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Research paper

Feasibility of Bluetooth Low Energy wearable tags to quantify healthcare worker proximity networks and patient close contact: A pilot study

Stephanie J. Curtis [a,b,*], Asanka Rathnayaka [c], Fan Wu [c], Abdulla Al Mamun [c], Craig Spiers [d], Gordon Bingham [e], Colleen L. Lau [f], Anton Y. Peleg [b,g], Mehmet Rasit Yuce [c], Andrew J. Stewardson [b]

[a] *Research School of Population Health, The Australian National University, Building 62 Mills Road, Acton, Canberra, Australian Capital Territory, 2601, Australia*
[b] *Department of Infectious Diseases, The Alfred Hospital and Monash University, 85 Commercial Road, Melbourne, Victoria, 3004, Australia*
[c] *Department of Electrical and Computer Systems Engineering, Monash University, 14 Alliance Lane, Clayton, Melbourne, Victoria, 3800, Australia*
[d] *Alfred Brain Program, Alfred Health, 55 Commercial Road, Melbourne, Victoria, 3004, Australia*
[e] *Information Development Division, Alfred Health, 55 Commercial Road, Melbourne, Victoria, 3004, Australia*
[f] *School of Public Health, University of Queensland, 288 Herston Road, Herston, Queensland, 4006, Australia*
[g] *Infection and Immunity Program, Monash Biomedicine Discovery Institute, Department of Microbiology, Monash University, Clayton, VIC 3800, Australia*

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Abstract *Background:* The hospital environment is characterised by a dense network of interactions between healthcare workers (HCWs) and patients. As highlighted by the coronavirus pandemic, this represents a risk for disease transmission and a challenge for contact tracing. We aimed to develop and pilot an automated system to address this challenge and describe contacts between HCWs and patients.
Methods: We developed a bespoke Bluetooth Low Energy (BLE) system for the hospital environment with anonymous tags worn by HCWs and fixed receivers at patient room doors. Proximity between wearable tags inferred contact between HCWs. Tag-receiver interactions inferred patient room entry and exit by HCWs. We performed a pilot study in four negative pressure isolation rooms from 13 April to 18 April 2021. Nursing and medical staff who consented to participate were able to collect one of ten wearable BLE tags during their shift.
Results: Over the four days, when divided by shift times, 27 nursing tags and 3 medical tags were monitored. We recorded 332 nurse—nurse interactions, for a median duration of 58 s

* Corresponding author. Research School of Population Health, The Australian National University, Building 62 Mills Road, Acton, Canberra, Australian Capital Territory, 2601, Australia.
E-mail address: stephanie.curtis@anu.edu.au (S.J. Curtis).

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[interquartile range (IQR): 39—101]. We recorded 45 nursing patient room entries, for a median 7 min [IQR: 3—21] of patient close contact. Patient close contact was shorter in rooms on airborne precautions, compared to those not o transmission-based precautions.

Conclusion: This pilot study supported the functionality of this approach to quantify HCW proximity networks and patient close contact. With further refinements, the system could be scaled-up to support contact tracing in high-risk environments.

Highlights

- We successfully developed and piloted a system to construct proximity networks in the hospital setting.
- Patient close contact was shorter in rooms on airborne precautions, compared to those not on transmission-based precautions.
- With further development, the system can be scaled up in high-risk environments.

Introduction

There is a critical need to protect healthcare workers (HCWs) from infectious diseases to maintain the capacity of the health system to care for hospitalised patients and to prevent illness amongst HCWs. High rates of HCW infection with coronavirus disease (COVID-19) emerged early in the pandemic. In Australia, outbreaks occurred in healthcare settings during low community prevalence of COVID-19, which highlights the high-risk of disease transmission in these settings [1].

Conventional contact tracing methods used to prevent onward transmission of infectious diseases are limited by cost, workforce capacity and rely on subjective data collection to recall events. The use of technology can help address these limitations, however there is a scarcity of evidence on the effectiveness of digital solutions [2,3]. Bluetooth Low Energy (BLE) technology is well established and can be used to augment conventional contract tracing through collection of objective data [4].

This study investigated how a BLE system can provide data to construct proximity networks in the hospital setting. Our primary aim was to record the frequency and duration of primary close contact between HCWs and patients to estimate the average HCW exposure time per patient-day.

Methods

Study design and setting

We performed a pilot contact network epidemiology study in four negative pressure rooms at the Alfred Hospital, Melbourne, from 13 April to 18 April 2021.

Participations

The study population were nurses and doctors providing care to a patient in one of the four rooms. The sample size was determined pragmatically by the number of HCWs that consented to participation and wore an anonymous BLE tag during their shift. There were five nursing tags and five medical tags available for use at any point in time. E-consent was obtained through Research Electronic Data Capture, hosted by Monash University [5,6].

Data collection

We developed a bespoke BLE system for data collection, consisting of wearable tags, BLE receivers and an edge gateway device. The system was built and tested in an engineering laboratory, and previously piloted and validated on the study setting ward through observational cross-checking. The architecture of the system is presented in Fig. 1 and technical specifications are in Appendix 1.

The wearable tags functioned continuously with an anonymised identification number and retained a list of interactions with other tags and the BLE receivers. Tags were placed in the HCWs pocket, bag or clipped to their existing identification badge. BLE receivers included two proximity sensors that recognized the tags, recorded entry and exit according to the direction the HCW moved through the door and forwarded data to the gateway via long-range data transmission. Receivers were fixed in the anteroom of negative pressure patient rooms and in the corridors to regularly transfer data from tags to the gateway. The edge gateway securely received, stored and forwarded data to the cloud server via Wi-Fi.

Data analysis

The BLE system was programmed to define proximity parameters during deployment. Close contact interactions between HCWs were defined as tags within 1.5 m from each other for at least 30 s consistently, or if the tags return to be within 1.5 m within 20 s since the previous interaction it was aggregated with the recent interaction. Close contact between HCWs and patients was inferred by tag-receiver interaction that captured room entry and exit, for at least 30 s consistently. A

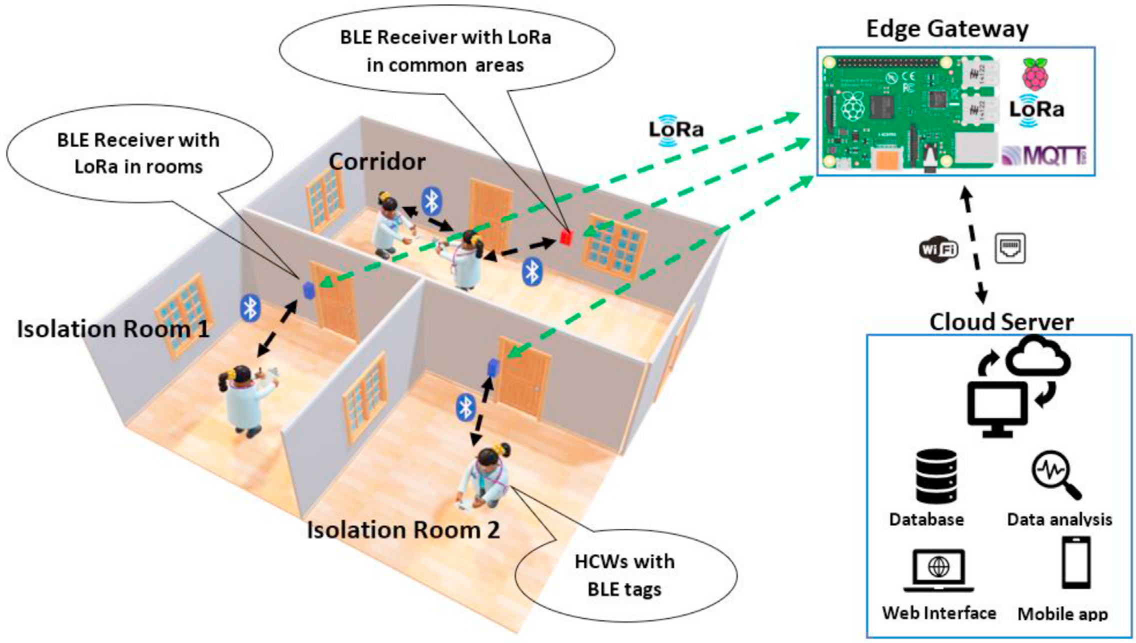

Figure 1 The architecture of the Bluetooth Low Energy system in the hospital setting.

Table 1 Nursing interactions and patient close contact, by nursing shift times.

Data metric	Total	Morning	Afternoon	Night
Tags active, N	27	8	11	8
Nurse—nurse interactions, N (%)	332	213 (64.2)	90 (27.1)	29 (8.7)
Median time of nurse—nurse interaction [IQR] (seconds)	58 [39—101]	65 [41—113]	50 [37—71]	52 [34—92]
Nurse-patient close contact events, N (%)	45	23 (51.1)	15 (33.3)	7 (15.6)
Median time of nurse-patient close contact events [IQR] (minutes: seconds)	6:58 [2:57—20:36]	8:25 [2:59—29:00]	5:32 [2:51—11:12]	9:30 [3:59—14:48]

IQR = Interquartile range.

received signal strength indication of ≤65dBm assumed tags were within 1.5 m of each other or the receiver.

Data were extracted from the cloud server, cleaned and analysed using Microsoft Excel and R Version 4.0.2, including the 'igraph' package for network analyses [7]. Descriptive analysis summarised data, with continuous variables summarised as median with interquartile range (IQR) and ordinal variables as count with percentage. As the same tags were available continuously, we estimated the number of nursing tags monitored over the study period, by dividing data into shift times; morning (7:00—1:59), afternoon (14:00—21:29) and night (21:30—06:59).

Results

Over the four days, when divided by shift times, 27 nursing tags and 3 medical tags were actively monitored. Table 1 presents total nursing interactions and patient close contact recorded. A total 332 nursing interactions recorded, with a median duration of 58 s [IQR: 39—101]. A total 45 patient close contact events were recorded, with a median duration of 6 min 58 s [IQR: 2:57—20:36]. Most tags were active (used by a participant) in the afternoon, HCW interaction duration was similar across all shifts, and patient close contact duration was longest during night shift.

Fig. 2 presents network graphs of all HCW-HCW interactions, by cumulative count and minutes. There was a total 545 min of close contact recorded, with a median 36 min [IQR: 5—66] per HCW tag pair. Nurse tags 4 and 5 had 211 min of interaction and nurse tags 2 and 4 had 72 min of interaction, as represented by dense clustering of the edges between these HCW nodes in Fig. 2B compared to Fig. 2A. Only one medical tag (D01), recorded two interactions with one nursing tag, for a cumulative 2 min 46 s.

There were a total 622 min of nursing-patient close contact across all rooms. No medical tags recorded patient close contact. One room was on airborne precautions for the four days, an additional room was on airborne precautions for day 3 and 4, and for all other rooms and days, there were no transmission-based precautions. Nursing-patient close contact was for a median 4 min 19 s [IQR: 3:42—4:55] for rooms with airborne precautions, compared to 8 min 25 s [IQR: 2:55—21:42] for rooms without transmission-based

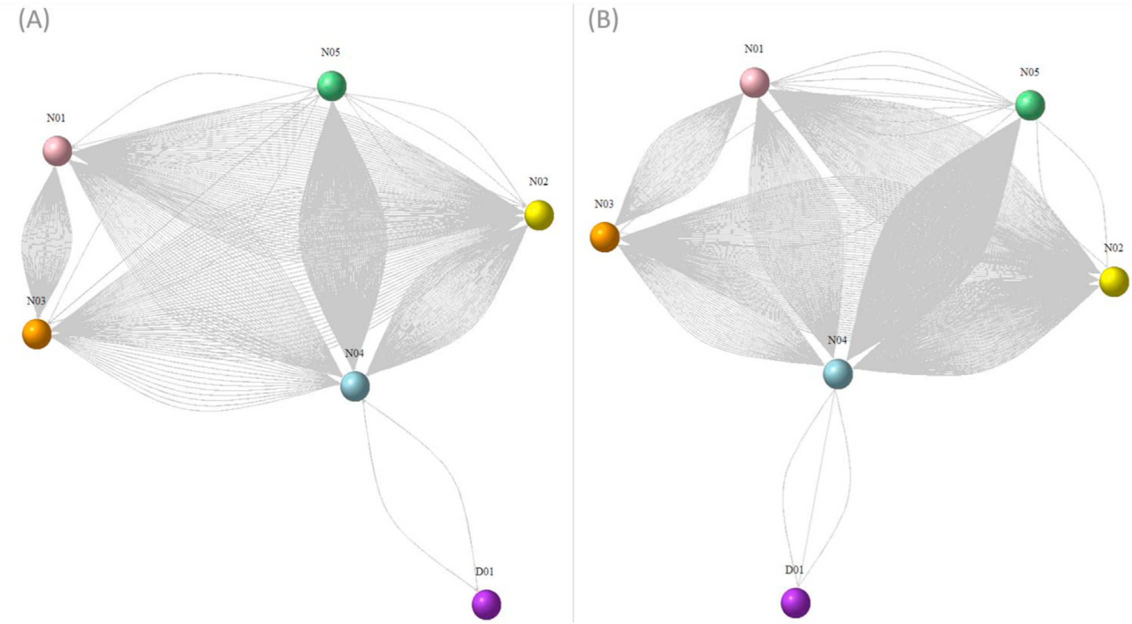

Figure 2 Network graphs of interactions recorded; (A) total number of interactions; (B) total minutes of interactions.

precautions ($p = 0.989$). Per patient-day, the median exposure time was 31 min [IQR: 1:37—68:18].

Discussion

We successfully developed a BLE system that constructed proximity networks in the hospital setting. The median interaction between nursing staff was 58 s, and the median patient close contact event was 7 min. We estimated an average nursing exposure time of 31 min per patient-day. Close contact was shorter for patients in airborne precautions, compared to those without transmission-based precautions.

The results of our pilot study may not be directly comparable with other studies due to differences in study design. However, other studies also report mostly brief interactions between HCWs, the least interactions by medical staff, and short duration of close contact for patients in airborne precautions [8—10].

Our study was limited by lower uptake of wearable tags than anticipated, particularly for medical staff. Although we used anonymous tags to increase HCW acceptability, participation may have been limited by privacy concerns, understanding or engagement [11]. Additionally, cumulative interaction data over shifts and days may not enable conclusions as it likely represents tags used by different participants, however this contributes to an understanding of potential analytics from this system, which will be more meaningful through data collection over a longer period and with increased participation. Overall, we have sought to contribute to the gap in evidence on digital solutions for outbreak response to augment conventional contract tracing [3].

Future deployment of the system will require an increase in the number participants, and expansion of the BLE receivers across the ward to investigate critical opportunities for intervention to reduce potential infectious disease transmission. Future research could also focus on barriers to participation and ensure meaningful stakeholder input in the systems development.

Conclusion

This pilot study supported the functionality of the proposed BLE approach to collect data on proximity networks. With further refinements, the system could be scaled-up to augment contact tracing in high-risk environments such as COVID-19 wards in hospitals, hotel-quarantine, or for future infectious diseases outbreaks and/or pandemics.

Ethics

The project was approved by the Alfred Health Human Research Ethics Committee (2020/651).

Authorship statement

Conceptualisation — SC, AS and MY. System design and development - AR, FW, MAAM. Project implementation — SC, AR, FW, CS, GB, AS. Formal Analysis — SC. Manuscript writing — SC. Supervision — AS, AP, CL and MY. All authors reviewed, edited and approved the final version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.idh.2021.10.004.

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