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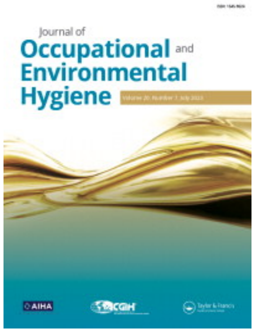

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Evaluating the Performance of Wearable Devices for Contact Tracing in Care Home Environments

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ABSTRACT

COVID-19 has had a devastating impact worldwide, including in care homes where there have been substantial numbers of cases among a very vulnerable population. A key mechanism for managing exposure to the virus and targeting interventions is contact tracing. Unfortunately, environments such as care homes which were most catastrophically impacted by COVID-19 are also those least amenable to traditional contact tracing. A promising alternative to recall and smartphone-based contact tracing approaches is the use of discrete wearable devices that exploit Bluetooth Low Energy (BLE) and Long-Range Wide Area Network (LoRaWAN) technologies. However, the real-world performance of these devices in the context of contact tracing is uncertain. A series of experiments were conducted to evaluate the performance of a wearables system which is based on BLE and LoRaWAN technologies. In each experiment, the number of successful contacts was recorded and the physical distance between two contacts was compared to a calculated distance using the Received Signal Strength Indication (RSSI) to determine the precision, error rate and duration of proximity. The overall average system contact detection success rate was measured as 75.5%; when wearables were used as per the manufacturer's guidelines the contact detection success rate increased to 81.5%, but when obstructed by everyday objects such as clothing or inside a bag the contact detection success rate was only 64.2%. The calculated distance using RSSI was close to the physical distance in absence of obstacles. However, in the presence of typical obstacles found in care home settings, reliability of detection decreased, and the calculated distance usually appeared far from the actual contact point. The results suggest that under real-world conditions there may be a large proportion of contacts that are underestimated or undetected.

Keywords: Bluetooth, COVID-19, digital devices, LoRaWAN, sensors, wearables

INTRODUCTION

Up to half of all COVID-19 deaths in many countries have occurred in residential care homes (Farrell 2020). Cases in care homes result from both resident-to-resident transmission as well as transmission from staff to residents. Many care homes experienced significant restrictions to control transmission including periods with no visitors and extremely limited social interactions (GOV.UK 2021). This had a substantial negative impact on the wider health and wellbeing of care home residents (Cahill and Diaz-Ponce 2011; Valtorta et al. 2016; Chu et al. 2020; Bethell et al. 2021).

Contact tracing is a key infection prevention and control (IPC) measure enabling identification and isolation or testing of potentially infected cases. Contact tracing offers a possible means of targeted IPC approaches that pose fewer restrictions on other staff and residents. However, traditional contact tracing involves individuals recalling from memory their contact(s) with potentially infected people - when and where they happened, and the length of exposure. Up to 70 percent of care home residents have some form of memory or cognitive deficit (Gruber-Baldini et al. 2000), staff have many contacts on each shift, and such contact is unavoidable as it is a key mechanism for providing quality care (Haunch et al. 2021). Reliably recalling information on the number and duration of contacts is therefore difficult for both residents and staff.

Digital contact tracing can be an effective way to collect data on close contacts, location, mobility of people and their health status. The study by Grekousis and Liu 2021 provided a review of the use of digital devices to interrupt the chain of infection and suggested such devices can overcome manual contact tracing regardless of technology limitations and trade-offs between privacy and effectiveness. Contact tracing using smartphone apps that exploit Bluetooth Low Energy (BLE) technology has been the subject of considerable interest during the pandemic

(Parker et al. 2020; Jalabneh et al. 2021; Madoery et al. 2021), and includes analysis to estimate COVID-19 risks from BLE contact data sets (Aljohani et al. 2021). The smartphone approach can effectively record contacts with other app users and has been shown to be workable in the wider community. However, it has limited utility for care homes as residents rarely use phones and staff are often discouraged from using phones at work. Wearable BLE devices are a potentially low-cost means of digital contact tracing (Rawat et al. 2020). They consume little energy, exchange minimal data efficiently, are lightweight, small and can be worn in a variety of forms. Wearable fobs and other stand-alone devices have been suggested as being potentially beneficial for collecting data or getting alerts for older people or other vulnerable groups (Wilmink et al. 2020).

This study is part of the CONTACT trial, a UK National Institute for Health Research (NIHR) funded study in care homes evaluating the feasibility of BLE-enabled wearables for contact tracing and informed IPC decision making; to the best of the authors' knowledge this is the first application of wearable Internet of Things (IoT) devices for contact tracing in care homes. The overall purpose of the CONTACT trial is to understand how, based on device-enabled information, care home managers can employ infection prevention and control measures, including restrictive measures such as isolation and quarantining specific residents and staff. These restrictions in care homes mean that it is vital that BLE wearable devices are accurate and reliable to avoid imposing unnecessary constraints.

The CONTACT trial's wearables are intended to capture and store data when individuals wearing the devices are within 2 m of each other for 15mins or more. This threshold is in line with WHO Guidance for the highest risk exposures for Covid-19 (WHO 2022). However, it is important to understand whether this contact threshold can be measured effectively by the wearable devices. This study reports the performance of wearable devices during a series of controlled experiments and simulations of differing building layouts, materials, and usage that are representative of likely situations in care homes. The main contributions of this study are as follows:

- Evaluation of system performance: The study provides a comprehensive evaluation of the performance of the wearable system in different scenarios, quantifying its reliability and accuracy.
- Identification of contact detection success rates: The study measures the overall average system contact detection success rate and highlights the impact of following the manufacturer's guidelines on increasing the success rate.
- Understanding the impact of obstructions: The study explores the effect of everyday obstructions, such as clothing or bags, on the accuracy of the system, emphasizing the need to minimize obstructions for accurate contact tracing.
- Comparison of device types: The study finds that different forms of BLE devices (watch, fob, card) have similar accuracy, suggesting that different types can be used effectively for contact tracing.

These contributions provide valuable insights into the performance, limitations, and factors affecting the accuracy of wearable BLE-based solutions for contact tracing in care home environments, aiding in the development and implementation of effective contact tracing strategies.

BLE AND LoRaWAN TECHNOLOGY FOR CONTACT TRACING

BLE devices are self-contained battery powered devices that work by "advertising" themselves to contacts in the vicinity. BLE devices broadcast a periodic message containing data including the date and timestamped transmitted signal power at the antenna, which allows the receiver to detect and estimate the power level of the advertising device. The receiver estimates theReceived Signal Strength Indication (RSSI)measured in decibels of received power relative to a milliwatt (dBm). RSSI can therefore be used as a proxy to estimate the physical distance between BLE devices.

The LoRaWAN (Lee et al. 2019) is a low-power and wide area networking protocol which functions using the LoRa, a sub-gigahertz radio frequency network. LoRaWAN is designed to wirelessly connect battery operated devices to the internet, and also to manage communication between local devices and network gateways involved in the process. In the CONTACT trial, LoRaWAN hubs are used to provide a local network for recording and transmitting contact data between BLE wearables. LoRaWAN devices are low energy and can run for ten years on a small battery (Rawat et al. 2020; Flueratoru et al. 2022).

A number of studies have studies the network architecture for contact tracing systems. Ng et al. (2021) proposed a Smart Contact Tracing (SCT) system for contact tracing using RSSI values for proximity sensing in close contacts and showed promising results in a restricted environment. Cunche et al. (2020) discussed the implementation model of BLE and other technical aspects on different smartphone operating systems. An evaluation framework based on mobile contact tracing solutions is proposed by Dar et al. (2020) to speed up the process of manual tracing. They conclude that the proposed solutions are not appropriate for all general scenarios and recommend open source solutions to avoid security issues. Solutions using fobs/wearables are suggested to be suitable for the organizations or environments where privacy is a priority (Barthe et al. 2022; Flueratoru et al. 2022) with location beacons alongside wearables to identify areas for contact tracing.

Accuracy and reliability in digital contact tracing is important and needs to consider the epidemiological sense of sensitivity [probability of recording a contact when there really has been one] and specificity [probability of ruling out no contact when there really has not been one]. Many factors can influence the accuracy of BLE devices. Other devices using the same frequency (Wi-Fi, mobile phones, wireless technology such as speakers or baby monitors) can interfere with signals. Different building materials, furniture, and objects within the environment can affect signal strength, as can humans that block direct line-of-sight propagation (shadowing). Antenna patterns when BLE devices scan can be anisotropic, with large variations in gain from differing angles and polarization (Schulten et al. 2019). Propagation indoors is vulnerable to multipath (Rayleigh) fading from nearby reflections. These factors make an evaluation of the accuracy and reliability of the CONTACT trial's BLE wearables necessary.

System Architecture and Data Flows

The CONTACT trial and the experiments conducted in this study used a combined BLE - LoRaWAN gateway system from MICROSHARE (Microshare Ltd, London). The system comprised of the following components (See Figure 1):

LoRaWAN Gateway

Comprises a Kerlink iFemtocell Evolution, which receives radio transmissions from wave scanner devices and an integrated cellular/mobile connection that sends encrypted data to cloud servers.

Wave scanner devices

Local hubs that collect contact data from BLE devices, reset the memory and clock of the devices, and transmit data to the LoRaWAN gateway.

Location Marker

Small, fixed position BLE devices placed in a designated area.

Wearable BLE Devices

Designed as a card or fob to be worn on a lanyard, or fob on a key ring or wristband, which were assigned to residents, staff, and visitors.

When a fixed or wearable BLE device senses another device within range, the duration and the signal strength are both recorded. During the CONTACT trial, the BLE system was set such that when contact was <2 m and for a duration of more than 15min, a "proximity event" was recorded. The duration and proximity information was captured by the Wave scanner devices and uploaded to a central cloud server-hosted database by the Gateway where data was then downloaded for analysis (see Figure 1). In the experiments carried out in this paper, contacts at greater distances were also recorded to test the accuracy of the BLE devices.

METHODS

Test Scenarios

To assess the accuracy of the devices, a series of 200 experiments over 13 scenarios were conducted under controlled conditions. In all cases, the contact duration and/or distance as calculated from the BLE device using the RSSI were compared with the measured physical distance. All the experiments were carried out in a domestic environment, simulating typical scenarios from care homes (see Table 1). Experiments were set up by positioning one or more devices and a location marker at known locations, and then recording the presence or absence of contact between the device and location marker (or between two or more devices) as well as the signal strength. Experiments initially considered measurement of distance via devices at fixed locations (Cases 1 and 2 in Table 1), followed by several proximity event scenarios that incorporated mobility by recording the contact detection during a pre-defined sequence of locations. The specific set up for each case is detailed with the results.

All proximity events were recorded by the BLE wearable devices and then data were sent to the data server via the wave scanner device. The recorded data includes a number of parameters including RSSI value, contact time, duration of a contact, battery level, and the unique QR code of the BLE device. The experiments in Case 1 were carried out with a range of different BLE devices: a fob mounted on a wrist bracelet, a fob on a key-chain, and a card that can be worn on a lanyard. Bracelet-mounted fobs are easier to wear and change the battery and are easily visible to staff. Lanyards are commonly used by staff, and the card form BLE battery lasts at least twice as long (but is harder to change) and is easier to clean. All wearable forms use the same technology but device orientation and likely location relative to clothing and body shape can affect signal strength. All other experiments were carried out using the key-chain fob device.

Several experiments considered the influence of obstacles. In the real-world conditions of the CONTACT trial, it was apparent that residents with cognitive impairments such as dementia were prone to removing devices and placing them into containers such as drawers, baskets, or tissue boxes. Some devices were also relegated to a handbag or pocket or wrapped in a handkerchief or scarf. Any material that comes between two fobs/cards with potential for signal absorption constitutes an obstacle. To understand the effects of these obstacles on signal propagation, performance using various items as experimental absorbers was evaluated. The experimental absorbers included placing one or more BLE devices under a scarf, inside a bag, or inside a tissue box.

Distance Computation

The strength of a device's Bluetooth signal power (RSSI) is recorded by the receiving device during a contact event. Devices detected each other when the RSSI was higher than -70dB (1m distance). To log an event, each device should detect each other four times or more in a window of seven scans, which required a minimum time of 160s to complete the process. In the experiments, the physical distance between devices was measured before recording proximity events. The calculated distance based on the RSSI value was computed using the following formula (Qureshi et al. 2019):

$$Distance = 10\text{^}\{\frac{P-RSSI}{10*N}\} \quad (1)$$

Where:

N = Power profile

RSSI = Received Signal Strength Indicator

P= Measured power, the expected RSSI at 1m to the beacon

The power profile 'N' decays with distance. Normally, the N=2 (i.e. in free space), but varies from 2 to 4 (low to high), depending on the environmental factors. In the considered scenarios, the objective was to detect proximity events within a range of 2m with limited obstructions, which is therefore considered a normal value. Measured Power is usually set by the manufacturer, which indicated the expected RSSI at 1m to the beacon (a value of -69). When combined with the RSSI, the distance between the device and the beacon can be estimated. For each scenario the "contact detection success rate" is defined as the successful recording of a contact event and "contact detection failure rate" as the absence of any record of an event despite an actual occurrence of the event.

RESULTS

Table 1 highlights the contact detection success rate for each group of experiments in terms of whether the scenario was recorded as a contact or not. The total number of experiments were 200; 130 were conducted without any obstruction, while 70 were conducted in presence of one or more obstacles. Overall, *75.5%* of events were successfully recorded (among them 53% and 22.5% were without and with obstruction, respectively). The contact detection success rate of standalone experiments in the absence of an obstacle was recorded as *81.5%*, while the average contact detection success rate was *64.2%* in the presence of obstacles. A higher error rate was also observed in the presence of obstacles as discussed below.

Evaluation of distance between fixed devices

Figures 2 and 3 compare the calculated distance with physical distance for two devices at fixed distances from *0.5* to *2.5m*. Case 1 (Figure 2) has no obstructions between devices, while

Case 2 (Figure 3) considers BLE fobs and cards placed in drawers, bags, beneath a scarf, mixed with clothing in a laundry basket or inside a tissue box. All other parameters - environment, objects present in the room - were held constant.

Results indicate that the signal strength in the card form was stronger and more reliable than the other two wearable forms. This is likely due to the card orientation, when worn on a lanyard, having a more reliable orientation between devices. Differences in signal strength between all three types of devices were not high, but the key-chain fob tended toward more false negatives where the calculated distance was greater than measured physical distance. Experiments with obstacles indicate that each type of material can disrupt the Bluetooth signal differently. There was a poor signal quality when devices were placed inside a polyester bag, hidden under a scarf (cotton), or placed in a tissue box. In these cases, the calculated distance appeared greater than the physical distance, whichcan lead to a false negative indication of a contact. This can be significant, particularly for contacts at greater distances. As shown in Figure 3, some of the contacts at a physical distance 2.5m were estimated as far away as 10m when obstructed. There was no significant difference in signal strength if devices were placed in an open basket or box or worn as instructed.

Single Proximity Events between Devices

The first two proximity scenarios tested are presented in Figure 4. Case 3A (Figure 4(a)) represents a single contact event between two people recorded at location marker, L_1, installed in a kitchen. People carrying BLE fobs X_1 and X_2, stayed at marked points 2m apart for *15min,* after which X_2 was sent to another room (study) where the wave scanner was installed to collect and synchronize fobs when in contact. The study was on a different floor of the building and was considered to be of sufficient distance as to not be regarded as a proximity event. The experiment was repeated five times with a successful contact recorded on three occasions, and the calculated distances were close to the physical distance, indicating accuracy of the system when events were recorded.

Case 3B considered a sequential proximity event with three BLE fobs i.e*.,* X_1, X_2, X_3 and two Location markers L_1 and L_2 (see Figure S1 in supplementary information). L_1 was installed inside the kitchen, and L_2 is placed in the living room, both on the ground floor. X_1 and X_2 were positioned 1m apart in the kitchen; the distances of X_1 and X_2 to L_1 were *2.5m* and *1.5m,* respectively. After *20min*, X_2 was moved to the living room, where X_3 was already present at a distance of *1.5m*. After *30min*, X_2 moved to the study to download data via the wave scanner. The experiment was repeated five times, but the logged data was received only four times. The results again showed that in most contacts there was no significant difference between real physical and calculated distance. However, X_1 and L_1 were calculated to be *2.5m* apart, when they were *2m* from each other; in this case, the contact would be missed if the proximity for detection is set at 2m.

Cases 4A and 4B included outdoor proximity events to test whether distances recorded remained accurate in a setting without the influence of walls and furnishing on the Bluetooth signal. Case 4A followed the same sequence as 3B, however X_3 was located outdoors in a park, and the outdoor contact between X_2 and X_3 was at *0.5m* for *15min.* In Case 4B, the sequence involved X_2 and X_3 in the park, followed by X_2 and X_1 in the kitchen, and then a second contact between X_2 and X_3 in the study. Full details of both scenarios are given in the supplementary information (Figures S2 and S3). Both cases were repeated five times with contact detection success rates of 4/5 and 3/5 for cases 4A and 4B respectively. In Case 4B for the remaining two attempts, X_3 activity was recorded only one time, and no activity was recorded for all tags in the final attempt. Where events were successfully recorded (see figure S4 in supplementary information), the average computed proximity was a good representation of the real distance for both cases. However, it is noticeable that there was a much greater range of predicted values for the scenarios involving outdoor events compared to all the other results from this study.

Proximity Events for Complex Scenarios with Mobility

In Case 5A, multiple proximity events were recorded at four separate places within a home (see Figure S5 (a) in the supplementary information). This scenario was designed to replicate a care worker who may visit several residents in a care home sequentially. Six fobs (X_1 to X_6) and a location marker L_1 (installed in the kitchen) were used. X_1 and X_2 were first located *2.5m* and *1.5m* to L_1, respectively and had contact for *15min*. X_2 then had contact with X_3 for another *15min* in the living room at *1.5m*. Then X_2 sequentially visited two bedrooms and the study where it contacted X_4, X_5 and X_6, espectively, each for *15min*. Five replications of this experiment were carried out. As shown in Figure 5, the calculated and physical distance are again similar. In a few cases, the calculated distance appeared closer than the physical value. As an example, the *2.5m* distance between X_1 and L_1 was calculated as *~2m* which may indicate that the device would log a false positive event.

Multiple proximity events at a single location in which the distance between each contact person was not the same were measured in Case 5B. The scenario (see Figure S5 (b) in the supplementary information) used seven fobs separated by distances between *1.29m* and *2.84m* with a single location marker. Each fob was present for *15min* at the location. The experiment was repeated five times and successfully recorded all activities, with similar findings to previous experiments regarding accuracy of the measurement (see Figure S6 in the supplementary information).

Results from multiple proximity experiments suggest that accuracy and success in detecting a contact are independent of the number of sequential contacts recorded and are comparable between BLE fobs.

False Positive/Negative Proximity Events with Obstacle

The final set of experiments considered proximity events with the presence of an obstacle. Cases 6A to 6C were single *20min* proximity events between L_1, X_1 and X_2 in the same room. X_2 was placed inside a handbag in Case 6A while it was located under a scarf in Cases 6B and 6C. In Case 6C fob X_1 was also located under a scarf, while it was uncovered in the other two cases. Case 6D considers proximity events between L_1 and fobs X_1 and X_2 with both an open and closed door to observe the impact on signal propagation. L_1 was installed in the kitchen and X_2 was positioned in the living room. X_1 was in the corridor between the kitchen and living room for *20min* located *3m* away from L_1 and 1m from X_2. Diagrams showing each scenario in Case 6 are given in the supplementary information (Figures S7 -S10).

Figure 6 shows that the accuracy is substantially lower in the three cases with obstacles, with the calculated distance significantly greater than the physical distance. This concurs with the trend shown in the static measurements in Figure 3. It is also noticeable that there was a greater discrepancy in the measurements between the two fobs (X_1 and X_2) compared to the measurement to the location marker, L_1. As with the outdoor data, these events show much greater variability in the signal strength, which led to a greater variance in the calculated distance. Obstacles also affected the detection characteristics; in Case 6A, the event duration was 20mins, however it was only recorded as 15min by the devices.

In Case 6D (see Figure S11 in supplementary information), contacts were successfully recorded for 5/5 events with the doors closed but only 4/5 events when doors were opened. The signal propagation was good with an open door and the calculated distance is close to the physical distance, although it was overestimated. However, the data would suggest that X_1 and X_2 had contact, but in fact, both were in the different rooms. In this scenario, a false proximity event is reported. With the door closed, the devices appear a little farther from the physical distance, but a false event is still recorded between X_1 and X_2 at $2m$ distance. This highlights that some recorded activities were not true due to signal propagation through walls and obstacles.

DISCUSSION

This study involved approximately 200 experiments to observe the deployed BLE wearable system behaviour in terms of contact event detection, accuracy of measurement, and to evaluate the successful data flow through the dedicated network and collected data from cloud servers. The experiments included static fobs, single proximity events, multiple proximity events and measurements in indoor spaces, outdoor spaces and with the presence of obstacles.

Overall, the majority of contacts were recorded during the experiments with over 90% contact detection success rate when the devices are indoors and not obstructed. However, obstructions can reduce the successful detection of contacts substantially. As highlighted in Table 1, the contact detection success rate dropped to as low as 60% for scenarios with an outdoor contact and in some cases as low as 50% for scenarios where fobs were hidden by everyday obstacles.

Exploration of accuracy indicates that recording of contacts based on a threshold value may also have led to false negative or positive contacts. It was observed that the calculated distance using signal strength was usually close to the physical distance, but there were occasions where the system under or overestimated the distance, which may lead to false positive or negative contacts being recorded. This is particularly the case in the presence of obstacles where the calculated distance appears greater than the physical distance, and this difference can be substantial. For example, the physical distance between X_1 and X_2 in scenario presented in Figure 6 Case A was only 1m however the calculated distance based on signal strength was *2.7m*, which would be recorded as false negative contact - the contact happened but the event would not have been recorded because of a false distance estimation. The results overall show that the presence of obstacles weakens the signal propagation which affects both the calculated distance as well as the overall system performance.

The experiments reported here are designed to replicate scenarios that are found in typical care home environments in terms of the type of setting (domestic), the objects used as obstacles, and the distance and duration of contacts. The experimental results therefore give an insight into the relative factors that influence the reliability and accuracy of the system, and include scenarios to represent multiple contacts that would be seen in a real care home environment.

LIMITATIONS

The experiments carried out in the study were idealised with controlled placement of devices and without the complex behavioural factors that are present in a real-world scenario. Therefore it is important to consider the limitations of the work. These include:

- *Sample size and duration of contacts:* The study was conducted on a relatively small sample size of using a maximum of seven BLE devices at any one time. The experiments were also conducted for a limited duration of 15-20 mins, which may not have captured the full range of interactions and contacts that occur in care home environments. In a care home setting, there would likely be many more devices deployed and therefore further study would be needed to assess the performance of the system with many contacts happening in some cases simultaneously.

- *Detection of mobile contacts:* The study focused on static contacts and contacts where mobility happened between specific locations with at least 2 min duration between the movement of a device. Detection of continuously moving contacts was not considered in the experiments. The contact detection mechanism of the system required at a duration of least 160s to detect a contact. Therefore, high mobility case scenarios may be challenging to detect with good accuracy, particularly where devices come into close proximity for very short periods of time.
- *Application to real-world environments:* The experiments were conducted in a domestic environment which is representative of the physical setting of a care home and considered some of the typical behaviours that may obstruct or result in inaccurate contacts. However all of the measurements were made under controlled conditions which may therefore not fully reflect both the real-world physical conditions and behaviours with BLE devices in care homes. Further study, particularly to understand how people use BLE devices in real-world settings, would be valuable to compare to the controlled measurements reported here.
- *Application to other devices and settings:* This study only evaluated a limited range of BLE-based devices from one supplier, which may not represent the full range of devices available in the market. The study only focused on evaluating the performance of the wearable system for contact tracing and did not explore other potential applications of the technology in care homes or other settings.

It is likely that these real-world complexities may challenge the accuracy and reliability of devices further than was measured here, and the results presented in this study may represent a best case scenario for contact detection. Further data to evaluate the contact detection success rate and reliability of BLE devices in a real-world setting would be valuable, however it is likely to be challenging to effectively collect data on large numbers of real contacts and physical distances to compare to the calculated data from the devices.

CONCLUSIONS

Contact tracing is a proven method of mitigating the spread of infectious diseases, and digital technologies could help to ease this process. This study evaluated the performance of a wearable BLE based solution combined with LoRaWAN technology, using experiments in a range of different scenarios to quantify the reliability and accuracy of the system. The results show that the system performance depends on the environment, with the following key conclusions drawn:

- The overall average system's contact detection success rate was measured as *75.5%*. When wearables were used as per the guidelines the rate increased to *81.5%*., but when obstructed the rate was only *64.2%*.
- The difference in accuracy between different forms of the BLE devices (watch, fob or card) was small, suggesting that all types of devices can be used in a similar way.
- Everyday obstructions such as placing the device in a bag or under a scarf significantly reduced the accuracy of the system, with calculated distances greater than physical distances. This is likely to lead to false negative contacts when used with a particular time-distance contact threshold.

- Contacts measured outdoors were accurate in terms of distance but had a greater variance and a lower contact detection success rate than for experiments conducted indoors.
- Bluetooth propagation through walls and doors means that false positive contacts can be recorded by the system even when devices are located in different rooms.

Based on the results of the experiments reported here, BLE devices are likely to provide an effective proximity detection system in environments where the mobility of participants is not significant, and the devices are worn correctly without obstruction. However, in settings such as a care home where there may be multiple close contacts and devices may be routinely obstructed by obstacles the approach lacks reliability. To reduce the false positives and negatives, the contact tracing device systems require the design and data collection mechanisms to improve. Application of devices in practice is likely to be very dependent on behaviour and successful deployment would need actions to reduce the likelihood of participants reducing the signal strength through obstructing the devices.

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DATA AVAILABILITY

The study data is available at https://github.com/kishibutt/contact-experiments-data

DISCLAIMER

The views expressed are those of the authors and do not necessarily reflect those of the NIHR or the Department of Health and Social Care.

REFERENCES

Aljohani AJ, Shuja J, Alasmary W, Alashaikh A. 2021. Evaluating the dynamics of Bluetooth low energy based COVID-19 risk estimation for educational institutes. Sensors. 21:6667. DOI:10.3390/s21196667.

Barthe G, de Viti R, Druschel P, Garg D, Gomez-Rodriguez M, Ingo P, Kremer H, Lentz M, Lorch L, Mehta A, Schölkopf B. 2022. Listening to bluetooth beacons for epidemic risk mitigation. Sci. Rep. 12: 5558. DOI: 10.1038/s41598-022-09440-1.

Bethell J, Aelick K, Babineau J, Bretzlaff M, Edwards C, Gibson JL, Hewitt Colborne D, Iaboni A, Lender D, Schon D, McGilton KS. 2021. Social Connection in Long-Term Care Homes: A Scoping Review of Published Research on the Mental Health Impacts and Potential Strategies During COVID-19. J. Am. Med. Dir. Assoc. 22 (2): 228-237.e25. DOI: 10.1016/j.jamda.2020.11.025

Cahill S, Diaz-Ponce AM. 2011. 'I hate having nobody here. I'd like to know where they all are': Can qualitative research detect differences in quality of life among nursing home residents with different levels of cognitive impairment? Aging Ment. Health. 15(5): 562–572. DOI: 10.1080/13607863.2010.551342

Chu CH, Donato-Woodger S, Dainton CJ. 2020. Competing crises: COVID-19 countermeasures and social isolation among older adults in long-term care. J. Adv. Nurs. 76 (10): 2456–2459. DOI: 10.1111/jan.14467

Cunche M, Boutet A, Castelluccia C, Lauradoux C, Roca V. 2020. On using Blue-tooth-Low-Energy for contact tracing. [Research Report] Inria Grenoble Rhône-Alpes; INSA de Lyon. hal-02878346v5

Dar AB, Lone AH, Zahoor S, Khan AA, Naaz R. 2020. Applicability of mobile con-tact tracing in fighting pandemic (COVID-19): Issues, challenges and solutions. Comput. Sci. Rev. 38: 100307. DOI: 10.1016/j.cosrev.2020.100307

Farrell C. 2020. COVID-19 has had a devastating effect on oncology patients and staff. Cancer Nurs. Prac. 19(4):5. DOI: 10.7748/cnp.19.4.5.s1

Flueratoru L, Shubina V, Niculescu D, Lohan ES. 2022. On the High Fluctuations of Received Signal Strength Measurements With BLE Signals for Contact Tracing and Proximity Detection. IEEE Sens. J. 22 (6): 5086–5100. DOI: 10.1109/JSEN.2021.3095710

GOV.UK. 2021. More restrictions eased for care homes - GOV.UK [online]; [Accessed 15 Nov 2022]. https://www.gov.uk/government/news/more-restrictions-eased-for-care-homes

Grekousis G, Liu Y. 2021. Digital contact tracing, community uptake, and proximity awareness technology to fight COVID-19: a systematic review. Sustain. Cities. Soc. 71:102995. DOI: 10.1016/j.scs.2021.102995

Gruber-Baldini AL, Zimmerman SI, Mortimore E, Magaziner J. 2000. The validity of the mini-mum data set in measuring the cognitive impairment of persons admitted to nursing homes. J. Am. Geriatr. Soc. 48 (12): 1601–1606. DOI: 10.1111/j.1532-5415.2000.tb03870.x.

Haunch K, Thompson C, Arthur A, Edwards P, Goodman C, Hanratty B, Meyer J, Charlwood A, Valizade D, Backhaus R, Verbeek H, Hamers J, Spilsbury K. 2021. Understanding the staff be-haviours that promote quality for older people living in long term care facilities: a realist review. Int. J. .Nurs. Stud. 117: 103905. DOI: 10.1016/j.ijnurstu.2021.103905

Jalabneh R, Syed HZ, Pillai S, Apu EH, Hussein MR, Kabir R, Arafat SM, Majumder M, Azim A, Saxena SK. 2021. Use of mobile phone apps for contact tracing to control the COVID-19 pandemic: A literature review. In: Nandan Mohanty S, Saxena SK, Satpathy S, Chatterjee JM (eds.). Applications of Artificial Intelligence in COVID-19, Medical Virology: From Pathogenesis to Disease Control: Springer, Singapore. p. 389–404. DOI: 10.1007/978-981-15-7317-0_19

Lee JJ, Souryal Y, Tam D, Kim D, Kang K, Koo DD. 2019. Building a Private Lo-RaWAN Platform. Int. J. Eng Adv. Tech. 9(1S3): 291-295. DOI: 10.35940/ijeat.A1055.1291S319

Madoery PG, Detke R, Blanco L, Comerci S, Fraire J, Montoro AG, Bellassai JC, Britos G, Ojeda S, Finochietto JM, 2021. Feature selection for proximity estimation in COVID-19 contact tracing apps based on Bluetooth Low Energy (BLE). Per. Mob. Comp. 77:101474. DOI: 10.1016/j.pmcj.2021.101474

Ng PC, Spachos P, Plataniotis KN. 2021. COVID-19 and Your Smartphone: BLE-Based Smart Contact Tracing. IEEE Sys. J. 15 (4): 5367–5378. DOI: 10.1109/JSYST.2021.3055675

Parker MJ, Fraser C, Abeler-Dörner L, Bonsall D. 2020. Ethics of instantaneous contact tracing using mobile phone apps in the control of the COVID-19 pandemic. J. Med. Ethics. 46 (7): 427–431. DOI: 10.1136/medethics-2020-106314

Qureshi UM, Umair Z, Hancke GP. 2019. Evaluating the implications of varying Bluetooth low energy (BLE) transmission power levels on wireless indoor localization accuracy and precision. Sensors, 19 (15), 3282. DOI: 10.3390/s19153282

Rawat AS, Rajendran J, Ramiah H, Rana A. 2020. LoRa (Long Range) and Lo-RaWAN Technology for IoT Applications in COVID-19 Pandemic. Paper presented at: 2020 International Conference on Advances in Computing, Communication and Materials (ICACCM); Dehradun, India. p.419–422. DOI: 10.1109/ICACCM50413.2020.9213067

Schulten H, Kuhn M, Heyn R, Dumphart G, Trosch F, Wittneben A. 2019. On the crucial impact of antennas and diversity on ble rssi-based indoor localization. Paper presented at: IEEE Vehicular Technology Conference (VTC2019-Spring); Kuala Lumpur, Malaysia. p. 1-6. DOI: 10.1109/VTCSpring.2019.8746717.

Valtorta NK, Kanaan M, Gilbody S, Ronzi S, Hanratty B. 2016. Loneliness and social isolation as risk factors for coronary heart disease and stroke: Systematic review and meta-analysis of longitudinal observational studies. Heart. 102 (13): 1009–1016.DOI: 10.1136/heartjnl-2015-308790

WHO. 2022. Contact tracing and quarantine in the context of COVID-19: interim guidance, 6 July 2022 [online]. Available from: https://www.who.int/publications/i/item/WHO-2019-nCoV-Contact_tracing_and_quarantine-2022.1 [Accessed 8 Dec 2022].

Wilmink G, Summer I, Marsyla D, Sukhu S, Grote J, Zobel G, Fillit H, Movva S. 2020. Real-Time Digital Contact Tracing: Development of a System to Control COVID-19 Outbreaks in Nursing Homes and Long-Term Care Facilities. JMIR Public Health Surveill. 6(3):e20828. DOI: 10.2196/20828

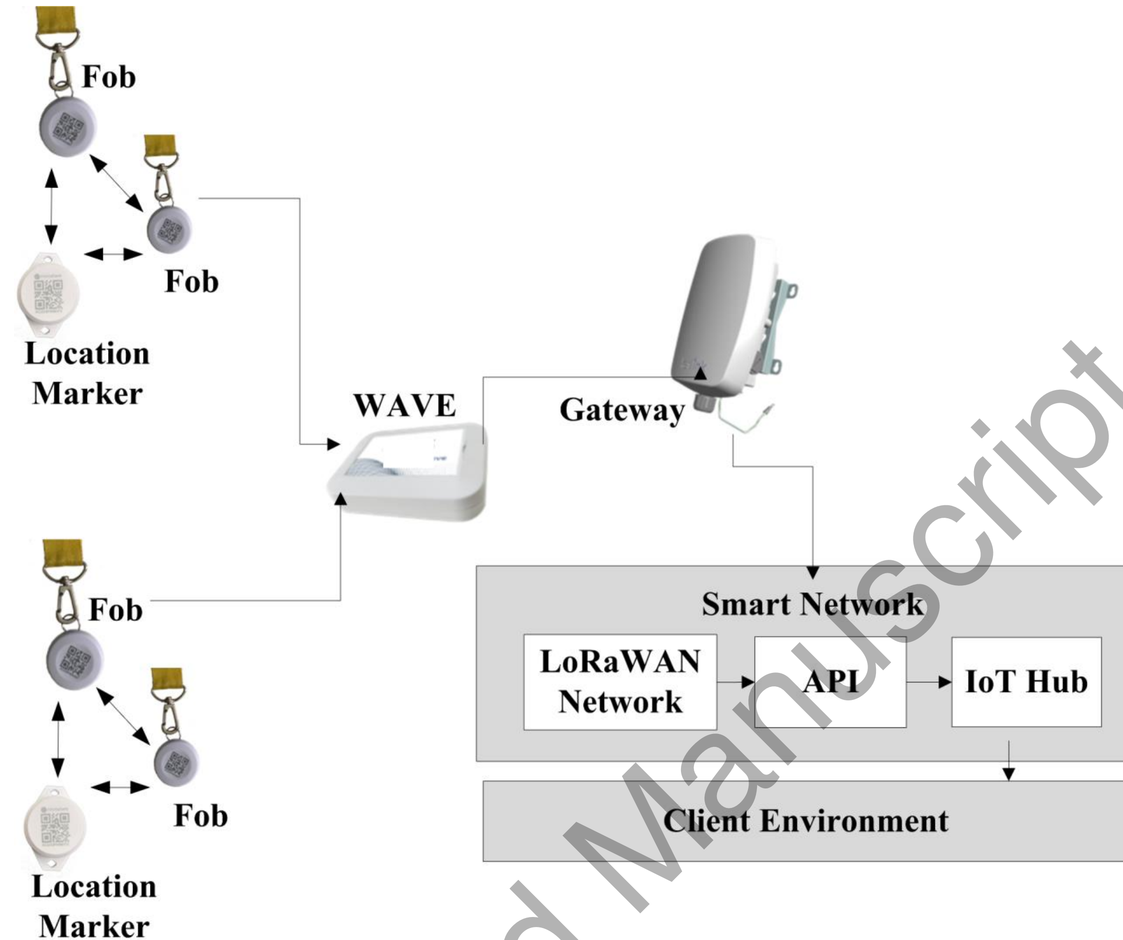

Figure 1. Data flow procedure from BLE devices (in this case key-chain fobs) to the client environment via a smart network

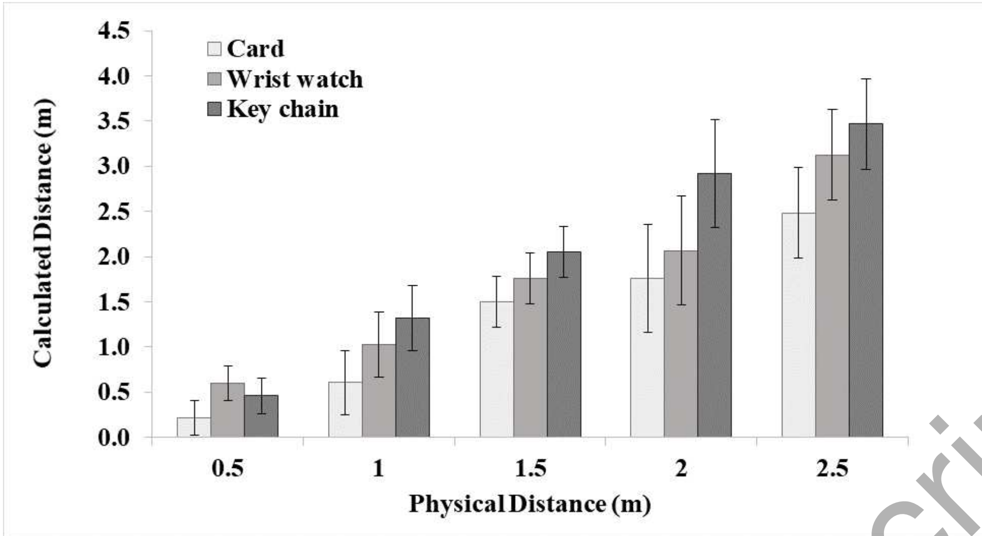

Figure 2. Case 1, Comparison between calculated distances based on RSSI (with standard deviation) for different wearables placed at the same physical distance

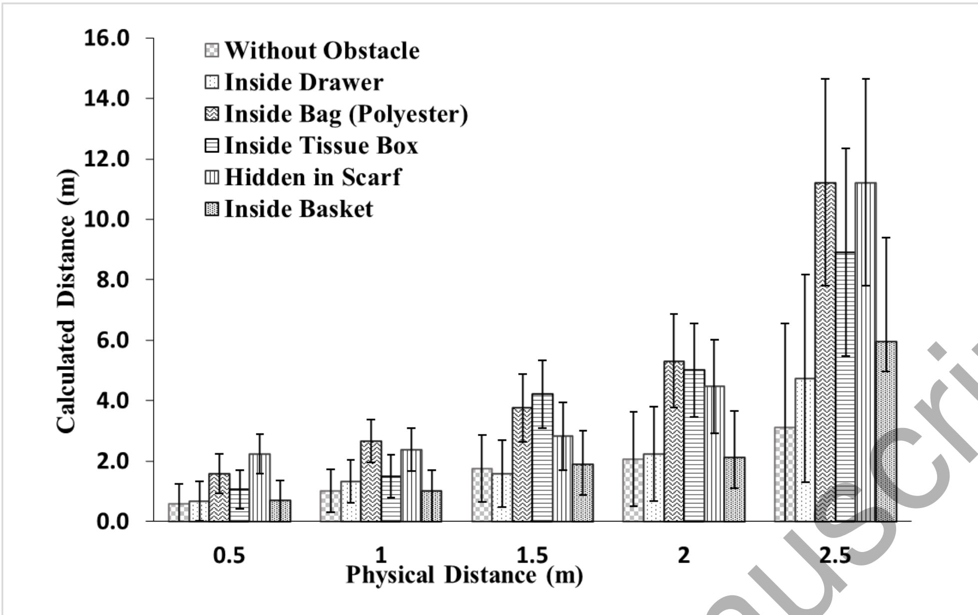

Figure 3. Case 2, calculated distance compared to physical distance for a BLE wearable (key chain, wrist watch and cards) in the presence of obstacles. Error bars represent one standard deviation.

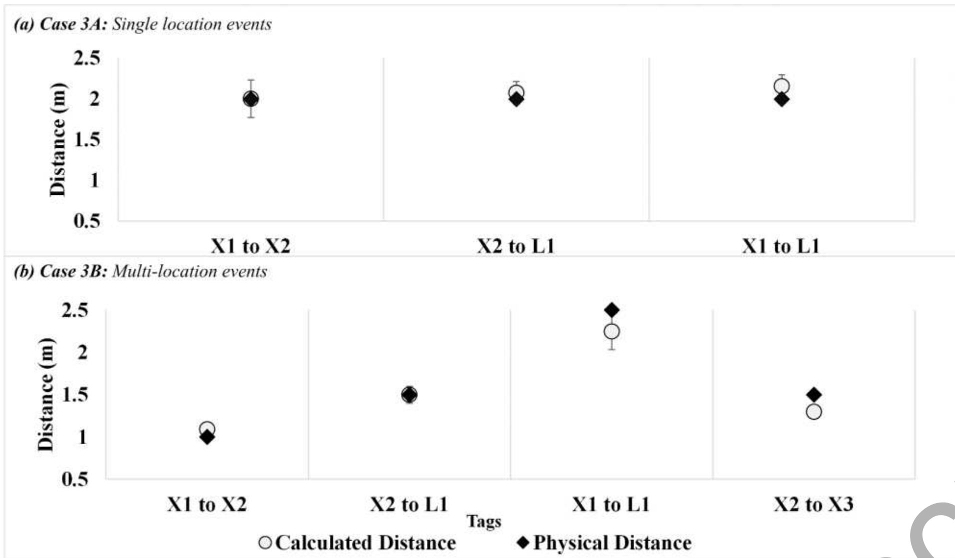

Figure 4. Cases 3A and 3B, Physical distance compared to calculated distance for single indoor proximity events. Values indicate the average calculated distance and error bars show standard deviation

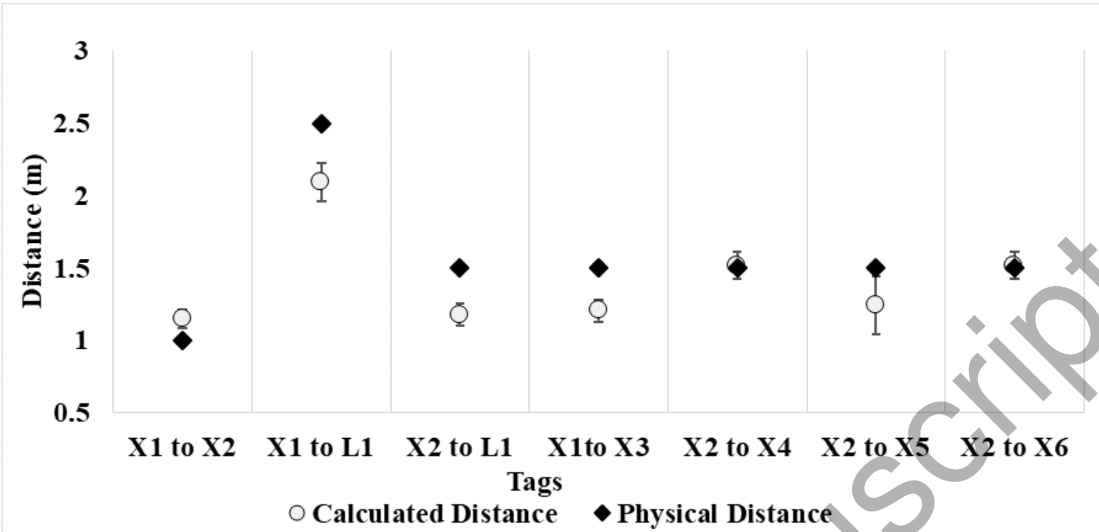

Figure 5. Case 5A, Physical distance compared to calculated distance for multiple indoor proximity events. Values indicate the average calculated distance and error bars show standard deviation

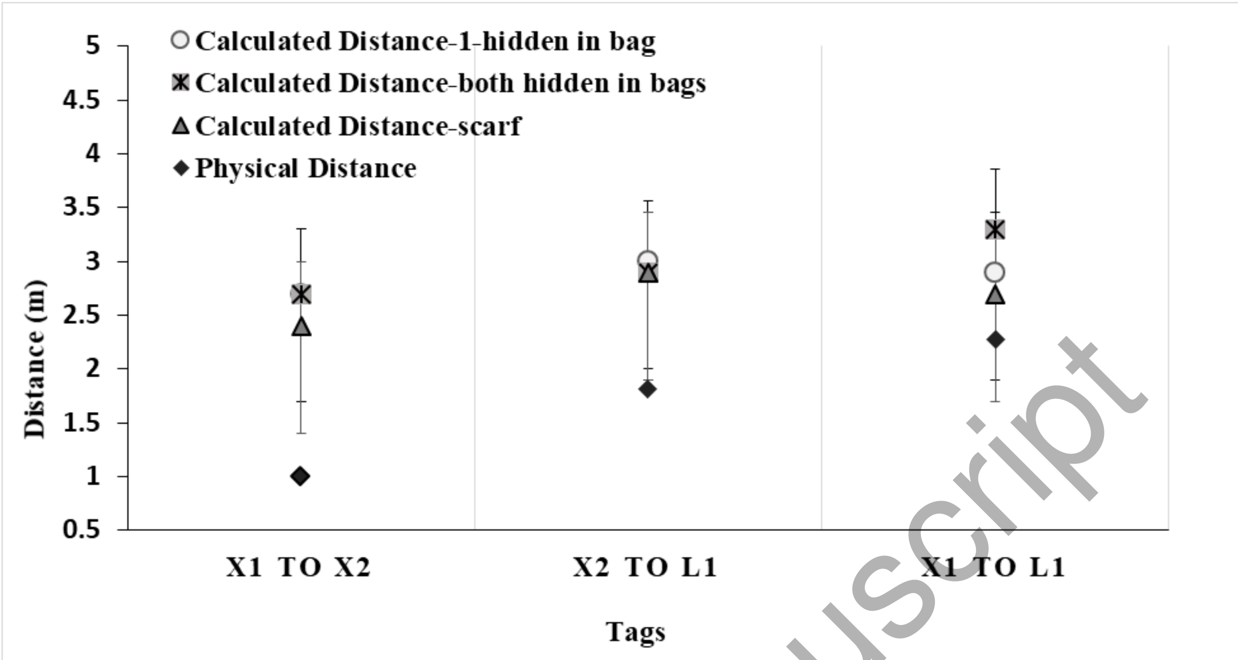

Figure 6. Cases 6A to 6C, False Positive/Negative Proximity Events with Obstacles

Table 1. Summary of considered scenarios along with number of experiments and success rate

	Scenario	**Conditions**	**N Experiments**	**Success rate (%)**
Evaluation of distance between fixed devices				
1	Comparison of different wearable	Without obstacles	70	84.7
2	Effect of obstacle on signal strength	With obstacle	30	50
Single proximity events between devices				
3A	Proximity event(s) between two devices	Without obstacles	10	80
3B	Proximity events between three devices in two separate places	Without obstacles	10	90
Single proximity events including outdoor contact				
4A	Proximity events between three devices with one outdoor location	Outdoor/indoor	10	70
4B	Outdoor and indoor proximity events	Outdoor/indoor	10	60
Multiple proximity events between devices				
5A	Fob X_2 records multiple proximity events in various places	Without obstacles	10	100
5B	Multiple proximity events in same location	Without obstacles	10	100
Single proximity events with obstacles				

6A	Proximity event with one tag inside a hand-bag	With obstacle	10	90
6B	Proximity event with one fob under a scarf	With obstacle	10	50
6C	Proximity event with both fobs under a scarf	With obstacle	10	50
6D	False proximity events with open and closed door	With obstacle	10	70