, "TS 123 501 - V15.3.0 - 5G; System Architecture for the 5G System," *3GPP TS 23.501 Version 15.3.0 Release 15*, 2018. < https://portal.etsi.org/TB/ETSIDeliverableStatus.aspx>

[56] Network Data Analytics Function (Built for 5G Data Insights 5G OPC 2.0), 2021. <https://www.amdocs.com/sites/default/files/202106/Openet%20NWDAF%20Data%20Sheet.pdf>

[57] Networks That Learn and Improve, *Ericsson*, 2021. <https://www.ericsson.com/en/core-network/5g-core/network-data-analytics-function>

[58] M. Rahman, R. Khan, M. Khandaker, M. Sellathurai, M. Salan, "An automated contact tracing approach for controlling COVID-19 spread based on geolocation data from mobile cellular networks," *IEEE Access*, vol. *8*, pp. 213554-213565, 2020.