Optimizing Clinical Spatial Resources with IoT

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ABSTRACT

The cost of healthcare is significant within Australia where \$185.4 billion was spent in the 2017-2018 financial year. This expenditure represents 10% of Australian GDP and grew by a ten-year annual average of 3.9% to 2015-16 financial year. There is limited ability to demonstrate the efficient use of existing healthcare spaces while Capital Works expenditure continues to grow. Executive decision-makers and front-line managers currently lack tools to optimize space utilization, as current techniques are either burdensome, costly, or challenging to implement at scale. There is related literature that demonstrates the feasibility of using Internet of Things (IoT) to understand the utilization of non-clinical healthcare spaces. However, these technologies have not previously been validated as effective in an operational clinical setting. This paper presents findings from the introduction of an IoT-based space management system applied to a multi-disciplinary outpatient clinic in an operational public hospital fulltime across a six-month time period. Preliminary data validates IoT technology is appropriate for operational healthcare environments and is superior when compared to manual data collection methods.

CCS CONCEPTS

• Information systems~Sensor networks • Information systems~Expert systems

KEYWORDS

Internet of Things, Space Utilization, Clinical Space Utilization, Healthcare Resource Optimization, Architectural Informatics

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1 Introduction

Australia spent \$185.4 billion providing healthcare services in the 2017-2018 financial year, representing 10% of Australian Gross Domestic Product (GDP). Australian GDP has increased every year for the last 27 consecutive years, increasing by 2.8% in the 2017-18 financial year, but the cost of providing healthcare services in Australia has grown at a ten-year average rate of 3.9% per annum [1] to the 2015-16 financial year. Growth in healthcare expenditure is exceeding GDP growth which is not sustainable in the mid to long term as the cost of providing healthcare will take up an increasing percentage of Australian GDP, and accounts for 7% of Australia's Carbon Dioxide (CO₂) emissions [1]. Capital Expenditure is the fastest growing category of healthcare expenses for the 10 years to 2015 [2]. Expenses in this category include the cost of purchasing real estate, building new assets (e.g. new hospitals), purchasing new equipment (e.g. medical imaging equipment) or renovating existing physical assets to keep up with changing technology, models of care, and to maintain service levels as spaces age. Utilization of existing clinical spaces must be optimized, to increase access to healthcare services for Australian citizens, reduce the pressure to expand the footprint of Australia's healthcare system (both physical and ecological), and therefore reduce the growth in costs of providing healthcare services.

In this paper, findings are presented from the introduction of an IoT-based space management system applied to a multi-disciplinary outpatient clinic in a live public hospital fulltime across a six-month time period. In the bulk of existing literature exploring aspects of space utilization in healthcare environments explored below, study periods are relatively limited except for those reliant on historical data, with typical study periods from two days to two weeks. Preliminary results from the

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introduction of IoT devices using Photovoltaic Infrared (PIR) sensors to record occupation of individual clinic rooms suggest these low-cost, robust and reliable thermal motion sensors, common in both commercial and residential applications (e.g. lighting and security), are appropriate to understanding occupation patterns of individual rooms. These sensors provide non-personally identifiable occupancy data recording Boolean data ('occupied' vs. 'unoccupied'). Despite their low data-resolution, the insight they can provide to healthcare decisionmakers over extended periods is significant, when presented in person-centered 'dashboard' format to support evidence-based decision making by front-line and executive level staff alike.

Preliminary data validates that IoT technology is appropriate for live healthcare environments and is superior when compared to manual data collection methods. A comparison is made between results from previous manual observation techniques to understand average utilization vs. results from the innovation of IoT-based data gathering methods. Comparisons includes typical limitations of manual methods, and the benefits of long-term data gathering through non-invasive IoT devices gathering ambient, low-resolution data. Higher-resolution data-gathering has been demonstrated as effective in understanding clinical space utilization beyond simple 'occupancy', but the technology used to gather this data may raise potential privacy and civil liberty issues to the often disrobed patient occupants of these spaces, in addition to perceptions of increased non-clinical workloads for staff [3]. Exploration of the human-element of using IoT technology in healthcare environments to gather increasing levels of information resolution is proposed as future work.

This paper is organized as follows: Section 2 introduces the background of related works and literature; Section 3 describes the implementation of the project; Section 4 details the analysis and results; and Section 5 concludes with commentary on the implications for future healthcare research, practice and policy.

2 Background

Research in the area of space utilization as a category of healthcare research is under-represented in the literature, with initial explorations on optimizing use of space found in related studies of universities [4]. Literature in healthcare environments primarily focuses on aspects of time, either patient-focused or healthcare-practitioner-focused or both [5-7], or on layout [8, 9]. Despite the need to optimize the use of clinical spaces, few tools exist to help executive decision-makers or front-line service delivery managers optimize their space utilization. These decision makers currently lack tools to optimize space utilization, as current techniques are either burdensome [2], costly [3], or challenging to implement at scale with limited return on investment in the short term [10]. Data gathering in related research is either undertaken through physical observation [11, 12], historical data [13], or a combination of these, principally incorporating simulation [12] [14] and increasingly, machine learning [15-17].

Looking beyond healthcare research there is a wealth of literature using a variety of sensors to detect human presence. Recent methods of human occupation prediction include monitoring of WiFi traffic [18], CO₂ sensors [19, 20] often combined with Machine Learning, with promising recent research in privacy-protective environments using LIDAR [21] Doppler radar systems [22] and audio-processing [23]. Each of these has increased challenges in a healthcare setting however, with the latter having increased privacy concerns in clinical settings beyond domestic or commercial applications. Occupancy prediction using WiFi traffic is dependent on all participants carrying active, WiFi-capable devices which cannot be guaranteed in a public healthcare environment. One recent study has concluded that using data from CO₂ sensors, combined with light sensors and various machine learning techniques provided near 100% occupancy detection [24]. This strategy may be appropriate in isolated individual rooms in an education setting, but it may not be appropriate for studying clinical rooms in a healthcare environment, such as a multi-service outpatient clinic suite, as multiple rooms are serviced as a zone by a single air-conditioning system which recycles conditioned air, hence levelling out CO₂ profiles. Also, these zones can have banks of lighting connected to a single switch so room lights turn on without necessarily being occupied, and glazed corridor partitions can provide false-positive light readings.

There is related work that demonstrates the feasibility of using IoT devices to understand occupation for non-clinical healthcare spaces [4]. However, these technologies have not previously been validated as effective in an operational clinical setting. The problem addressed by this research is that both executive and front-line decision makers currently lack non-manual data-gathering tools to understand how their clinical spaces are used. Clinical spaces are expensive healthcare resources to be optimally utilized like any other, though research focused squarely on the optimization of space utilization is under-represented in the research

3 Methodology

The most common method of understanding the utilization of spaces in the literature relies in part on human observation and manual data gathering. Manual data gathering for the purposes of space utilization studies involves an observer, a timepiece and a recording device such as a clipboard and pen. The observer moves around the target zone recording occupation in clinical rooms applying judgement based on predetermined criteria set by the research team. In the case of one such observation, if the room was observed to be occupied by either clinical service provider or a consumer, the space was determined to be occupied [25]. As this type of data gathering involves repetitive actions, and high-attention, and the application of judgement, the data may be prone to human error [26]. These studies typically rely on a small sample size (typically two weeks or less) which does not account for the variability of healthcare service delivery affected by many uncontrolled variables including the weather [27]. Data collectors tend to be either volunteers, students or staff undertaking activities outside of or in addition

to their normal roles, making long-term manual data gathering highly resource intensive, and ultimately impracticable.

Clinical spaces are diverse, supporting a variety of functions suggesting different levels of use should be considered 'optimal'. For example, a treatment room in an outpatient clinic is an unreserved space used ad-hoc by healthcare providers to administer a higher level of healthcare services than can be supported by a consult room. An education room is also used ad-hoc across the clinic, providing a lower level of clinical interaction than a consult room. The Consult Room is the most versatile of these three spaces and is the only space type that is an actively managed space by clinical staff using an appointment scheduling system. Human observers require the application of judgement in the categorization of healthcare spaces; depending on the experience of the observer in the healthcare sector, this may lead to erroneous results if not carefully managed. In the healthcare sector privacy of clinician-patient encounters are protected by Australian law, which also drives their design. Design responses to the need for visual and acoustic privacy, such as solid corridor walls and doors without viewing panels, make the judgement as to whether a space is occupied or vacant with a closed door effectively guesswork.

Other data sources include historical patient records which may say little about the spaces within which services were delivered, or the use of wearable technology such as Radio Frequency Identification Tags [28-30] which require continuous management, can be expensive, and burdensome [3]. Each IoT device provided 6 months of operation using 2x AA batteries, and each was hard-coded to a single 'hub', transmitting data directly over low-band radio frequency. Since existing methods of data gathering to understand the use of spatial clinical resources are sub-optimal, new methods are required. These devices were stated to enable placement in a 15m radius from 'hubs' though some trial-and-error was required to confirm optimal distribution accounting for building-services-intensive healthcare environments. Data was gathered by IoT sensors in 10-minute intervals as this typically the shortest interval reserved for clinician-consumer encounters. This research introduces IoT devices into a live outpatient clinic zone in a public hospital setting and presents data to clinical and corporate end-users supporting evidence-based decision making.

4 Implementation

The participating healthcare zone to test the capacity of IoT for space-utilization data gathering was a multi-disciplinary ambulatory outpatient clinic. The space consisted of several different room types servicing different clinical needs which were part of the group of rooms studied including: Consult Rooms (21x), Treatment Rooms (2x), and Education Rooms (3x). The target clinic zone contains several other rooms that were outside scope, such as: corridors, public and staff toilets, waiting rooms, staff-only admin areas, etc. The former group are clinician-patient encounter spaces, while the latter are non-clinical spaces within the clinic zone. As clinician-patient encounter spaces are where healthcare services are provided and consumed, these (26x total) rooms represent the highest-value

spaces in the clinic zone which require the highest level of use-optimization. The remaining rooms in the clinic zone from the latter group above were excluded.

Clinician-patient encounter spaces host confidential activities and interactions protected by Australian privacy laws, so all research activities were bound by strict regulations as identified in the approved Health Research Ethics Committee approval obtained prior to sensor installation. To study operational clinical spaces using IoT devices, available off-the-shelf devices commercially available in Australia were surveyed using a weighted decision matrix which excluded devices containing sensors that either collect or could be reasonably perceived to collect personally identifiable information. The deciding factors were total cost of implementation, the need for battery operation to avoid connecting to 'mains' power, and the cost to scale to the target zone. The final selection was a battery-operated, PIR sensor made by OccuPeye. The IoT device transmitted wirelessly to a designated 'hub', connected via network cable to a 4G SIM-ready router. Using the cellular networks with saturated coverage across the healthcare campus, data was transmitted to online 'middleware' for storage and analysis. The sensors were installed in locations shown in the clinic zone as per Figure 1. Sensors were mounted with double-sided, damage-free, repositionable manual connectors rated to over 3x the weight of the devices, which were mounted above each space's entry door wall, directly above the door leaf to minimize the risk to patients and staff of sensors falling. This sensor location, discovered through trial-and-error, also maximized the sensor's room coverage and avoided false positives from the adjacent corridor when the room door is open.

Figure 1 - Diagram of sensor layout in ambulatory clinic zone including hub location and coverage radius, modified from McNabb et. al [31]

5 Analysis and Results

Data reported below was collected over a six-month period from March to October 2019, collected from 28 clinical spaces, 7 days per week, 24 hours per day consisting of 733,824 data points. By comparison, a manual room utilization study in the same clinic was able to collect 1,292 data points in 15 minute intervals,

which was affected by the volunteer data collector being unable to attend for two of the five scheduled observation days due to illness [32]. Decisions made on the IoT system versus the manual system, would be relying on an increase in data resolution of approximately four orders of magnitude.

Table 1 - Showing Average % Occupancy, excluding public holidays from March 1st to October 1st, 2019 filtered for various times of the day (TD), days of the week (DW), space type (ST) and period (PD) including graphical legend, one space/room per chart bar [33]

The target clinical spaces were recorded as unoccupied 15.9% of their total available time by the IoT system. (refer 'A' in Table 1). Limiting the data to more traditional clinic operational hours from 8:00am to 5:00pm, the % occupancy improves 36.0% occupancy (refer 'B' in Table 1) further improving to 49.3% occupancy if weekends are removed (refer 'C' in Table 1). The data show that Thursdays are on average the most occupied weekday at 56.2% average occupancy (refer 'E' in Table 1), with Fridays the least occupied at 45.0% over 6 months. On the 'most occupied' Thursday, Consult Rooms were on average most occupied was on the 07th of March 2019 with the sensors recording 69.7% occupancy.

In all accessible literature, the concept of 'utilization' was applied during operational clinic hours only, with non-clinic hours either dismissed, or ignored. While the concept of a 24-hour outpatient clinic may be undesirable, extending clinic hours to some degree would be one way to improve access to healthcare services without increasing the physical footprint of the healthcare system.

Figure 2 demonstrates the challenges of manual data collection, as volunteers were only available on a single Monday,

Thursday and Friday in the week of March 14th 2019 [25]. Data from the IoT sensors indicates that Monday (53.5% occupancy) and Fridays (45.0% occupied) are the least used weekdays for Consult Rooms. The average utilization determined from the manual observation study was 41% Consult Room occupancy while the sensors recorded an average of 53% occupation.

Figure 2 - Comparison of manual data gathering for Monday, Thursday and Friday in the week of March 14th 2016 (top graph excerpt from [2]) vs. the IoT-gathered data averaged over 7 months from March 01st 2019 to October 01st 2019 limited to Mondays, Thursdays, and Fridays (bottom graph excerpt from <https://www.occupeye.com/> on 12-10-2019)

Within this data, peak utilization from the manual data was a single reading on Thursday March 17th at 79% at 10:15am, while peak occupation from the IoT data shows 16 occasions where peak occupation was 90% or higher, with the highest peak at 95.2% at 12:10pm on Thursday August 08th, 2019 at 95.2%. While the IoT data is easily filterable to only clinic operation times, the daily average data shown through this report contains a 'dip' over the lunch period when the clinic is closed, which lowers average occupancy similar to the effect of including 24 hours of data, 7 days a week (refer 'A' in Table 1). Excluding this hour in the calculation improves percentage occupied 1.3% to 70.65% occupancy.

The ecosystem of technologies that constitute IoT devices, delivers benefits beyond accurate data over extended time periods. The sensors in this research not only save data locally on the individual devices, they have the capability to transmit time-stamped data to cloud-based repositories hosting middleware applications providing advanced analytics in a

dashboard format (see Figure 3). Dashboards provide the ability for non-technical end users to query the dataset, providing a lens to answer an array of their own research questions, and analyze the data in ways that are meaningful to them rather than struggle with the interface. This enhanced capability will enable end users, such as front-line service providers and executive decision-makers to query data, looking for improvement opportunities, and perhaps most importantly being able to evaluate if any implemented improvement initiatives were successful. This last step of post-intervention re-evaluation was missing in most of the literature, but without it the process of improvement cannot iterate, and return-on-investment for utilization improvements cannot be demonstrated.

Figure 3 - Excerpt from proprietary dynamic cloud-based data dashboard showing occupation data all spaces in the target clinic for a nominal period from [33]

6 Conclusion

The data collected through this research represents occupation, rather than utilization. Additional work would be required to understand if the spaces are used well when they are occupied, rather than being able to identify only that they are occupied, or more importantly, sitting vacant. To understand if spaces are being well utilized, one would need increased data resolution moving from data on occupation (presence) to data on the number of people in a space (count) [34]. Future work will focus on the application of machine learning algorithms to predict future occupancy based on historical patterns.

The technology used in this research may not be scalable for a healthcare services with thousands of rooms and dozens of campuses. To cover one of 4 floorplates in the broader hospital studied in this research, well over 100 hubs would be required, and over \$1000 per hub, scaling is unsustainable. Future research will explore technology supporting privacy-friendly IoT devices at scale suitable for the optimization of space utilization in healthcare systems that have a significantly improved range and battery life.

This research has demonstrated that IoT devices can provide information on the occupancy patterns of clinical spaces. What hasn't been explored through this research is how these devices, and the increasing amounts of information they can collect, may

affect the occupants of these spaces. If too little information is collected, opportunities for improvement may be missed. If too much information is collected, the privacy and civil liberties of the occupants may be affected. Exploring the balance between the drive for increasing amounts of data and the effect on the occupants of healthcare spaces will be explored in future stages of this research. One Canadian survey found just over 50% of respondents said their existing methods of spatial resource allocation were either 'good' or 'very good' leaving abundant room for improvement [35] over existing methods. Accurate data drives improved decision-making.

This study has demonstrated data collection by IoT devices to understand patterns of activity in clinical spaces is superior to manual data collection methods by 'the clipboard brigade'. Human presence-sensing in hospitals needs to be designed to fit the specific use-case as a PIR system suitable for understanding occupation of clinic rooms is different, for example, than sensors required to study Operating Room utilization [36]. The time period over which data can be collected and analyzed provides a more accurate picture of average occupation, and perhaps more importantly provides the ability to understand the occurrence and timing of both 'peak' and 'trough' occupation levels. It is the 'troughs' that represent opportunities for maximum improvement with minimal effort, while 'peaks' drive the need to build more clinical spaces, increasing both the physical and ecological footprint of the healthcare system, and continuing to drive up the cost of providing healthcare to not only Australian citizens, but all consumers of healthcare services worldwide.

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