RESEARCH

Optimizing spatial healthcare assets with Internet of Things

Tim McNabb , Trina Myers* , Kristin Wicking , Lei Lei and Wei Xiang

Abstract

Six percent of the total cost of healthcare delivery in Australia is from buying, building and maintaining physical assets. Current practice does not measure the efficient use of existing clinical spaces prior to making funding decisions for service expansion, remodeling or relocation. Healthcare service delivery can be increased through existing assets by optimizing the use of clinical space. The wait times for healthcare service consumers and capital expenditure pressures could be reduced, which would result in increased funds available for frontline services. Sensor technology has been used to study aspects of time in ambulatory outpatient clinics using Infra-red Tags or Radio Frequency Identification tags. This paper proposes the use of *Internet of Things* (IoT) technology to assist in the optimization of high-value clinical spaces and presents phase one of the project where a trial was held in a non-clinical location to evaluate sensor performance. In Phase two, sensors will be installed to count people across an ambulatory outpatient clinic in a live public healthcare environment to understand clinical space utilization and inform decision-makers. The data produced by the sensors on room use is processed for visualization in “dashboard” format so frontline and executive staff have evidence-based decision-making support for space optimization strategies. This paper presents the phase one trial and preliminary results that show the disparity space utilization patterns between the IoT sensed occupancy data with the current room reservation system in a non-clinical space.

Keywords: Internet of Things, Healthcare, Resource utilization, Optimization people counting, Ambulatory outpatient clinic

Introduction

Australia spends 10.3% of the *Gross Domestic Product* (GDP) on the provision of healthcare services, which is over \$161 billion annually [1]. Capital expenditure on healthcare facility expansion, renovation and maintenance exceeds \$9.5 billion annually, accounting for 6% of healthcare spending in Australia [1]. Frontline managers of outpatient clinics cannot easily demonstrate whether their service is operating below or above capacity when applying for funds. Executive-level decision-makers cannot identify underutilized spaces to inform evidenced-based strategic investment decisions or demonstrate the effectiveness of improvement strategies once implemented.

The throughput of healthcare service consumers in existing facilities can be increased if the occupancy of

clinical spaces is optimized. If the provision of services through existing assets can be increased, the pressure to build or renovate assets and the cost of healthcare services is reduced the growth of capital expenditure can be slowed. Further, funds that were previously targeted for facility expansion and associated maintenance regimes can be made available for frontline healthcare services.

The main focus in the current literature are aspects of time in outpatient clinical areas, such as outpatient scheduling [2] or patient flow [3]. Recent studies typically combine data with clinic simulation to produce improvements, most commonly using discrete event simulation [4]. However, data-gathering remains much as it did 20 years ago [5]. Research that focused on aspects of patient-flow gathered data using sensor technologies, such as the use of *Infra-red* (IR) badges [6] or *Radio Frequency Identification Tags* (RFID) [7], where tag loss, high operational costs and short study periods were problematic. Research in this field predominately relies on

*Correspondence: trina.myers@jcu.edu.au
James Cook University, Townsville, QLD 4814, Australia

manual data gathering techniques, for example, watches and paper templates [5], with direct observation [8] and self-reporting noted as “particularly weak” [9].

This paper presents the preliminary trial of the novel use of *Internet of Things* (IoT) technology to assist in the optimization of clinical space. In this first phase, two motion-detection sensors were installed in a non-clinical trial location to demonstrate the sensors’ effectiveness in demonstrating “room as used” versus “room as reserved”. Data from this non-clinical trial location will inform phase two of the project, which is a wider installation of multiple sensor types across operational clinical outpatient environments within a healthcare facility.

The project aims to extend the installation from phase one into live clinical outpatient environments in phase two to provide time-stamped human occupancy data. The commercially available thermal sensors will be deployed at room entry points of high-value ambulatory outpatient clinical spaces in a 24-h operational public healthcare facility. Three types of clinical rooms with distinct functions will be monitored for occupation and utilization, representing the highest-value clinical spaces. Patterns of occupation and use in these clinical spaces will be explored using the IoT devices.

Background and methods

The clinical spaces

The clinical spaces targeted in this project’s phase two are broken into three primary categories: (1) consult rooms; (2) education rooms; and (3) treatment rooms, which are the three highest-value spaces to patients, clinicians and management (Table 1). Notably, there are other space types that support the operation of an outpatient clinic, including waiting rooms, reception, corridors, among others. However, the three clinical spaces are the primary care areas in a typical outpatient clinic, and cost approximately five times what typical commercial spaces cost to build and maintain.

Internet of Things: planned sensor installation

IoT is the applied use of devices in the physical world that can extract information from raw sensor data to affect changes either directly through switches, valves etc., or indirectly through information “dashboards” to human decision-makers. IoT devices can be designed to be automated, cost-effective, unobtrusive and accurate long-term with negligible ongoing maintenance.

The three sensor types to be deployed during the final phase include: (1) infra-red break-beam; (2) *photovoltaic infra-red* (PIR); and (3) photovoltaic array (Fig. 1). Infra-Red Break-Beam sensors, referred to “sensor type 1” or “S1”, are a low-cost motion detector that is usually

Table 1 Types of outpatient clinical rooms targeted for study

Type	Description	Typical images
Type 1: consult room	Rooms used for observation/diagnosis where patients discuss health issues with healthcare providers & where physical contact may require clinician hand washing between patient visits, typically containing an examination table
Type 2: education room	Rooms where diagnoses or procedures are explained to healthcare services consumers through either interaction with healthcare service providers or via multi-media presentation, and appear as a typical office space
Type 3: treatment room	Functions as an aseptic room where clinicians directly apply healthcare services onto/into patients’ bodies. These rooms often smell like disinfectant and typically contain bed trolley, hand basin, basic stores and a preparation area

Sensor Type 1 (S1): Infra-Red Break-Beam Unit Cost: \$450 AUD Installation: Low Impact Data Resolution: High Clinical Suitability: Low	Sensor Type 2 (S2): <i>Photovoltaic Infra-Red</i> (PIR) Motion Unit Cost: \$250 AUD Installation: Low Impact Data Resolution: Low Clinical Suitability: High	Sensor Type 3 (S3): Photovoltaic Array Unit Cost: \$2,085 AUD Installation: High Impact Data Resolution: High Clinical Suitability: High

Symbol:	Symbol:	Symbol:

Fig. 1 Sensor types chosen to study outpatient space utilization across a multi-disciplinary clinic within a live public healthcare environment

installed in the doorway to count movement in and out of a room. These sensors (S1) produce high data quality and are battery-operated but are not solely suitable for clinical spaces because they are located at the corridor side of doorways, so both staff and public occupants are conscious of being monitored. Also, S1 sensors are mounted at an accessible height on the 'corridor' side of most rooms (due to inward door swing) and consequently are prone to damage, theft or tampering.

The PIR sensors are referred to "sensor type 2" or "S2" and are also a low-cost motion detector with a low-cost installation strategy of adhesive tape to ceiling surfaces. The PIR S2 data resolution is low because it tracks only occupancy without data on activities and utilisation. However, the clinical suitability of the PIR sensors is high due to the low purchase cost, low cost of installation (surface adhered), low-power (battery operated) and discrete mounting location (ceiling-based) that supports broader coverage with fixed budgets. Notably, while the data is low-resolution, the level of information is a significant improvement on current room monitoring techniques.

The third sensor type, "S3", is the photovoltaic array, which is a high-cost people counter. The deployment will have a moderate to high impact as the installation of this relatively expensive sensor requires mechanical fastening to and through existing ceilings and constant 240 V

power supply. The data resolution and the suitability for clinical deployment is high due to the value that the ability to count occupants passing under the sensor adds to information on room utilisation.

Phase one deployment: proof of concept

As a proof of concept, phase one involved the deployment of two PIR S2 sensors in an administrative, non-clinical space to compare "room as reserved" versus "room as occupied" data. In the phase one trial, a high traffic room was required that minimized risk to patients so the sensors were deployed in a non-clinical room to test the effectiveness of the sensors and compare to the actual room reservation data. The two sensors are labelled "sensor A" and "sensor B" for the purpose of this paper and were mounted at shoulder height in the phase one trial space (Fig. 2).

The occupancy data from the sensors was collected over a 1-week period and compared to data from the target room's reservation system. The data was combined into a single dataset for the consideration of "occupancy" for a 1-week period between 6 a.m. and 6 p.m., Monday to Friday. Sensor A was mounted adjacent to and perpendicular with the room entry door and sensor B was mounted approximately $\frac{3}{4}$ through the room. The outcome of phase one is intended to inform the placement of sensors in the full phase two deployment (Fig. 2).

Results

The target space was *Reserved* (R) during the 1-week timeframe on average 288 min per day and *Occupied* (O) 390 min per day within a daily period of 720 min (i.e., 12 h). This room use can be expressed as a percentage of the daily period by $R=40.0\%$ and $O=54.2\%$. Room occupancy data graphed versus room reservation data for the phase one trial room during the 1-week period is presented in Fig. 3. The figures changed to $R=48\%$ and $O=60.7\%$ between 7 a.m. to 5 p.m., which are the standard business hours of the healthcare system.

The greatest alignment between R and O was on Tuesday while the greatest discrepancy was on Friday when the room was booked for 4 h and was wholly unoccupied. These discrepancies could be due to a combination of ad-hoc meetings, inaccurate room booking, or a casual approach to reserved time limits. Spontaneous or ostensibly unplanned events may or may not constitute appropriate use of space depending on how the space was designed to support the organization.

There was disparity between sensors A and B as they provided different measurements for occupancy due to their placement in the room. As sensor B was deployed $\frac{3}{4}$ of the length inside the room, it recorded a subset of sensor A, which was fixed at the entryway. Sensor B detected

presence in the room only 49% and zero occupancy outside the occupation periods of the period recorded by sensor A. This could be attributed to some occupants not needing to move to the rear of the room, which can inform on the decisions of optimal internal room usage.

Reservations averaged 2.8 h in length, and gaps between reservations averaged 2 h. Occupation blocks averaged 1.7 h, and gaps between occupations averaged 2.3 h. The comparison of these averages suggest opportunities for optimization to better align reserved times with occupation events.

Correlations of space usage as a percentage of the daily maximum of 720 min is shown in Fig. 4 which demonstrates patterns of use for this space across a typical week. The total average utilization, combining all occupied periods, is 54% for the target week (67% with Friday discounted), which suggests the target room may be underutilized. However, a longer study period to record multi-week patterns would be required to accurately determine utilization.

IoT devices have been demonstrated capable of providing occupancy data as the first step towards optimal space utilization. Bespoke measurement for individual rooms through IoT technology combined with accessible presentation of occupation data together provide critical

Fig. 3 "Room as occupied" versus "room as reserved" for non-clinical, reservable space

Fig. 4 Correlation of usage from 6 a.m. to 6 p.m

steps towards the optimization of spatial assets for large estate-asset owners whether in healthcare systems or other corporate entities in either the public or private sectors worldwide.

Discussion

Service improvement strategies can be better informed with combined "reservation" and "occupation" data streams that identify both peak loads and "non-attendance events" in the long term. A broader study that includes multiple "reservable" rooms may inform policy

changes required to implement optimization strategies. One example is the cancellation of reservations for unoccupied spaces, which could allow for increased ad-hoc meetings.

Motion sensors, such as the PIR S2, on their own are appropriate for comparing how spaces are reserved versus whether they are occupied. PIR sensors may be suitable to explore "occupation" for single-person micro-spaces, such as workstations, where occupation more closely aligns with utilization. However, without "people count" data, PIR sensors have limitations on establishing

how the spaces are used and in identifying “occupation”, which suggests their capacity to capture information of multi-person spaces is restricted. Notably, PIR sensors are wireless and cost-effective with a simple “stick-on/forget” installation so there is a trade-off between information resolution versus cost and ease-of installation.

More information is required, such as the number of people who physically inhabit a room, to understand more about the utilization of a space rather than its occupation. Phase two will add count data for high-value clinical rooms and record a combination of sensors to explore both “count” and “occupancy”. The low-cost and portability of the PIR S2 sensors that focus only on occupancy will be compared with the greater data resolution of the Infra-Red Break-Beam (S1) sensors combined with Photovoltaic Array Sensors (S3) to gain a more complete picture of ‘utilization.’

Conclusion

This paper presented phase one of a project that aims to explore the use of IoT to support evidence-based decision-making for optimization strategies to improve the use of spatial assets in healthcare services. Phase one involved the deployment of two PIR sensors in a non-clinical healthcare space to compare “room as reserved” versus “room as occupied” data as a proof of concept. The data from the sensors showed a distinct disparity between the actual room occupation and the room reservation system. The results from this phase show that PIR motion sensors applied alone are a suitable method to understand patterns of occupation. However, additional information on people count is required to optimize space use, which will require a combination of motion detector technologies.

Phase two is future work that proposes to incorporate multiple sensor types to compare and contrast “count” data with “occupied” status seeking a balance between data resolution and purchase/installation costs.

This greater resolution of automated IoT data can better inform optimization decisions of existing high-value spaces and reduce the pressure to expand the footprint of healthcare services and supporting infrastructure. Ultimately, capital expenditure and the cost of providing healthcare services could be reduced through targeted use of IoT technology.

Acknowledgement

This research has been funded by the Townsville Hospital and Health Services; Study, Education, Research Trust Account (SERTA) Grant.

Received: 1 August 2018 Accepted: 20 August 2018

Published online: 18 September 2018

References

1. Australian Institute of Health and Welfare. Health expenditure Australia 2015–16. <https://www.aihw.gov.au/getmedia/3a34cf2c-c715-43a8-be44-0cf53349fd9d/20592.pdf.aspx?inline=true> (2017).
2. Cayirli T, Veral E, Global I. Outpatient scheduling in health care: a review of literature. *Prod Oper Manag.* 2003;12(4):519–49.
3. Ahmadi-Javid A, Jalali Z, Klassen KJ. Outpatient appointment systems in healthcare: a review of optimization studies. *Eur J Oper Res.* 2016;258(1):3–34.
4. Farahmand K, Karim R, Srinivasan R, Sajjadi SR, Fisher L. Clinic space design using discrete event simulation. In: *IIE annual conference. Proceedings*, pp. 1–8 (2011).
5. Cote MJ. Patient flow and resource utilization in an outpatient clinic. *Socio-Econ Plan Sci.* 1999;33(3):231–45.
6. Overmoyer B, et al. Using real time locating systems (RTLS) to redesign room allocation in an ambulatory cancer care setting. Alexandria: American Society of Clinical Oncology; 2014.
7. Stahl JE, Drew MA, Kimball AB. Real-time location systems, normative messaging and modifying clinician behavior: a pilot study. *Health Syst.* 2014;3(3):165–72.
8. Harper PR, Gamlin H. Reduced outpatient waiting times with improved appointment scheduling: a simulation modelling approach. *OR Spectr.* 2003;25(2):207–22.
9. Bratt JH, Foreit J, Chen P-L, West C, Janowitz B, De Vargas T. A comparison of four approaches for measuring clinician time use. *Health Policy Plan.* 1999;14(4):374–81.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.