McNabb, Timothy G. (2024) *IoT devices optimising clinical space utilisation: effective, appropriate, acceptable.* PhD Thesis, James Cook University.

https://doi.org/10.25903/ezfj%2D7r72

IoT DEVICES OPTIMISING CLINICAL SPACE UTILISATION: EFFECTIVE, APPROPRIATE, ACCEPTABLE

by

TIMOTHY G. McNABB

Submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY
(ENGINEERING)

James Cook University
College of Healthcare Sciences
September 2024

DEDICATION

This thesis is dedicated to the memory of my parents Bill and Sylvia McNabb, who passed during the creation of this work. Their abundant love and generous support provided the solid foundation upon which my life is built. They were gone too soon and remain forever in our hearts and minds. Though their loss was challenging to navigate, their love of life and each other inspired all of us lucky enough to know them.

Also, this thesis is dedicated to my loving, kind and supportive extended family who supported the emotional side of this research projects' production and celebrated every success with me. Together we thrived through three floods, four renovations on two continents, and an international pandemic during the creation of this thesis. The incredible love and support received from my amazing in-laws, good friends and neighbours has been integral to achieving the goals of this work. A special mention goes to my wonderful wife Lara who has supported my many dreams and ambitions as together we experience *our great adventure*. An extra-special mention goes to our incredible child Xan who inspires me daily with good humour, natural talents, developing skills and inquisitive drive; may this achievement inspire you to aim high.

Special thanks go to my incredible advisers Kristin Wicking and Trina Myers for their support through this journey. Kristin Wicking is an incredibly special person whose wisdom, care, compassion, intuition, humanity, abundant enthusiasm, knowledge and guidance were critical to the creation of this thesis. Kristin kept me on the path to completion and away from the many shiny objects alongside it. Trina Myers is an inspiring powerhouse of a human whose passion for discovery, inquisitive intellect, experience, energy and drive have been critical to this thesis. If Kristin kept me on the path, Trina propelled me forward. I feel extremely fortunate to have had Kristin and Trina as my advisory team and cheering squad. I will be forever grateful to this tightly knit team for their support and guidance though the challenges and triumphs of this work; may we continue our shared research journey for years to come.

ACKNOWLEDGMENT OF THE CONTRIBUTION OF OTHERS

I would like to acknowledge the generous support of the Townsville Hospital and Health Service (THHS) through multiple Study, Education, Research Trust (SERTA) grants. I am especially grateful for the Research Fellowship grants supporting the final completion of this work. Also, I would like to acknowledge my colleagues and management team who have been supportive, encouraging and understanding while I have navigated full-time work and part-time research.

I would also like to acknowledge the contribution of many other third parties involved in supporting this research project including:

- The THHS Data Lab for providing rigorous technical support.
- The James Cook University's Workplace Integrated Learning students: (A. Libera, J. Togo, N. Barty, P. Pannam) for creating a predictive data artefact, including machine learning model and user interface.
- INCORP Australia loaned PIR sensors for preliminary experimentation.
- Livesense Pty Ltd provided technical support as middleware vendors.
- Many third-party commercial goods and services suppliers who provided support and education through the many technological hurdles overcome in the production of this research project.
- Advisers T. Myers and K. Wicking for editorial support.

ABSTRACT

IoT DEVICES OPTIMISING CLINICAL SPACE UTILISATION: EFFECTIVE, APPROPRIATE, ACCEPTABLE

September 2024

TIMOTHY McNABB, B.ARCH., CARLETON UNIVERSITY, CANADA

PhD DISSERTATION, JAMES COOK UNIVERSITY, AUSTRALIA

Directed by: Dr Kristin Wicking, and Professor Trina Myers

Delivering public healthcare is a complex and expensive endeavour. Many categories of expenditure compete for limited funding within fixed annual budgets. Similarly, in each healthcare system, diverse services compete for limited space. Without appropriate clinical space, most clinical services cannot be provided. Clinical space is therefore a critical resource to every healthcare system and its utilisation requires careful management. Using existing clinical spaces efficiently will optimise consumer access to healthcare services. Improved access results in timelier healthcare services delivered to healthcare consumers in need. Receiving healthcare services sooner reduces reliance on more intensive and costly downstream services such as the emergency department and ambulance services.

Despite this criticality, prior to this research there has been no sustainable way to collect data on the use of clinical spaces, making management of clinical space across a health system challenging and nearly impossible at the state level. Previous methods of studying clinical space utilisation typically required ongoing human resources to manage if fully implemented. Therefore, study periods were typically short and did not reflect the dynamic reality of healthcare services delivery which is constantly in flux. Also, the findings of previous researchers were challenging to translate into 'coal face' efficiency gains without significant ongoing human resources funding.

This research explored the capacity of Internet of Things (IoT) devices to support the optimisation of clinical space utilisation by demonstrating how these spaces are used. These network-connected sensor devices recorded human activity for 25 months in 25

clinical spaces across an operational multidisciplinary outpatient clinic within a regional tertiary teaching hospital in Australia. Human-centric data visualisation and exploration was facilitated through dynamic data dashboards incorporating analytical and predictive support tools. This research demonstrates that IoT devices are effective in providing data on clinical space utilisation. Further, by processing this data, historical use patterns can be explored, and future vacancies can be predicted.

This research project also explored the opinions of healthcare workers on both the appropriateness of IoT technology in a clinical setting, and its acceptability for use in their workplace. Despite the demonstrated success of this technology, the human response to their implementation remained unknown. For example, were these systems appropriate for use in operational clinical environments? How comfortable would staff feel, working in spaces under constant electronic observation? To explore their feelings on the potential implementation of these technologies, staff at the host HHS for this research were asked for feedback through a series of one-on-one interviews and an all-staff survey. Staff responses indicate that this feasible, sustainable approach to managing clinical space utilisation was considered appropriate for deployment in operational clinical environments. Also, staff were comfortable with low-density collection of human activity data to optimise clinical space utilisation in their workplace with several critical caveats.

Clinical space utilisation data can now be sustainably recorded, visualised and predicted. Data can be transparently shared within and between healthcare service groups. Clinical spaces can be shared by agreement between service groups to dynamically manage peak loads without physically expanding the healthcare system. Alternatively, with the capacity for near-live feedback, the management of clinical space could be re-organised entirely. The capacity to effectively manage clinical space has now been demonstrated at the local level. Efficient use of existing spatial resources can now also be demonstrated to local and state-level entities prior to funding expansion activities.

Optimising the use of existing clinical spaces means a reduction in the need to expand the physical footprint of the healthcare system. At a cost of approximately $240,000 per consult room to construct, and many more times that to operate, the public service has an obligation to demonstrate efficient use of its spatial clinical resources. This obligation is especially true when allocating resources to expand the physical and ecological footprint of the healthcare system. Improved access to healthcare services reduces wait times and improves the healthcare experience of consumers while simultaneously reducing the overall cost of delivering these services. With positive implications for financial, social, ecological and quality aspects of healthcare services delivery, this research project has demonstrated potential positive impacts to the quadruple bottom line of the public healthcare system. The potential benefits from this research project's findings for society could be high if the concerns of occupants can be suitably addressed.

STATEMENT OF ACCESS

I, the undersigned author of this work, understand that James Cook University will make this thesis available through the university library, and via the Australian Digital Thesis network. I understand that, as an unpublished work, a thesis has significant protection under the *Copyright Act 1968*, and I do not wish to place any restriction on access to this thesis.

Parts of this thesis have been reproduced with permission from the copyright owners –authorisation to re-publish has been included adjacent to these works in the relevant appendices.

08/11/2024

Signature   Date

DECLARATION

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institution of tertiary education. Information derived from the published or unpublished work of others has been acknowledged in the text and a list of references given. Every reasonable effort has been made to gain permission and acknowledge the owners of copyright material. I would be pleased to hear from any copyright owner who has been omitted or incorrectly acknowledged. All research procedures reported in the thesis received the approval of the Townsville Hospital and Health Services Human Research Ethics Committee and the James Cook University Human Research Ethics Committee.

08/11/2024

Signature | Date

TABLE OF CONTENTS

Section Page

LIST OF APPENDICES

LIST OF TABLES

LIST OF PUBLICATIONS

McNabb T, Myers T, Wicking K, Lei L, Xiang W. Optimizing spatial healthcare assets with *Internet of Things. Health Information Science and Systems*. 2018 Sep 18;6(1):11

McNabb, T., Wicking, K., Myers, T., & Lei L. (2020, February). Optimizing clinical spatial resources with IoT. In *Proceedings of the Australasian Computer Science Week Multiconference* (pp. 1-6)

McNabb, T., Wicking, K., Myers, T., (2023, July). Occupation versus Utilisation of Clinical Spaces Using Internet of Things Devices: Are Consult Rooms Well Utilised? In *Proceedings of the International Conference on Health and Medical Informatics*;

LIST OF PRESENTATIONS

McNabb, T., Wicking, K., Myers, T., (2022, November 15-December 31). Preliminary Interview Results About Working in Smart Health Buildings – how do health staff feel about electronic and manual data gathering in healthcare spaces? *Poster for TropIQ: Townsville Research Symposium*

UNPUBLISHED WORK

McNabb, T., Wicking, K., Myers, T., Schnetler, R., Barty, N., Pannam, P., Libera, A., Togo, J., Crowley, B. (2023, November). 'Predicting Optimisation Opportunities for Clinical Space Utilisation' *Unpublished*

LIST OF FIGURES

Figure Page

CHAPTER 1

INTRODUCTION

1.1 Introduction

Providing healthcare at the scale of a large modern hospital is complex, dynamic and expensive. Beyond financial costs, there were environmental and societal costs that must be considered when seeking to quantify the cost of providing healthcare services at a national level. Regardless which area of healthcare services one chooses to consider, the physical built form of the healthcare system touches nearly all of them in some way. Despite this broad underpinning of the healthcare system, research on the physical healthcare environment itself remains underrepresented in the literature.

First, the cost of providing healthcare in Australia is high and growing, with $220.9 trillion spent in the 2020/21 financial year. This spending has experienced more than 25 per cent growth from the 2015/16 to 2021-22 financial years. Though operational and financial impacts on the healthcare system from the recent COVID-19 pandemic must be acknowledged, growth in healthcare expenditure has outstripped Gross Domestic Product (GDP) growth for a long time. To meet the demands of a growing system, ways to reduce inefficient practices must be found to ensure the provision of healthcare services are as efficient as possible.

Next, one area of healthcare spending that grew by a 10-year annual average of 3.9 per cent to the 2015-16 financial year is capital expenses. These expenses are those spent on building, buying and renovating healthcare spaces. These funds are distinct from, but are directly related to, the recurring costs of operating and maintaining any expansion of the built healthcare environment. Since healthcare contributes seven per cent of Australian greenhouse gas emissions [6], reducing the growth of the physical footprint of the healthcare system also reduces growth of its environmental footprint.

Finally, in any modern healthcare system, independently operated services are functionally interconnected with other services, both clinical and nonclinical, in a constant ebb and flow. This web of healthcare delivery is experienced sequentially by healthcare consumers as they progress through their healthcare journey. Improved access to healthcare services leads to earlier healthcare interventions, and reduced reliance on more intensive downstream services. Each of these services affects the others should capacity exceed demand, and in all cases the healthcare journeys of consumers are negatively affected. These effects manifest in longer wait times, increased congestion in emergency services, and increased backlog in ambulance services, and other negative downstream clinical service impacts.

Each of the above aspects of providing healthcare services, including the overall financial costs, environmental costs, and social costs has at least one common critical resource: space. Without healthcare spaces to supporting the delivery of modern clinical care, delivering healthcare services to the level of the Australian or any modern healthcare system would not be possible. This reliance on space is equally true of ambulatory outpatient services. Research literature is abundant on the flow of patients through respective clinical services. Many of these had the aim of optimising elements of time, either patient or provider time. Others seek to optimise the use of limited clinical resources, yet few mention 'the elephant in the room': the room itself. Despite supporting the delivery of outpatient healthcare services around the world, limited research has been devoted to optimising the use of the clinical space itself. This may be due to a lack of effective tools to study how these spaces are used. Alternatively, it may be due to the lack of appropriate methodologies to study these spaces. Perhaps there is a reluctance to pursue this type of research due to the vagaries of the primary current tool: human observation of human behaviour? Whatever the reasons, research on the optimisation of the use of these high-value, limited-quantity resources is underrepresented in the literature.

The aim of this research project is to demonstrate effective tools for healthcare staff to better understand how their spaces are utilised. Managers typically understand how the spaces in their care are *intended* to be used. However, there is currently no long-term, cost-effective means to verify *intended* use against *actual* use, and adjust accordingly. Similarly, the capacity to demonstrate the effectiveness of any optimisation strategies, once they were implemented, is also limited. The suite of technology hypothesised as ideal for this role is collectively termed the 'Internet of Things' (IoT). These IoT devices are increasingly common 'smart' objects in everyday life, such as clothes washers, vehicles and of course phones. This research demonstrates that IoT devices are effective in providing data on clinical space utilisation. Further, by processing this data, historical use patterns can be explored, and future vacancies can be predicted.

Introducing new technology into standard clinical spaces may not be considered appropriate in healthcare settings. Similarly, healthcare staff may not feel comfortable being under the constant observation of these technologies. Should either of these possibilities be demonstrated to be true, the introduction of IoT devices to understand patterns of clinical space utilisation may not be feasible at scale. This research project also explored the opinions of healthcare workers on both the appropriateness of IoT technology in a clinical setting, and its acceptability for use in their workplace.

By demonstrating the first sustainable, acceptable, and appropriate suite of technology capable of identifying historic patterns of occupancy, and predicting future vacancies, this research advances the state of the art. Beyond being functionally effective, this technology is also lower cost, and more accurate compared with previous manual data-gathering methods. The technology operates independently with minimal maintenance for as long as the hardware lasts. Ambient information collected by electronic devices in nonintrusive, non-personally identifiable ways has the potential to revolutionise how humans use the built environment.

Optimising clinical space utilisation means more healthcare services can be delivered through existing resources. Increasing healthcare delivery opportunities leads to improved access to diagnosis and/or treatment for consumers and allows for earlier intervention opportunities. Improved access leads to reduced wait times, and less demand to increase the physical size of the healthcare system. Using exiting healthcare facilities more efficiently is cost-effective, potentially freeing up funds to increase core services. Beyond positive financial impacts, using our built environment more efficiently helps mitigate negative environmental impacts in Australia and worldwide. Using IoT technology to optimise clinical space utilisation can positively impact human society both individually and collectively. Now that this potential has been realised, implementation is inevitable.

1.2 Research problem

Few tools exist to support clinical managers to optimise the use of their existing healthcare spaces. Without the ability to accurately record space utilisation, clinic managers have had little data to demonstrate whether their services were at, or over, capacity. For executives, making data-driven decisions on capital allocation is challenging when efficiency of existing resources cannot be proven or disproven. The documented evidence of the disparity between the intended use of existing spaces and their actual use has historically been elusive.

Human observation, the most prevalent of current methods of determining space utilisation, is problematic in clinical settings. When spaces were *in use* for the provision/consumption of outpatient services, the necessarily windowless doors to clinical spaces remained closed. Interrupting clinical services to check whether spaces were occupied or vacant was equally problematic. Constant human observation inside clinical spaces would be equally disruptive. Ongoing self-reporting may negatively impact the timely flow of healthcare service delivery and has been demonstrated to have low accuracy. Human resources were costly, and therefore study periods tend to be short. Snapshot data gathering in a dynamic healthcare delivery environment is suboptimal. By the time improvement interventions can be designed and initiated, the state would have changed, making demonstrating the effectiveness of interventions challenging if not ineffective. Human-based data gathering is also error prone with the monotony of continuous monitoring across a clinic likely to further negatively impact the quality of data provided. This seemingly intractable problem may be reflected in the lack of clinical space use optimisation research in the literature. This research explores solutions to the inherent challenges of optimising clinical space utilisation. Through this exploration, emergent technologies were utilised to help resolve these problems by responding to several targeted research questions.

1.3 Research questions

From the research problems identified above, several research questions emerged. These questions have been provided below, including parenthesised references to where in this document they have been answered:

- Can IoT devices identify patterns of utilisation in operational clinical spaces? (Section 4)
- Can humans gain insight into historical patterns of clinical space utilisation by interacting with IoT data through data visualisation artifacts? (Section 4.2.5)
- Can future utilisation patterns be predicted from historical data? (Section 4.2.7)
- Do healthcare workers consider IoT devices appropriate to study space utilisation in operational clinical environments? (Sections 4.3 and 4.4)
- How comfortable are staff with being observed by IoT devices gathering human activity data in their workplace? (Sections 4.3 and 4.4)
- As the density of human activity data gathered by electronic devices increases, is there consensus within staff comfort levels? (Sections 4.3 and 4.4)

1.4 Research aims

This research responds to the above questions by demonstrating cost-effective solutions to challenging, previously irresolvable problems and confirms the viability of these solutions when applied to an operational clinical environment. Further, this research not only provides a window into historic resource utilisation, but provides a tool to predict future utilisation based on ongoing historical data and therefore supports improved spatial clinical resource utilisation in future. Such improvements aim to improve operational effectiveness of the clinic and help improve the healthcare journey for consumers, reduce daily stress on operational staff, and ultimately reduce the cost of providing public healthcare services. Abundant research exists exploring human energy consumption through the built environment, and the associated environmental impacts. Research into optimising patient scheduling and clinical flow is equally abundant. Finally, this research project explores the timely, emergent opportunity for a multidisciplinary approach to addressing the intractable challenges associated with optimising clinical space utilisation.

1.5 Outcomes

The prediction was that patterns of occupancy would be clear in the data obtained from the sensor units through post-report examination and statistical analysis. This data would then form the basis for making evidence-based recommendations for strategies targeting improvements in outpatient clinical space use. The intent of the final design artefact was to provide short-term feedback on the effectiveness of employed space utilisation strategies to frontline managers and executive staff alike.

The capacity for targeted intervention with IoT technology has been demonstrated to improve opportunities for clinical space optimisation initiatives. Realising these opportunities would provide numerous improvements. First, it would improve access to clinical services. Also, it would reduce demand to increase the physical size of the healthcare system. Finally, it would provide some mitigation of the inherent environmental footprint of providing healthcare in Australia. If access to healthcare services could be improved by increasing opportunities to provide healthcare through existing spatial assets, consumers of these services can receive clinical attention more rapidly. Earlier intervention would reduce reliance on riskier, more intensive, and more expensive downstream services, and improve the healthcare journey of consumers. In summary, better utilisation of spatial assets improves individual healthcare outcomes while reducing the cost of providing healthcare and the impact of providing healthcare on the environment. This opportunity can be realised if historical challenges in data gathering, data visualisation, dissemination and future use prediction can be overcome by the results demonstrated through this research.

1.6 Motivation

This research project originated from a simplistic query posed to the author (Principal Investigator) as an employee of a regional tertiary teaching hospital in Queensland, Australia: ‘are our clinical spaces well utilised?’ When existing solutions based on human observation provided only ‘snapshot’ data resulting in substandard outcomes, the answer to this seemingly simple question grew more elusive, not less. Early on, the scale of the potential positive worldwide impact that resolving this issue could make for individuals, organisations and environment became evident. The potential to make such a positive contribution created sufficient drive to progress a formal inquiry through to completion. When the inspiration to use sensor devices was included in an awarded research funding grant, the hunt for a viable solution began in earnest.

With abundant support from colleagues, managers and the passion and guidance of two incredible advisers, the journey to find an answer to the core research question began. Each phase of discovery increased the passion to demonstrate potential solutions to this vexing question. This progressively building passion supported a seemingly unstoppable momentum, through two moves, family trauma, three house floods, three renovations, personal health crises and an international pandemic. In summary, a determination to resolve a simple yet apparently intractable question with a cost-effective, scalable solution provided sufficient motivation to see this research through to conclusion.

1.7 Potential solution

Privacy-preserving, internet-connected sensor devices were proposed for installation into clinical spaces to detect human presence and/or provide insight into human activity in these high-value clinical spaces. Data collected was nonpersonally identifiable, environmentally ambient, and collected by noncontact means without any maintenance burden on clinical staff. Once collected, data was presented to staff in a dynamic data dashboard to facilitate personal exploration and identification of improvement opportunities. Further, the tools of machine learning were applied to the data to explore the predictive capacity in identifying future optimisation opportunities for clinical space utilisation. Finally, staff opinions on the use of electronic observation to study patterns of human activity within clinical spaces were confirmed through one-on-one staff interviews and an all-staff survey.

1.7.1 Scope

Sensors were installed in 25 healthcare spaces within a fully operational multidisciplinary outpatient suite, on the main campus of a regional hospital and health service (HHS) in Queensland, Australia. Data gathering was ceased for practicality purposes after 25 months of continuous operation. Once the digital survey was completed, nine interviews and an HHS-wide survey were undertaken to explore staff perceptions of various data gathered by either human or electronic observation.

1.7.2 Sequence of activities

Activities outlined in this section and further expanded in Chapter 3 occurred sequentially, each building upon lessons learned in previous activities. Except for sensor selection and calibration activities, the results of each of the following were either presented at an international conference, published through international journal articles, were under consideration for publication, or are pending submission for publication. The sequence of activities undertaken for this research project are presented in Table 1.

Table 1: Schedule of research activities with approximate timing

Phase/Activity	Description	Start
Phase 1a: RFID Access Control Exploration	Explore capacity of existing staff Radio Frequency Identification (RFID) badges, and existing door access control system to inform space utilisation.	April - May 2018
Phase 1b: Multi-sensor Calibration (24hr. data collection)	Multiple sensor types placed in an enclosed, non-clinical administrative space compared data quality from numerous sensors	May 2018
Phase 2: Administrative Sensor Installation (one week data collection)	Sensors placed in a non-clinical space attached to a reservation system to compare intended utilisation to actual utilisation, Data collected on network-isolated, battery-operated Pyroelectric Infrared (PIR) Sensors	June - July 2018
Phase 3: Clinical Sensor Installation (100-week data collection)	Sensors placed in operational outpatient clinic captured data on human occupancy patterns over time; Data was imported to a proprietary cloud-based data dashboard, JCU Students in a Workplace Integrated Learning subject applied machine learning to IoT data to predict future occupancy patterns	Feb. 2019 - Feb 2021; Nov 2021
Phase 4: Interviews and staff survey	In-person interviews with nine staff seeking opinions on appropriateness and acceptability of IoT sensors studying clinical space utilisation, All-staff email survey released for 16 days to assess perception of a broader audience	Oct 2022

1.8 Research contributions

This research fills the gap in the literature studying clinical space utilisation in an operational multidisciplinary outpatient environment. A multidisciplinary approach was taken to resolve this issue, bringing together the fields of building science, computer science and healthcare. A summary of the contributions of this research has been outlined below.

1. Demonstration of IoT devices capacity
   Scalable IoT devices collecting space-management data in an operational multidisciplinary clinical environment with a focus on the optimisation of clinical spaces.
2. Longest and most comprehensive study of clinical space utilisation
   Long-term study of clinical space utilisation over 25 months continuous collection of data.
3. Demonstrated acceptability of IoT devices by staff in their workplace
4. Demonstrated appropriateness of IoT devices studying clinical space utilisation
   (3&4) qualitative data collected exploring healthcare staff opinions on the use of IoT devices in healthcare settings to collect clinical space utilisation data.

1.9 Thesis structure

This thesis follows a standard introduction, methods, results, and discussion (IMRAD) presentation style. This style was chosen due to its functionality and familiarity to most academic audiences. The thesis has been structured as per the following five chapters.

Chapter 1: Introduction

This chapter introduces the research. The context is established, the research problem is identified, and the research questions being addressed are stated. This chapter also provides a broad overview of how the research problem has been addressed, and outlines what the reader can expect from following chapters.

Chapter 2: Background

Existing research across multiple fields of inquiry are presented, including:

- types of sensible human qualities and various sensors designed to detect them
- use of sensors in other fields to detect aspects of human activity
- use of human observation in related fields of time optimisation
- a brief exploration of existing research on the optimisation of healthcare space both with and without IoT support technology.

Chapter 3: Methods

This chapter outlines how each phase of the research was planned and executed. The structure reflects the logical sequence of each consecutive phase of research (Table 1). Each phase builds on outcomes from previous phases.

Chapter 4: Results

This chapter follows the sequential pacing of activities established in Table 1. An overview of the results of each research activity is gathered, and conclusions are drawn from the data. Results are presented in summary form with additional supporting data available in the appendices.

Chapter 5: Discussion and Conclusion

Finally, this chapter summarises the thesis, provides context for this research within the existing literature, presents future extension opportunities, and presents reflections on the implications of the findings.

1.10 Summary

This chapter has provided an introduction for readers to the fundamental aspects of this research which has emerged to support the resolution of a simple yet challenging question '*Are clinical spaces well utilised*?' Underlying existing problems have been explored with the current state of clinical space utilisation data collection. Research questions emergent from the core problem have been articulated, and a potential solution to resolving the problems by answering the research questions is proposed. Initial trials were undertaken to explore the effectiveness of IoT sensors in collecting ambient, nonpersonally identifiable data and patterns of clinical space utilisation have been demonstrated. Lastly, feedback from staff was sought on the appropriateness and acceptability of using IoT sensors in clinical environments. This research project has demonstrated a suite of appropriate and acceptable technology that sustainably supports the optimisation of clinical space utilisation.

CHAPTER 2

BACKGROUND

2.1 Introduction

This literature review seeks to understand how previous researchers studied the use of operational clinical spaces. Initial results identified the direct research questions under-represented in the literature. The research questions initially trialled include those stated in Section 1.3 above including:

- Were IoT devices appropriate to study space utilisation in clinical environments?
- Can IoT devices identify patterns of utilisation in operational clinical spaces?
- Can humans gain insight into historical patterns of clinical space utilisation by interacting with IoT data?

With negligible results from the direct research questions above, the use of IoT devices to optimise clinical space utilisation, additional questions were required. The *literature search research questions* underpinning the review were guided by the genesis question of this research: are clinical spaces well utilised? These *literature search research questions* broadened the search from strictly IoT devices, to any electronic data gathering technology. Any method of collecting human presence data in clinical space that was (or could be) used for understanding human occupation patterns were also sought. These *literature search research questions* were as follows:

- What research existed that targeted clinical space optimisation using electronic data gathering technology, such as sensors or IoT devices?
- Which technology has been used by previous researchers to gather data, and what were the experiences of the researchers in the use of these technologies?
- Where was the focus of previous researchers if not directly related to optimising clinical space utilisation?

This research project sits at the intersection of multiple professions. Consequently, a multidisciplinary approach to the literature review was required. Three primary research disciplines underpin this research project: healthcare systems, information systems, and the built environment (Figure 1). Limited research relating to the core subject of this research project emerged from a structured search based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines [7]. Using the PRISMA literature search guidelines (or similar) is standard

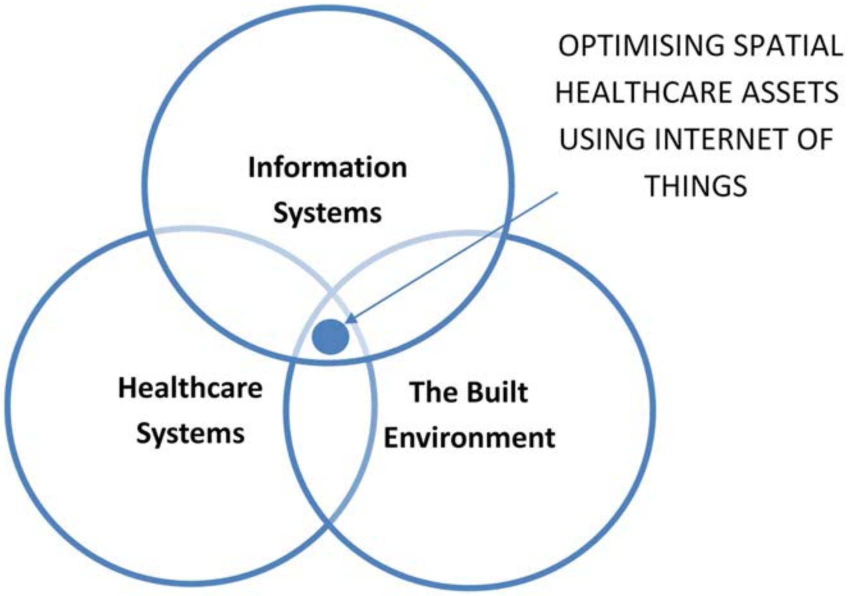


Figure 1: Venn diagram of research disciplines intersecting to establish the area of focus in this research project

practice in the healthcare discipline. Due to these limited results, a less structured search method common in computer science (information systems) was used, focusing on conference proceedings and recent publications. The latter approach used Google Scholar to identify relevant research using the same search terminology as the PRISMA search identified later in this chapter. In alignment with the PRISMA guidelines, methods and results from this search are presented along with a tabular summary. Results from all searches overlapped to a high degree, however. Consequently, results have been combined and presented as a single body of work for the remainder of this chapter. First, a brief introduction to human presence detection will ground the reader in aspects that underpin all research discussed through the remainder of this chapter.

2.2 Properties of human presence/activity detection

The observation of humankind through sensor technology comprises many different fields of inquiry. Consequently, a common nomenclature and taxonomy of human-observation technologies would help establish a common language across the various fields. In their work, Teixeira, et al. [8] establish a taxonomy of human sensing. Their work defines three subcategories of the 'observable properties' of humans: physiological properties, behavioural properties and spatial-temporal properties.

Physiological properties of humans, such as blood pressure, heart rate, temperature, etc. have generally been widely studied in research. Focus on these properties has increased recently with the application of IoT technology. Recording physiological properties to '*address paediatric and elderly care, chronic disease supervision, private health, and fitness management*' using IoT has become popular. This data gathering technique has formed the basis for a myriad of research, as explored in the literature review of Islam, et al. [9].

Behavioural properties of humans relate to how humans act either alone or in groups. Insights have been gained from the study of human behaviour. These studies contain a variety of subgenres, such as research on social patterns, and the study of urban dynamics. For example, Guo, et al. [10] studied large-scale data mining techniques to understand human social patterns, based on the digital traces these interactions create. Their results suggest the emergence of an embedded intelligence created by the digital traces left by human interaction with IoT devices. There are many kinds of digital traces humans leave behind that support this embedded intelligence. The IoT interventions proposed by the Principal Investigator (PI) create abundant de-identified traces of human activity in both space and time.

Spatio-temporal properties relate to observable properties of humans that establish aspects of human presence at a fixed point of time and space. Within this broad subfield of inquiry, many subdisciplines exist in the literature, even when limiting literature to research related to indoor presence detection. Each of the sections explored below has distinct fields of inquiry with associated bodies of knowledge. Consequently, the review of literature in each was necessarily brief, sufficient to understand their opportunities and challenges. The taxonomy of Teixeira, et al. [8]

defines spatio-temporal aspects of human-sensing in some depth, further splitting attributes into ‘intrinsic’ and ‘extrinsic’ human attributes. Intrinsic attributes relate to individual human emanations, such as the emission of heat, and CO_2 gas, etc. Extrinsic attributes exist beyond bodily functions, but still relate to individual humans, such as the wearing of electronic ID tags or badges, and mobile device interaction, etc. Observable human traits in both intrinsic and extrinsic spatio-temporal categories can be further broken down into two subcategories. Static subcategories (S) reflect slowly changing aspects of humans, such as height and weight. Dynamic subcategories (D) reflect typical motion-based attributes of human existence such as gait.

2.2.1 Detecting human presence

By combining/adapting the taxonomy of Teixeira, et al. [8] with the human presence techniques categorised by Yang, et al. [11], the study of human presence detection can be represented as per Table 2 below. Each technique detects aspects of human presence based on associated human properties, which are categorised in the taxonomy. For each technique presented, technology exists to exploit features of the techniques. In most cases the technological response to exploiting these techniques is the utilisation of one or more sensor types. Each sensor could, in turn, be bundled together with power, data and network management systems into an IoT device capable of interacting with cloud-based middleware vendors for storage, visualisation or further processing.

Table 2: Techniques of presence detection with 'human trait' classification

			Human Feature Categories	
Techniques	**Benefits**	**Disadvantages**	**Intrinsic? Extrinsic?**	**Static? Dynamic?**
Survey /Interviews	Low cost	Resource intensive [2]	n/a	n/a
Ultrasound	Low cost	High false positives	Intrinsic	Static & Dynamic
Optical cameras	Accurate, high-res. data	Privacy issues [commonly noted in the literature of 'Section A']	Intrinsic & Extrinsic	Static & Dynamic
CO_2 sensors	HVAC demand control	Slow response time, environmental sensitivity, accuracy issues [3]	Intrinsic	Static
Indoor positioning systems (RFID, IR tags, etc)	Target location to 1.5m	Privacy issues, inconsistent connection, requires sensor 'saturation', resource intensive [4], indoor use challenges	Intrinsic & Extrinsic	Static & Dynamic
Infrared	low cost, low power, mature	Binary output, signal interference by wearer [5]	Intrinsic	Static
Thermal imaging	low cost/ power/ density	Constant power required, can operate in low-to-zero light	Intrinsic	Static

One of the ‘techniques’ indirectly referenced by Teixeira, et al. [8] and Yang, et al. [11] was the thermal array. These sensors collect infrared emissions but vary greatly from the features of the ‘infrared’ category as defined by Yang, et al. [11], relating more to ‘thermal imaging’ techniques. In their review Teixeira, et al. [8] mention thermal imagers sensing emissivity as a category within intrinsic/static traits. These traits were defined as ‘produced whenever a person was present, irrespective of what he or she was doing’ specifically measuring emissivity. Emissivity relates to thermal radiation emitted by objects. Thermal imagers typically identify and most often visualise the differentiation of hot objects within a static background emissivity field.

2.2.2 Categories of detectable human activity

The above taxonomy categorises properties of human presence detection. Researchers use these properties to focus on aspects of human behaviour as they relate to their area of study. Combined with Teixeira’s taxonomy, these sensors provide researchers with the capacity to accurately categorise, compare and discuss the aspects of human behaviour they were studying. The PI has adapted and represented these categories of increasing information density (Figure 2) to include floor plans to establish a healthcare context. The latter figure provides a visualisation of these categories to aid recognition. Each category of increasing data density contains all aspects of the previous category and has been referred to repeatedly throughout this thesis. For example, if the location of everyone is known (category 3), the quantity of individuals is known (category 2) and the occupation status of the room is known (category 1). Each category contains detectable features of human activity (Table 2), which in response has driven sensor development.

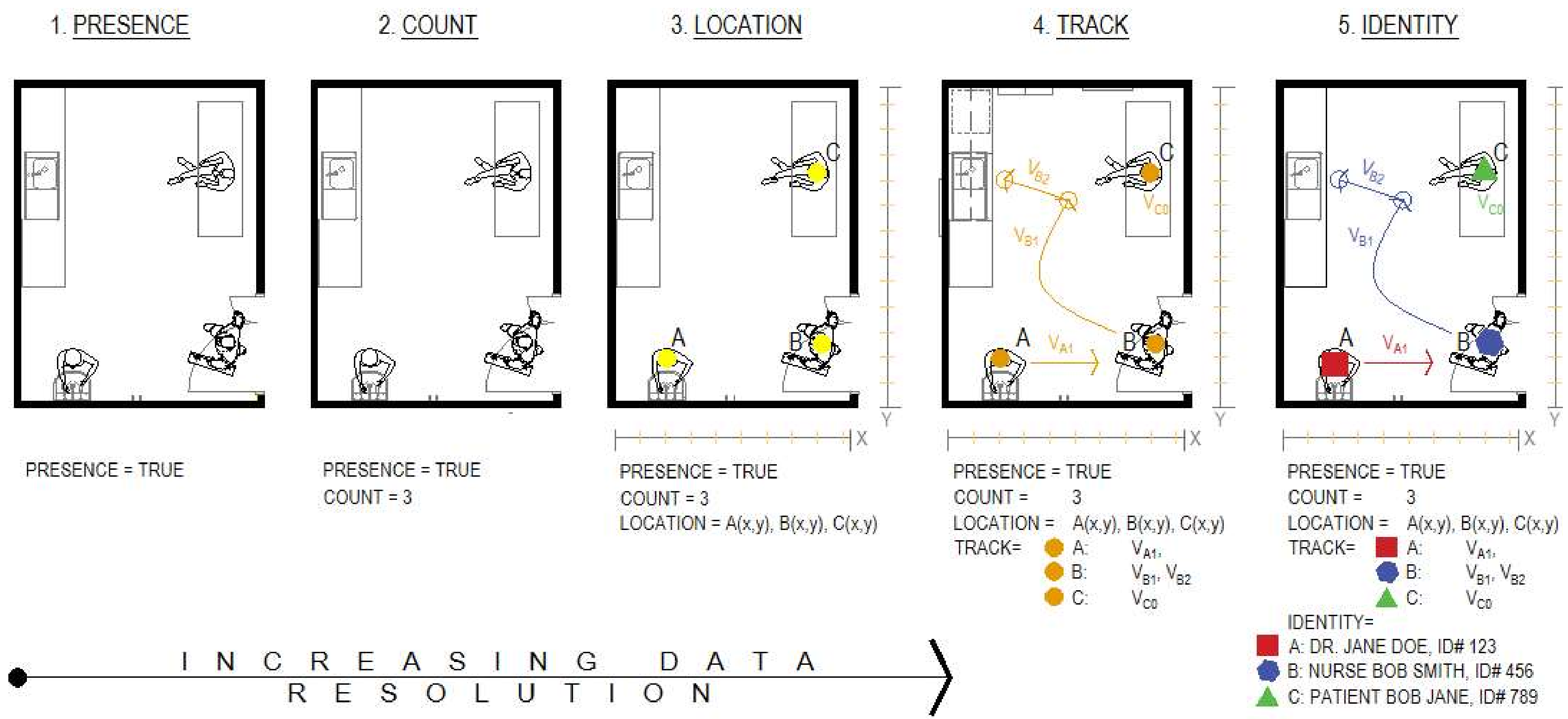


Figure 2 – Teixeira categories of spatio-temporal properties adapted and extended by McNabb et. al

.

2.3 Guideline-based literature search

The core focus of this research was the use of technology to improve the utilisation of clinical spaces within live healthcare environments. A systemic review was required to collate existing research as close to the core research subject area as possible. This healthcare-based review utilises the PRISMA guidelines [12] as a basis for undertaking and presenting research. This subsection presents the method and summary of results from the PRISMA search typical in the healthcare discipline. Results from the PRISMA search will be combined with results obtained through the methods of computer science described above.

2.3.1 Eligibility criteria

To assess if research was to be included in the review, eligibility criteria were used. The primary delineation for excluding research on the use of clinical spaces using remote electronic data gathering was a time-bar. Sources were time-screened due to the focus on IoT technology, from 1990 to present day. The date of the time-bar was informed by what was regarded as the first IoT device (a toaster) being accessed and operated remotely via. the internet Zhilenkov, et al. [13] in 1990. Only research on clinical space utilisation after 1990 was considered eligible due to the lack of available technology prior to this year. After this year, numerous prior 'networked appliances' existed, but these devices were typically limited to monitoring and reporting functions. One early example of a networked appliance is the vending machine connected for remote monitoring in 1982 by students at the Carnegie Mellon University [14]. Research papers were further narrowed using the following exclusion criteria:

- Results NOT relating to outpatient services in healthcare
- Results NOT directly or closely relating to utilisation of clinical spaces.

2.3.2 Information sources

Initial information was sought from ProQuest (https://www.proquest.com) however the search produced more than 24,000 results, but far fewer relevant results: 94. Similarly, search for the above criterion using MEDLINE (https://www.nlm.nih.gov/medline/index.html) produced only seven studies, with no relation to this research context. These searches were performed in mid-2017, followed by additional database searching through Google Scholar (www.scholar.google.com) with follow-up direct searches using reference which produced additional relevant results (59). ProQuest and MEDLINE searches were repeated on 30-09-2021 with two additional relevant results found for a total of 61. Two additional references were found on Google Scholar and were incorporated into the body of this chapter.

2.3.3 Search strategy

The same search string used in each database is identified above (Table 3). This initial screening method identified 150 results after duplicates were removed as shown in the PRISMA Flow (2009) diagram (Figure 3). Additional results were identified through 30-09-2021 which have been included in the body of the search results presented in this chapter.

Table 3: Table of databases and common searched terminology used

Database	Search Terms
Medline ProQuest Google Scholar	(optimising physical resource utilisation room space outpatient clinic) AND (IoT OR internet of things) OR RTLS (Real Time Locating System) OR RFID (Radio Frequency Identification) OR sensor networks or machine learning)

2.3.4 Selection strategy

Articles were selected through a manual selection process undertaken by the PI due to their relevance to the research questions. No automated selection tools were used in the process. Relevant articles were considered for inclusion initially by reviewing the abstract, and if relevance existed, the remaining paper was evaluated.

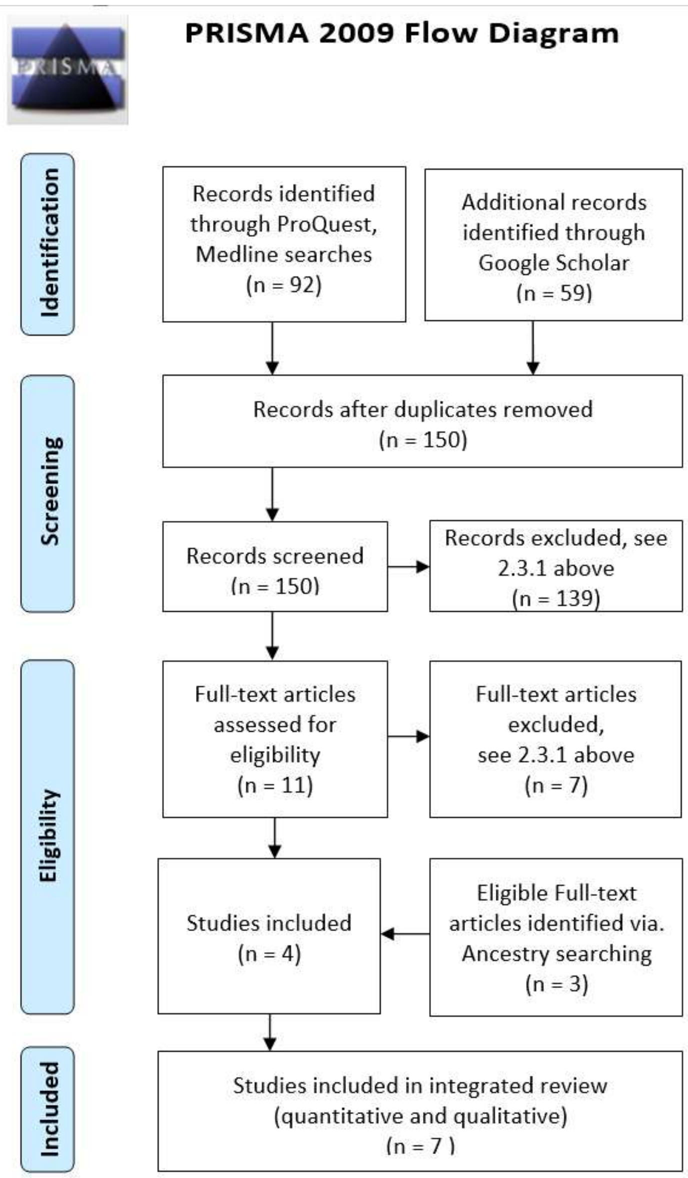


Figure 3 - PRISMA flow diagram results of guided literature search

Study Selection/Characteristics

The results from the selection process were contained in the PRISMA Flow diagram (Figure 3). This process resulted in seven papers for in-depth review. The characteristics of each selection resulting from this process have been summarised in Table 4. Following the presentation of these two elements, the results from all search results are combined for the remainder of this chapter.

Table 4: Summary of Studies

Author(s) / year / article title / journal	Aim/Purpose (paraphrased)	Data collection method	Study duration	Analysis/ simulation technique used	Limitations / Strengths (L: / S:)
Bratt, John H.; Foreit, James; Chen, Pai-Lien; West, Caroline; Janowitz, Barbara; De Vargas, Teresa /1999/ A comparison of four approaches for measuring clinician time use / Health Policy and Planning	Which of the four methods of observational time-motion studies were most accurate?	Method 1: Traditional time-motion: tone every 3 minutes, record activity on template Method 2: patient-focused activity patients carried forms, encountered staff recorded start/stop times on form with synchronised watches Method 3: Interviews: staff were interviewed	One day /clinic, 3 clinics (i.e. 3 days)	'statistical analysis'	L: short study, resource intensive, self-reporting S: comparison of different techniques
Bryant, M; Essomba, R/1995/Country Measuring time utilisation in rural health centres / Health Policy and Planning	How can we better understand how health workers in rural health centres use their time?	Active sampling used. SAMPLE SIZE: 19,080 observations (64, nurses 20 health centres)	5 days staff role (50 days)	not mentioned	L: resource intensive, human observation, analysis technique unclear S: long /broad study
Cote, Murray J./1999/ Patient Flow and Resource Utilisation in an Outpatient Clinic / Socioeconomic Planning Sciences	Can Discrete Event Simulation be used in an outpatient clinic to increase resource utilisation?	Patient-Flow study was undertaken using 'tracking forms' carried by patients and filled-in by healthcare workers through the course	140 days	Discrete Event Simulation	L: resource intensive, high consumer resource requirement S: simulation

Author(s) / year / article title / journal	Aim/Purpose (paraphrased)	Data collection method	Study duration	Analysis/ simulation technique used	Limitations / Strengths (L: / S:)
Guarisco, Steven; Oddone, Eugene; Simel, David /1994/ Time analysis of a general medicine service; Journal of General Internal Medicine	Optimising physician teaching time by better understanding 'house-staff' activity patterns	Gave staff/interns beepers that went off randomly, staff documented either 22 work activities or 13 contact events	6 days	binomial proportion model	L: human error potential, short duration, location unclear, self-reporting, resource intensive S: innovative approach
Overmoyer, B; Kadish, S; Haskett, C; Sanderson, K; Benneyan, J; Reilly, C; Vitale Pedulla, L; Brown, L; Camuso, K; Bunnell, C / 2014/Using real-time locating systems (RTLS) to redesign room allocation in an ambulatory cancer care setting / American Society of Clinical Oncology	Can IR tags in an existing RTLS installation demonstrate the effectiveness of room utilisation improvement initiatives in a cancer outpatient clinic?	IR Tags were worn by patients (staff handed out tags, collected them upon leaving clinic) and staff for tracking throughout the clinic during operating hours	49-day postinterventio n period	Standard descriptive analysis	L: resource intensive, ID's must be worn/used correctly, single-discipline clinic S: innovative approach
Stahl, James E.; Drew, Mark A.; Kimball, Alexandra B./2014/Real-time location systems, normative messaging and modifying clinician behaviour: a pilot study / Health Systems	Can Radio Frequency Identification (RFID) tags be used to monitor clinician behaviour through open publication of records?	RFID tags worn by clinicians, results of the activities of clinical workers presented openly for all participants to see, improvements were noticed in most clinical 'face time'	140 days	Standard descriptive analysis and single / multivariable methods	L: only clinicians, high capital costs (will reduce with time) S: innovative approach, long study

Author(s) / year / article title / journal	Aim/Purpose (paraphrased)	Data collection method	Study duration	Analysis/ simulation technique used	Limitations / Strengths (L: / S:)
The following studies are updated search results provided for contemporary context in October 2024 (non-exhaustive list); papers published by the author of this thesis are excluded:					
Kambombo Mtonga / 2022 / Optimised patient flow process – a case of outpatient and surgical departments in sub-Saharan Africa healthcare systems [15] / Thesis,/ University of Rwanda Digital Repository	Can technology such as IoT, linear programming, queuing theory reduce overcrowding via 'smart bus' systems in the sub-Saharan African healthcare system?	Light-dependant resistors and a laser system counted bus passengers, combined with GPS/ route supported local patient re-distribution to minimise local overcrowding issues; this 'smart bus' system was used in combination with machine learning to integrate operation room and outpatient scheduling prediction	The research established a proof-of-concept IoT system; duration was not noted	Queuing theory in combination with general linear modelling to establish surgical model, smart bus system to distribute patients	L: laser and light-based presence detection may not work in all contexts such (e.g. at night), or with groups of individuals S: translatable research concept for other healthcare systems
Moore, Philip T; Sharma, Mak / 2013 / Enhanced patient management in a hospital setting [16]/ IT Convergence Practice	Can RFID-based systems, be combined with existing healthcare systems to tracking all patients, staff and high-value equipment in a live hospital environment be combined with situational awareness analysis to improve patient experience and resource utilisation?	Passive RFID tags were used to collect location information, and data was visualised for human analysis	n/a Illustrative Scenarios used to describe how future systems (designed /implemented by others) might function	Comparative analysis	L: Paper identifies "ethical issues" but does not address their resolution S: combining situational awareness with location data has great potential and is directly translatable to IoT clinical space utilisation research

Author(s) / year / article title / journal	**Aim/Purpose (paraphrased)**	**Data collection method**	**Study duration**	**Analysis/ simulation technique used**	**Limitations / Strengths (L: / S:)**
Osman, Mohd Shafarudin; Azizan, Azizul; Hassan, Khairul Nizam; Ghani, Hadhrami Ab; Hassan, Noor Hafizah; Yakub, Fitri; Daud, Salwani Mohd; Latiff, Liza Abdul/ 2021 / BLE-based real-time location system integration with hospital information system to reduce patient waiting time [17] / 2021 / iEEE / International Conference on Electrical, Communication, and Computer Engineering	Can the combination of real-time locating systems and existing hospital information systems be used to reduce wait times in an Emergency and Trauma department in Malaysia?	Bluetooth low energy devices (iTags) were used to provide real-time location status of patients	3 months	Descriptive analysis	L: patient safety and privacy risks from integrating tags with patient data, and ongoing management to issue /associate/ return tags S: BLE devices are long-lasting reducing maintenance over
Safdar, Saria; Khan, Shoab Ahmed; Shaukat, Arslan; Akram, M. Usman / 2020 / Genetic algorithm based automatic out-patient experience management system (GAPEM) using RFIDs and sensors [18] / iEEE Access	Can a combination of technologies such automated surveys, RFID, and existing clinical management systems, supported using genetic algorithms be used to collect and analyse data to understand aspects of the patient experience in outpatient clinics?	RFID tags carried by patients were used to register presence (patient flow) and environmental data at consecutive clinical activity stations in an outpatient clinic, which was combined with user survey data	Data of 120 patients used	Genetic algorithm	L: ongoing system management required to issue and associate RFID tags for each patient S: patient flow optimisation is improved by using electronic patient satisfaction survey and genetic algorithm analysis

2.3.5 Guideline-based literature search result

Results have been presented in the simplified literature review matrix [19] (Table 4). This matrix was used, to ensure ‘a systematic and orderly plan to pursue and critique germane literature’ [20]. These results typically rely on limited data collection methods to collect human activity data within clinical spaces, no identified papers used IoT devices specifically, though some used their precursor technologies. The most common method of data collection is human observation in various formats, typically associated with the broad category of time-motion studies [21]. These consisted of having data collected on clinic activity by nurses [22], doctors [23], or all staff [2]. Similarly, Cote [24] relied on data collected by all staff plus patients, then applied discrete event simulation to the data. Each of the preceding studies were variations on time-motion studies, reliant on consistent human observation and other activities to gather data. Aspects of these types of data gathering techniques/technologies, and the types of studies they inform are discussed later in subsection 2.4.1.

The three remaining research papers from this method of literature search experimented with forms of semi-autonomous real-time locating systems (RTLS). These systems relied on humans to wear locating devices based on various technology such as infrared (IR) participant tags [25] and RFID participant tags [26, 27]. Like the time-motion results above, aspects of semi-autonomous data gathering methodologies are presented in subsection 2.4.2 below.

2.3.6 Guideline-based search summary

This section has reviewed literature emergent from applying the PRISMA search methodology. While limited research resulted from this process, the summarised research focused on studying human activity patterns inside clinical spaces, even indirectly. Though research using IoT devices specifically was not found, numerous examples of electronic data gathering exist with varying degrees of success. The electronic interventions trialled all had a common challenge: they relied on humans in some capacity to undertake one or more activities regularly and consistently. Reliance on human resources requires ongoing funding that could otherwise be directed to the core function of entities that provide healthcare: delivering healthcare services. To further explore research outcomes that have addressed similar multidisciplinary problems, sources outside the nominated healthcare databases were required.

2.4 Healthcare-based literature review

Due to the low number of papers in clinical space utilisation using IoT devices identified through the guideline-based literature search, the search methods were expanded. The online search aggregator Google Scholar [28] was utilised, based on the same search terms used in Table 3. This search aggregator has been utilised on multiple occasions throughout this research project up until final submission. Despite this search expansion, literature focused on the research topic directly was not identified. Numerous other research projects were identified that employed similar methodologies to those identified through the guideline searches above, but almost all were variations of the same broad categories:

1) Time-motion studies.
2) Semi-autonomous RTLS-based studies.
3) Spatial simulation studies.
4) Results from the extended literature search have been blended with results from the guideline-based literature search and presented in a single review section below. After the following expansion on these three categories of research responses in the literature above, the literature search will be further expanded to include nonhealthcare research on human presence detection.

2.4.1 Time-motion based studies

Time-motion studies that involved human observation and/or participation of patients and staff were the most common method of data collection in the healthcare literature. These predominantly manual studies typically involved participants (patients/staff) carrying paper forms with time marked by various devices. Staff typically note the timing of activities using either synchronised watches [23], randomised beepers [2] or regular broadcast tones [29]. None of the studies identified in the literature used IoT devices. Though these types of time-motion studies were found to be the most effective of the nonsensor-based methods (Bratt, et al. [23]), data collection was interruptive to clinical flow and not sustainable beyond short study periods.

Alternately named clinical flow studies also involved manual timer/paper-based manual recording studies of either clinician's time ([2, 22, 23]) or patient's time ([30-33]) with Isken, et al. [5] suggesting a trade-off between the two was unavoidable. In their study of 64 health workers in 20 health centres which resulted in 19,080 direct observations, Bryant and Essomba [22] found 27 per cent of a health practitioner's time was utilised in frontline health-related activities. While activities in time necessarily happen in space(s), the study of space utilisation was rarely identified as more than an incidental consequence of time utilisation. A few manual studies were directly aimed at 'resource utilisation' as a core purpose of the study. For example, Santibáñez, et al. [32] states:

> *This study was undertaken to address significant and increasing challenges regarding the use of space and resources* and *Physicians' office space, clerical support and examination rooms were often in short supply at times of peak volume leading to overcrowding, delays and concerns regarding patient safety.*

Such direct references to space availability being a fundamental part of the patient journey was not typical in the literature. While these time-motion studies inherently involved clinical space, spatial resource utilisation was rarely acknowledged. The focus of the above researchers, and many more found in the expanded literature search, was not on optimisation of clinical space utilisation, but on the optimisation of time. Also, the use of technology in these studies was limited to timekeeping and manual recording equipment. Consequently, a broader exploration of time-motion studies was not undertaken. Using more autonomous technology with less manual labour may have increased the duration of their studies and allowed them to broaden their focus.

2.4.2 Semi-autonomous RTLS-based studies

Previous research utilising time-motion studies relied heavily on manual data collection and simple timekeeping technologies. Research presented in this section comes closest to using IoT devices to collect data in ambulatory clinical areas, though most do not exclusively study outpatient clinics with one notable exception [25] which will be covered later in this subsection. Though they cannot be classified as IoT devices, sensor networks like these are the technological precursors to IoT devices. The systems reviewed in this subsection are broadly termed Real Time Locating Systems (RTLS). The RTLS-based research in this category contains three primary subcategories. First, a few researchers used infrared transmitters contained in participant-worn tags to collect data on clinical flow [5, 7, 25]. Second, participant activity was monitored using worn Radio Frequency Identification (RFID) tags [7, 26, 33-38]. The use of the latter technology was relatively common in research within hospital environments (e.g., tracking of inventory and equipment), however those noted were specifically focused on clinical flow studies. Finally, several emerging technologies have been trialled in clinical environments with varying success. These alternatives have been explored below in the category: *other RTLS research*. Common challenges using RTLS technology are presented at the end of this subsection after a brief review of each of the above subcategories, and their contribution to clinical space utilisation research.

2.4.2.1 Infrared transmitters in participant tags

Two researchers sought to use infrared (IR) transmitters, like a domestic television remote, to broadcast participant identification data within ambulatory healthcare environments. The first of these was essentially a trial of the technology to demonstrate the feasibility of collecting and preprocessing the IR sensor data. Its aim was an attempt to 'bridge the gap that exists in the acquisition and processing of large volumes of very detailed patient flow data that is necessary for effective simulation of outpatient clinics' [5]. In this research, small tags were attached to participants, and transmitted ID codes every 4 seconds via LED light with the intent of using the data to simulate the movement of people through target clinics. These tags were 'active' in that they broadcasted to waiting receivers. This set-up was contrasted by another researcher who used 'passive' participant-worn IR tags which were scanned at activity stations. This technique was used to track participant activity times through the study period, similar to the goal of time-motion studies [7]. Both these researchers used IR 'tags' for participants in a sensor network to capture location data supporting clinical flow analysis, though the latter referred to using RFID tags, but described IR technology.

Unfortunately, the IR transmitters and sensors used in both studies were line-of-sight systems. Their transmissions can be interrupted or blocked depending how tags were worn, as noted by Isken, et al. [5] that if tags were not properly worn, the system temporarily was unable to locate the user. This sentiment was echoed by Miller, et al. [7] suggesting enforcement of *proper* tag-wearing methods were required. Miller suggested appropriate tag placement must be enforced to ensure both patient and staff wore their tags above the waist and uncovered to prevent data loss (Figure 4). In a clinical environment with a high ratio of public to staff, such enforcement regarding continuous *proper* tag use may not be feasible long-term. Finally, compounding issues of tag placement, Miller, et al. [7] notes expensive IR tag losses through patients leaving the department without returning the tags, adding to the operational resources required by the system.

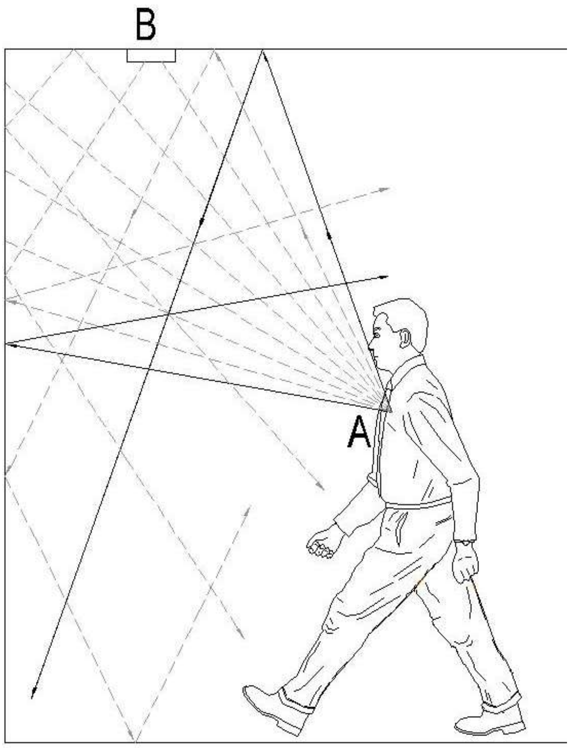


Figure 4 - Human-worn active IR tags broadcast to wall/ceiling-mounted receptors; tags had to be 'worn correctly' by all participants to record data

2.4.2.2 RFID participant tags

The use of RFID tags improved on results from the IR-based participant tags described in the previous subsection. This form of RTLS was not dependent on how tags were worn, whether belt or pocket. With RFID devices there was less ongoing operational costs beyond having to charge/replace tag transmitter batteries occasionally, if powered. The maturity of RFID technology, and widespread adoption and growing body of research, suggested RFID tracking was well positioned as a candidate to support space optimisation use in healthcare settings. They predominated in the tracking of physical objects such as equipment and supplies [39-41], which is beyond the scope of this review. Despite this, numerous researchers have applied RFID to look at elements of flow in ambulatory healthcare settings [27, 33, 37, 42-45] and many more. Despite sharing the same core technology there was some variety between studies though all involved participants wearing or carrying RFID tags.

Reduced participant tag loss experience by Stahl, et al. [27], with losses under 5 per cent may be a result of a focus on staff while excluding patients. This researcher noted the vigilance of staff in the timely return of participant tags inadvertently removed from the study area. Excluding patients and focusing on staff location to study clinical occupation activity avoids patient tag losses, however staff still require ongoing management until tags were ubiquitously issued.

In the discharge lounge of a hospital, Shim, et al. [46] placed lower-energy, directional RFID readers at each door to capture spatial location of patients wearing RFID tags. A similar strategy was employed by Chen and Collins [44] in a small healthcare clinic using simulated patient data. Other researchers simulated data using role-played scenarios in a simulated patient journey, and Shim, et al. [46] creating a digital simulation using ‘Arena’ software. This ‘point-in-space’ method of physically locating occupants was effective for understanding length-of-stay and maintaining an awareness of individual patient locations. RFID-based systems were improvements to IR-based systems. Despite challenges such as the high frequency of receivers and suboptimal accuracy below 1 metre, research in this field continues to improve [47]. Also, the literature did not demonstrate capability in multistorey environments of larger hospitals (Figure 5).

Locating individuals classified by role using RFID tags was explored by Min and Yih [42] in a small eye-exam clinic. These researchers developed fuzzy-logic-based algorithms to determine the probability of tags' presence in target space, rather than detecting every presence directly. As this study was confined to a single room, crosstalk of sensors between rooms was not explored. Like other RFID badge-based approaches in the literature, this study also relies on all occupants wearing tags, wearing the correct tags, wearing only one tag, etc. Also, this research assumes a one-receiver-per-room ratio which can be expensive. As Huang, et al. [48] suggests, the costs of such technology must be balanced against cost savings achieved through facility resource utilisation improvements. Despite the modest volume of research presented in this subsection, the use of RFID tags to track the utilisation of clinical space remains uncommon. Common challenges experienced by both 'tag' based systems are described in 2.4.2.4.1.

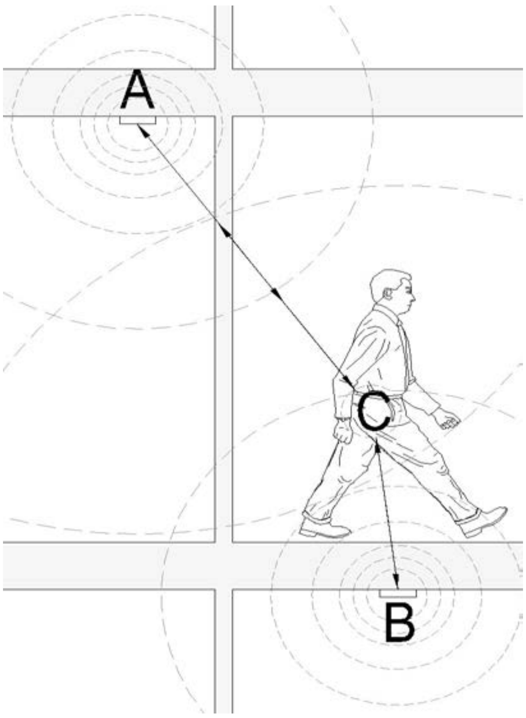


Figure 5 - RFID tags used as a Real Time Locating System (RTLS) send signals from emitter /receivers (A/B) to tags (C)

2.4.2.3 Other RTLS technologies

The field of RTLS is wide ranging, with applications from robotics to logistics, to any research seeking to identify the location of something in time and space. As complex entities with many moving parts, organisations providing healthcare are ideally suited to incorporating RTLS technology to support business operations. Tariq, et al. [49], summarised these technologies as: 'WLAN, Inertial Measurements Unit (IMU), Visible Light Communication (VLC), RFID Tags, Bluetooth, Global System for Mobile Communications (GSM), and so forth.' This subsection presents a brief look at promising RTLS technologies for future clinical-space utilisation research.

Spatio-temporal human activity data has been collected in healthcare settings by pervasive sensors. This technology was demonstrated by Prentow, et al. [50], who studied an entire healthcare campus, however the same technology could be focused for use at the clinic level once accuracy can be sufficiently improved. Other research into the use of sensors in healthcare environments was similar to RFID, the tracking of various assets [51] and remains outside the scope of this review. Similarly, Ultra-Wideband (UWB) [52] and Bluetooth [53] technology has been used to track healthcare assets throughout healthcare environments. Researchers using Zigbee tracked both assets and patients across the hospital [54] which seems feasible to adapt to the purpose of studying the efficient use of space rather than time as suggested by the authors. Despite some success, none of the alternatives identified above have studied clinical space utilisation, or similar research projects.

2.4.2.3.1 Time-focused research

With a primary focus on patient wait times, Overmoyer, et al. [25] made use of their existing RTLS patient/staff tracking system. Unfortunately, the underlying technology is not identified. Regardless, their research was the closest of any RTLS research projects to the research questions underpinning this literature search. They were able to demonstrate a 3.3-hour improvement to total patient wait time. This research compared a static service-to-room assignment system versus a pooled strategy assigning rooms on an ad hoc basis. Their ubiquitous data gathering system allowed them to demonstrate the effectiveness of an operational change process from a preintervention baseline. Further, their data gathering technique research could be extended to explore the effectiveness of other operational 'tweaks' in live healthcare environments. These ubiquitous systems were an appropriate method using ambient technology in an iterative way to adapt clinical functionality to dynamic healthcare environments, assuming privacy requirements were observed.

RTLS systems have been demonstrated above as being effective at tracking both assets and humans. There are numerous other kinds of RTLS technology in various stages of development, but these remain outside the scope of this review. Despite their obvious benefits, there are also several common challenges of using these systems to study clinical space utilisation.

2.4.2.4 Common properties of RTLS

The RTLS systems identified are the subject of ongoing development research. Each system identified to date has common properties that will briefly be touched on in this subsection. First the benefits, then the challenges of RTLS systems will be explored. Using RFID, IR or other RTLS systems allow researchers to study aspects of both patients [54] and clinicians [5] while capturing spatial location information. Both Vilamovska [40] and Li, et al. [37] list uses for these technologies. RFID technology is mature and improving with a large, active research base, with both transmitter size and the price continuing to shrink. These technologies have been demonstrated as capable of tracking both objects and people with relative accuracy and can be used in both passive and active modes depending on need.

2.4.2.4.1 Challenges with human participation

To date however, the explored opportunities are broadly limited to tracking assets and/or people in a broad sense throughout clinical environments. No identified studies used RTLS to study the use of clinical spaces, with one notable exception [25] as noted in 2.4.2.3 above. For example, Vilamovska [40] listed only staff, patient, clinical trial and portable asset-focused applications for the technology. Despite limited directly relevant research, this seems a logical extension for this branch of research.

Each of these technologies required all participants to consistently and properly wear/carry some kind of technology to support identification and tracking by the system. Tags still need to be issued and cross-referenced to individuals through a manual process. Despite improvements on pure manual data gathering, tag-based approaches based were time-consuming and human-resource intensive to manage. Due to the underlying requirement for ongoing human labour in all identified studies, the duration of each study is relatively short, from three days to 140 days.

The bulk of these studies were exclusively looking at either consumer or clinician activities in time [2, 21-24], despite each of these studies being undertaken within healthcare spaces. Their inclusion of space as a criterion has been a consequence of their existence in time as part of a series of clinical activities, rather than activities occurring in both time and space.

2.4.2.4.2 Challenges of manual labour

This manual process of issuing and receiving tags may have been taxing on staff as noted by Fisher and Monahan [4] in their study of other ‘tag’ based tracking systems. Also, staff at least would need to have accepted being personally, physically tracked throughout their workplace. As noted by Guo, et al. [35], healthcare staff ‘had shared concerns about the invasion of privacy and discomfort with one’s location being tracked’. In addition to personal privacy, potential privacy issues with the technology itself may have limited widespread adoption of this technology in healthcare environments [36].

Also, tag-based systems have numerous operational challenges. For example, identity verification: with removable tags they could be swapped around or combined, such as a parent with multiple children. If tags were removed, tracked entities would no longer be tracked through RTLS systems, which relied on consistent human behaviour to operate seamlessly. In addition to tag removal, consumers could wear multiple tags, such as a parent removing sensitive technology from multiple children. Beyond the operational and social and resource challenges of using RTLS in healthcare systems, there are several technological challenges faces by RTLS researchers.

2.4.2.4.3 Raw sensor data challenges

One key aspect which limited the collective technology described in this subsection is the capacity of these devices to process and store data on the devices themselves. Without preprocessing, as is common with IoT devices, raw sensor data can flood both networks and databases and make the extraction of meaningful information more challenging. For Isken, et al. [5], tags were worn by voluntary participants as a means of data gathering to support patient-flow-focused analytics. These authors placed considerable effort on the gathering and preprocessing of large volumes of sensor network data prior to translating into usable information (Figure 6). Similar data-volume issues were experienced by Miller, et al. [7] with large databases of ‘tag event’ data. The authors of this paper were forced to manually save data locally and emailed it to external programmers. Beyond the potential for data corruption, this was a labour-intensive method of data transmission prone to human error. Translating the high volumes of data into information, and eventually into knowledge as per the ‘data-information-knowledge’ pyramid (Figure 6) is one of the challenges of electronic data gathering. With IoT devices, processing was

Figure 6 – Data-Information-Knowledge Pyramid

typically done on the device itself [55]. Though this ‘edge processing’ greatly reduces the need for manual preprocessing of raw data, it comes with its own set of challenges which are beyond the scope of this literature review.

2.4.2.5 RTLS technology summary

Due to their semi-autonomous nature, RTLS systems collectively remain the closest to IoT devices in their demonstrated capacity to explore aspects of human activity in space. Of all the healthcare-related research found using RTLS systems only [25] used them to improve the utilisation of clinical spaces, though the focus was predominantly on patient flow. These systems as documented all have ongoing human-resource costs to consider. Since they track human activity, there is also the human response to being tracked that requires careful consideration prior to implementing these systems. Finally, there are technological and operational challenges remaining with these systems such as inherent privacy concerns and managing the vagaries of human behaviour. Some of the drawbacks of using RTLS technology could be mitigated if, instead of recording human behaviour, it could be simulated.

2.4.3 Spatial simulation studies

The final major theme emergent from the healthcare literature search was the use of simulation as a technique to either generate data, or iteratively explore collected data with the aim of improving patient flow. Though again none of these used IoT devices to collect their data, the study of spatial clinical relationships was now a core research focus. Discrete Event Simulation was commonly used in healthcare literature studying the flow of activity [56, 57] inside ambulatory clinics. Researchers used simulation to explore the flow of staff [58] and patients [59, 60] through clinics, their room allocation policies [61], and their physical layout [62].

The link between physical resources and operational efficiency for example was critical to the a ‘simulation-optimisation’ model used by Vahdatzad and Griffin [63]. This paper explored multiple proposed layouts of a healthcare clinic based on the integration of design and functionality rather than the optimisation of travel distances. The latter was more common in literature associated with health facility planning ([64], [65]). These results are informative for new clinic designs, though the method employed may be challenging to implement retroactively. One key unexplored aspect of this work is how these simulations could be used to support the optimisation of clinical space utilisation beyond the commencement of operations postconstruction. Though optimising physical layouts through simulation was closely aligned with the PI's research on clinical space utilisation, the utility of preconstruction simulation wanes in time after clinical operation commences.

Similarly, Gosavi, et al. [62] used virtual three-dimensional modelling and simulated spatial-temporal paths of travel through clinical spaces. Their work touched on aspects of physical form including spatial arrangement and functional adjacencies in exploring spatial utilisation as a key driver of operational clinic efficiency. This study was squarely focused on the need to optimise physical resource utilisation. However, this paper's authors again relied on resource-intensive data-collection processes in a mix of quantitative and qualitative observation. The aim of these authors was to improve operational efficiencies to reduce the cost of providing healthcare services. They referenced the high cost of remodelling healthcare spaces, noting: 'unfortunately this work is often done without analysis of performance data'.

2.4.3.1.1 Spatial considerations

In addition to demonstrating trade-offs in clinical layout design between privacy, travel distance efficiencies and patient experience, Gosavi, et al. [62] demonstrated space utilisation improvements using multiple 'models of care', such as patient-group appointments and flexible exam-room booking scenarios. This research was one of the few studies that explored the interplay between the built environment and the ability of clinic managers to optimise resource utilisation through innovative practices. Fully simulated human activity however may not be able to capture the more stochastic elements of human behaviour. Researchers in this category predominantly obtained their data manually through human observation as part of time-motion studies (see 2.4.1 above) and as such are subject to all their drawbacks.

The use of simulated data has been demonstrated to be an effective way to study the flow of physical objects and beings through both space and time in healthcare environments. This technology had many advantages in the creation of highly effective clinic layouts. Unfortunately, simulated activity approximated but did not directly mirror the many subtleties of human behaviour that direct recording of human activity can provide. In contrast, the data provided by IoT devices would be recorded data, not simulated data. Constructing preoptimised clinical layouts could maximise the operational efficiency when clinics first open. Regardless, simulated behaviour comes close to predicting future space utilisation. Though no IoT devices were used, these researchers had a core focus on optimising clinical space utilisation, despite sharing many common challenges underpinning the healthcare-based research identified.

2.4.4 Common challenges in healthcare-based literature

The healthcare-based literature reviewed that came closest to the study of clinical space utilisation reviewed thus far in this chapter have several common challenges. This subsection collates some of the challenges identified in the healthcare-based literature. First, there was an ongoing reliance on human resources (e.g., [7, 23, 32] etc.), manually gathering and processing data to some degree in all studies reviewed. Next, the research is typically restricted to studying single-discipline clinics (e.g., [32, 48, 60, 66] etc.), with notable exceptions [2, 30] thereby limiting the broader application of their research. Finally, for research relying on RTLS technology, a brief comparison of manual versus electronic data gathering suggests directions for future research in this field.

2.4.4.1 Challenges of relying on human resources

Each paper presented in this chapter thus far involves a beyond-nominal use of human resources to some degree. If these research methodologies were to be extended long-term, the cost of human resources would expand commensurately. Many researchers relied on human observation and data gathering such as in the time-motion studies (see 2.4.1 above) while others used pre-or-postdata processing (e.g. [5]). Even researchers exploring the use of RTLS systems (see 2.4.2 above) required ongoing human resources to issue, log and retrieve their tags or other devices. Of the known techniques used to study time and motion, these technologies all require patients, staff or both to do something consistently. Requiring consistent human behaviour was one of the most challenging aspects of applying these technologies affordably at scale. This challenge was especially prominent in healthcare organisations providing services to a predominantly older demographic. Though people aged 65+ account for 15 per cent of the population of Australia, this demographic represented 41 per cent of inpatients in the public healthcare system [43]. Studies involving ongoing manual labour attract high human-resource costs. The use of technology to augment this data-gathering stage would have been a significant improvement.

2.4.4.2 Humans observing humans

In any of the research described above that involved humans observed by other humans, these studies may have introduced so-called 'Hawthorne effect' [67]. This influence was noted by Bratt et. Al: 'The constant presence of the … observer may also have distorted clinician behaviour ...' [23]. Behavioural changes caused by direct human observation may alter the outcomes of research focused on space management, as presented later in the interviewee results in Chapter 4. These changes were not the only effect of using human resources to collect data on clinic utilisation. Lastly, studies involving human observation are naturally prone to human error. Across larger multidisciplinary clinics accurate and constant observation of all activities by a fixed number of humans may have been challenging.

2.4.4.3 Limited research on multiclinic environments

In a survey of literature on use of simulation on health care clinics, Jun, et al. [68] noted that limited research was available using simulation to study integrated multiclinic environments. This reinforced the challenging nature of data collection when exploring clinical flow optimisation, especially as complexity increased beyond single-discipline environments. This view was similarly echoed by Cayirli, et al. [69] in their literature review, adding that few studies involve multiphysician, multidisciplinary hospital outpatient clinic settings for similar reasons. Finally, the challenges of data collection were reinforced by Isken, et al. [5] who noted the challenges of data collection for simulation modelling purposes in outpatient clinics.

2.4.4.4 Manual data gathering versus semi-autonomous data gathering

Without the use of advanced technology, most manual methods of data collection were typically less than one-month duration, given the resource-intensive data acquisition process. Typically this process involves human observation, stopwatch [70], synchronised watches [23] and other techniques. Manual study periods typically either consist of multiple days Chand, et al. [70], or other relatively short timeframes like three days for Santibáñez, et al. [32] and Bratt, et al. [23]. Some manual methods put the onus on patients and trained staff filling in forms for extended periods, such as five months in the case of Cote [24].

2.4.4.5 Challenges with long study periods

Long manual study periods increase effects on clinical operations and risk of human error due to repetition, fatigue and attention loss. While Miller, et al. [7] collected IR tag data over two weeks, Isken, et al. [5] produced a sample size of 9,634 patients across two clinics over 56 days. This was a comparatively long study period in the literature. However, this duration was a relatively short period compared with the potential of a permanent, facility-wide installation. Repurposing potential was that used by Overmoyer, et al. [25] despite an actual study period of 49 days as they repurposed an existing system with committed funding. Exploring social aspects of tracking technology, Fisher and Monahan [9] found that in clinical spaces where staff locations were actively tracked through tags systems, nurses feel 'overly scrutinised'. Also, staff felt that the management models used to interpret the findings of such tracking systems do not necessarily reflect the constantly shifting frontline realities of hospital working environments. Finally, they found the responsibility for ongoing management of these tech solutions were typically given to clinical staff to manage in addition to their regular duties, resulting in negative staff feedback. As a counterpoint however, Guo, et al. [35] found 'the [healthcare practitioners] acceptance of the use of the RTLS tag in the hospital had the strongest association with the [healthcare practitioners'] willingness to use it' suggesting a potential link to personality type and acceptance of tracking technology. This counterpoint suggested more work could be done to clarify this apparent conflict.

2.4.4.6 Other challenges

All research reviewed in this section relies on volunteer data only, presumably including the cumbersome process of obtaining volunteer consent. This process is unlikely to capture all clinic activity, leaving nonvolunteers, of both staff [56] and patients [58] out of the dataset. For research focused on optimising appointment scheduling, these are based on manually forecast data [71, 72] or historical data gathered for other purposes [73]. How spaces were used was unknown as it is rarely recorded.

2.4.5 Healthcare-based literature review summary

This research project is multidisciplinary in nature. Therefore, this literature review is similarly multidisciplinary. The core focus of each of the research questions underpinning this literature review is based in healthcare literature. As already noted, many researchers have focused on improving operational aspects of outpatient clinic operations. Despite the abundance of research, the translation into practice remains a challenge. The impact of human observation and the cost of sufficiently skilled human resources to maintain implemented systems may have hindered development of this body of literature. Technical solutions have been trialled, but as yet none appears to have seen widespread adoption into clinical practice in part due to their cumbersome interventional nature, in part requiring humans to carry, hold, turn on or otherwise maintain technological artefacts for the duration of their clinical attendance. Improved technical solutions may re-invigorate this body of research, but to identify these solutions, literature beyond the confines of healthcare must be sought.

2.5 Literature search beyond healthcare

Literature covered previously in this chapter resulted from using the PRISMA guidelines [12] and Google Scholar [28] focused on healthcare-based literature. These searches were guided by the *literature search research questions*:

- What research existed that targeted clinical space optimisation using electronic data gathering technology, such as sensors or IoT devices?
- Where was the focus of previous researchers if not directly related to optimising clinical space utilisation?
- Which technology has been used by previous researchers to gather data, and what were the experiences of the researchers in the use of these technologies?

While the first two questions have been sufficiently addressed in the previous subsection, the third was limited to a small number of studies using RTLS technology and simulation. The latter required ongoing maintenance and management, while the second relied on manual data gathering. Aside from the technologies embodied by the research methodologies and tools themselves, the level of technological adoption had been relatively low. Outside the boundaries of healthcare literature though, literature on human-sensing technology is abundant, addressing the many inherent challenges of this field of research.

Data collection challenges were common enough in the research in clinical space utilisation research, that even incremental improvements could make significant impacts. What was needed to address these issues, were technologies that:

- Do not rely on ongoing maintenance by clinical staff
- Respect individual privacy and mitigate potential civil liberty risks
- Do not interfere with clinical 'flow', including both patients and staff.

As suitable technological solutions had not yet been demonstrated in the canonical healthcare literature, an examination of research outside the field of healthcare was required. The following section reviews literature from the disciplines of building sciences, engineering and computer sciences on how they collect and use similar data for different purposes.

2.5.1 Huaman presence detection in built environment research

Though limited healthcare-based research was identified that applied presence detection sensors within healthcare environments, very few used these sensors to study clinical space utilisation. Despite this underrepresentation in healthcare-based literature, human presence detection research was abundant in the 'built environment' field of research. This section explores some of the many technologies that have arisen to detect aspects of human presence.

Numerous sensor types had been explored in this section with a focus on their potential for application in clinical healthcare settings. Specifically, their suitability for use in the optimisation of healthcare clinical consult spaces was explored. Most sensors could have had some application in various healthcare settings. However, sensors that use optically based sensors, or were capable of recording audio, were deemed inappropriate for use in high-privacy settings. Optical information may be processed on-chip only, for example only postprocessing data leaves the device. However, determined attackers could compromise the optical or audio feed, so were immediately discounted. Infrared sensors seem most suitable for broad application in high privacy settings without significant investment and ongoing maintenance and management by clinical staff.

2.5.2 Identifying human presence/activity

A large body of research has gone into detecting and/or predicting the presence of humans in indoor environments. The potential applications of human presence detection were wide ranging, from healthcare, marketing and education to security, fire safety and military applications. Most literature focused on human sensing to optimise energy consumption either directly or indirectly ([74-78] etc.). The built environment has accounted for 20-40 per cent of total energy consumption worldwide and growing, which may explain this focus. Energy savings have been repeatedly demonstrated using occupancy sensing to optimise energy consumption across building services using a variety of techniques [79]. Building services affected include HVAC, lighting and hot water among others. For example, Yang, et al. [11] summarises that energy savings of 30 per cent in lighting energy consumption, and 30 per cent of cooling reduction were possible in commercial environments. Research in this area has expanded, as noted in recent surveys in IoT and smart building by [80] and occupancy detection systems [81]. The latter research noted the wide potential application of occupancy detection systems. The breadth of this technology reflected the recent increase in related research volume, and though still relatively sparse, notable examples were briefly explored below. As with the healthcare literature, the physical layout of the building was either ignored or incidentally mentioned. If mentioned, the research tended to focus on temporal events rather than events happening in unique physical spaces.

2.6 Building management systems

One subsection of research which may prove promising was the repurposing and fusion of existing building systems sensors' data, captured by centralised Building Management Systems (BMS'). These systems monitor and control various remotely operable parts of the buildings' services system, for example managing airflow according to set parameters. BMS data repurposed by Dey, et al. [82] included carbon dioxide (CO_2) levels, temperature and supply air volumes. Using a Random Forest classifier, Dey was able to predict occupancy levels so BMS systems could be tailored to building activity. Their system could accurately predict current room occupancy with an accuracy of 95 per cent against the ground truth through a sampling period of three months in a single room. The bulk of this accuracy came from CO_2 sensors (92 per cent) which had lag issues on either end of their ramp up/down cycles. However, CO_2 could be very accurate where occupants arrive, stay and leave in groups, such as in a movie or lecture theatre. Similarly, Dey, et al. [82] focused on lecture/lab spaces on a university campus, which were typically either full or empty, with most occupants arriving/leaving at approximately the same time. HVAC systems in assembly spaces adapt to high and low volume occupancy rates over short periods, and they are designed to have the capacity to ramp up/down accordingly.

2.6.1 Challenges using building-systems sensors

These methods may prove challenging when applied to rooms with different occupancy patterns across a suite of rooms as a single zone. In outpatient clinic suites for example, HVAC systems typically serve 'zones' comprised of numerous small rooms, designed for 2-3 people. Each space in the zone has a unique occupancy/utilisation pattern, and can often vary in shape/form, features such as natural light, and challenges such as the distance from the waiting room. There can be high variability in occupancy levels depending on the health service being provided, the day of the week and the time of the day. Consequently, depending on their technological maturity, sensors could advise about the occupation of a zone of activity but may struggle to report on individual rooms. To study bespoke spaces within a zone, additional sensors would be required that target these spaces individually.

2.7 Types of sensors used to study human presence/activity detection

As explored in 2.2 above, through the work of Teixeira et al. the features of human presence detection have been established. To detect and record these features, many approaches were possible. The most promising potential sensor types are presented in the following section, based on their capability to identify human activity patterns, and their suitability for deployment in live healthcare environments.

2.7.1 Ultrasound

Sensors using ultrasound indoors may be appropriate when used for human presence detection, though challenges remain prior to widespread adoption. While exploring 'object localisation', Qi and Liu [83] demonstrated a 10.2-millimetre maximum location error was possible. However, they found this level of accuracy relies on numerous receiver units distributed across each space studied. Scaling up such technology seems impractical if considered for use in a moderate sized healthcare clinic with more than 100 spaces. Also, their technology relied on tracked targets transmitting a beacon signal which was then located by receiver units. This multipart system inevitably suffered from the same human error and cost issues as other tag-based applications such as RFID or IR tag applications. Finally, ultrasonic localisation in a hospital environment may interfere with ultrasound-based medical imaging devices.

2.7.2 Optical cameras

By far the largest contribution to the literature in human presence detection was optical image processing using computer vision, but they were hampered by ongoing privacy concerns. Privacy issues were typically addressed in the literature by ‘processing’ imagery rather than storing/recording imagery. Nevertheless, there remains a small ‘moment of vulnerability’ after capture and before discarding of imagery which was addressed by Baccelli, et al. [84] preprocessing optical information using optical scattering techniques. Their research goes some way to technically preserving privacy. However, for consumers of healthcare services, it was both the technical preservation of privacy and the perception of privacy that was important. Unfortunately, high-sensitivity private clinical environments were inappropriate for optical image-capture technology as thus far demonstrated in the literature.

2.7.3 CO_2 Sensors

Humans constantly emit CO_2 gas. Detecting the number of humans in a room using CO_2 sensors can be highly accurate. For both presence detection and count data, Calì, et al. [85] achieved accuracies of 95.8 per cent and 80.6 per cent respectively. Unfortunately, these accuracies were only achievable in spaces without either mechanical or natural ventilation, since air exchanged from adjacent spaces produced ‘variable’ results in their research. These sensors were only commonly used for assembly spaces such as lecture halls and theatres which typically had self-contained HVAC systems and controlled external air inputs. Typical HVAC systems in larger corporate/commercial spaces had a dedicated air-handling plant to service many rooms contained in a single zone. This could consist of a single zone for small floor plates, or several adjacent zones for larger floor plates. These zones typically consist of both supply and return air systems, where the return air was mixed in some proportion with the supply air after cleaning. These sensors in return air ducts would have been variable unless the system was operating in 100 per cent fresh-air mode, or the system incorporated CO_2 filters. Controlling for return air CO_2 variables, Wang, et al. [3], Wang and Jin [86] achieved success in using CO_2 sensors to predict occupancy numbers in commercial facilities. They used these occupancy numbers to tailor air-supply to match occupant numbers, thereby reducing energy consumption. The methods of Wang, et al. [3] were inappropriate for understanding occupancy patterns of individual rooms in a zoned HVAC system. This challenge was underscored in clinical spaces with high turnover of occupants of 15 minutes or less, which greatly affected the performance of CO_2 systems [87].

Air within consult rooms was regularly mixed with corridor air when entry doors open and close, and not all spaces had return air ducts. These challenges were not insurmountable, however. Using a combination of BMS-controllable airflow dampers, full-fresh-air modes and scrubbers, their methods may be feasible. Unfortunately, the capital cost of this type of system was high and did not reflect common industry practice, and the return on investment was unclear.

2.7.4 RTLS systems literature beyond healthcare

The broad category of research identified as RTLS have been explored in 2.4.2 above to the extent they were identified in the healthcare literature. These systems were useful to understand general patterns of occupancy [88] but few had been applied to research aimed at optimising clinical space utilisation. Beyond how they have been applied to support healthcare research, RTLS is an umbrella term covering many branches of distinct research fields. In this section a summary of applicable RTLS technologies is provided with the intent to understand their future incorporation into healthcare literature

2.7.4.1 Wi-Fi outside healthcare applications

Looking outside the field of healthcare research, one reason limiting the adoption of Wi-Fi as an RTLS in the field of clinical space utilisation, despite Wi-Fi saturation in many hospitals, is a current accuracy of 3.3 metres accuracy in practice [89]. In practice though this technique may have required levels of Wi-Fi saturation beyond current practical norms. Looking at occupancy prediction using Wi-Fi combined with machine learning, Wang et. al [90] demonstrated accuracies of ‘80.9 per cent … and 93.9 per cent with a tolerance of two…and four occupants respectively'. These techniques assumed each occupant was carrying Wi-Fi enabled devices, the Wi-Fi signal was active and the device was on. Unfortunately, in healthcare settings this was not an accurate assumption, though demographics had shifted in their favour. In comparison, Zheng, et al. [91] have identified Wi-Fi localisation methods that do not require users to hold/wear technology to function with accuracies of 0.82m.

The field of Wi-Fi localisation has developed at a high pace. This development trajectory suggests that in time, Wi-Fi localisation may be highly capable of accurately locating each human within a multidisciplinary clinic, while avoiding personal identification. Should this be achieved, this technology would be ideal to study clinical space utilisation. Another emerging RTLS technology facing similar issues is the use of the Bluetooth standard.

2.7.4.2 Bluetooth

RTLS techniques using Bluetooth short-range wireless standard were reasonably common in the literature outside healthcare. For example, Wang et. al [92] identified human occupancy indoors using a multifeature classification algorithm with K-Nearest Neighbours (K-NN). Their algorithm achieved occupation prediction accuracy of nearly 93 per cent against ground truth. Similarly, recent work from Lorenc, et al. [93] reduced accuracy to 1.5m using Bluetooth Low Energy triangulation via Received Signal Strength Indicators and the application of a Kalman filter. Unfortunately, to date the Bluetooth-based systems suffer from the same drawbacks as systems. They both require specific techno-environmental conditions, which were suboptimal in live healthcare spaces.

2.7.4.3 Global positioning systems

One final RTLS technique determined worth mentioning was Global Positioning Systems (GPS). The use of GPS for the localisation of humans outdoors has developed into a highly accurate, mature technology in common use in residential applications. Indoors however, GPS-based systems suffer from signal path interruptions 'due to signal congestion and path complexity caused by the building structure'[94]. Though advancements have been made in combining GPS systems with other systems for internal-external continuity, for the study of clinical space utilisation this technology is not-yet sufficiently developed.

2.7.5 Infrared arrays

Infrared energy emitted from humans is used by many sensors, from single-sensor motion detectors to arrays of infrared sensors capable of sensing even minute motions, and capable of tracking humans across a space. These sensors differ from those discussed in 2.4.2.1, as they are building mounted, not human-mounted. This differentiation may eliminate many of the human-resource and tag-loss issues experienced by those researchers. There were numerous ways the infrared energy constantly emitted from humans was used for presence detection in the literature. Passive infrared (PIR) sensors technology for example has matured to the point of common domestic installation. When PIR sensitivity was increased, raw sensors were accurate for detecting human presence through even small thermal movements (example typing or reading). Unfortunately, high-sensitivity PIR sensors also increased the risk of false positives from very slight changes such a warm air current. Through use of a distributed array of PIR devices, Zappi, et al. [95] demonstrated improved results. They found a '100 per cent correct detection of direction of movement and 83.49-95.35 per cent correct detection of distance intervals'. This suggested further improvements were possible, though numerous sensors were required, increasing capital costs and recurrent maintenance expenditure.

Using PIR as a data collection method, and inhomogeneous Markov chains to predict future human occupancy patterns, Erickson, et al. [96] were able to simulate building occupation. Using an EnergyPlus model, HVAC systems were dynamically adjusted demonstrating a potential 42 per cent savings against the current best-practice strategies. Erickson (et al.) may have been able to realise further savings if their research were to move beyond PIR sensors. These sensors provide a binary presence-detected state of occupied/vacant. Incorporating 'count' data to match HVAC systems to predicted occupant load, or other spatio-temporal properties [8], may have increased their efficiencies. Recent lab-based results have demonstrated that arrays of these simple sensors [97] can locate individual humans, and calculate their trajectory through time using a generative adversarial network (GAN) to augment PIR data. As arrays of these sensors have been shown capable of detecting human presence in individual spaces, they are considered ideal to study clinical space utilisation, in the *occupancy* category at least if not *count*.

2.7.6 Thermopile arrays

Sensor types explored thus far have been used to detect Teixeira et al.'s five categories of spatio-temporal properties [8] up to the 'presence', and 'count' categories. Thermopiles had the capacity to fill a gap in presence detection/tracking field where privacy was a concern. Thermopiles were collections or 'piles' of thermocouples, which translate infrared radiation into temperatures. Temperatures of the thermocouples were averaged, and this becomes the data sent by the thermopile sensor. Arranged in a grid formation, thermopiles at low resolution maintain occupant privacy, such as eight by eight square matrices, or four by 14 rectangular thermopile matrices. These thermopile arrays (TA) also had the capacity to increase the human feature detection category [8] anywhere from *count* up to *tracking* category in a cost-effective manner. For example, TA sensors were demonstrated effective to identify individual humans by numerous researchers [98-102]. Also, using TA sensors Karlsson and Rabiee demonstrated 'tracking' human behaviour over time was possible using a multi-Bernoulli system [103]. TA sensors were effective in small spaces and can also be combined. For example, a distributed array of TA sensors across a space were shown by [104] to be effective in localising human activity. The potential of these sensors suggest they may dominate the human presence/activity detection sector in high privacy spaces in future. The TA sensors return an array of temperatures that change over time. This format created local fields of high temperatures across the relatively 'flat' background heat in the grid. Detecting conglomerations, known as blobs, were common in computer vision and data science fields. Many researchers have taken these techniques and applied them to the TA data stream.

2.7.6.1 Blob detection

The bulk of the research on TA devices take the form of ongoing improvements in determining human presence. The majority of TA research was focused on progressively improving ‘blob detection’ [105] to classify human presence. Consequently, a brief overview of the current state of research was provided.

Breaking down the blobs, Basu and Rowe [99] used feature extraction from raw TA data to identify individual humans using sequential processing of sensor data. Connected component analysis, commonly known as blob detection, followed by Support Vector Machine classification, proved the most accurate. They were able to identify four individuals in a 2.5-metre by 2.5-metre target zone with 80 per cent accuracy. Using a four by 16 array thermopile, in 2016 Tyndall, et al. [98] built on previous research [106] combining thermopile arrays with machine learning classifiers. They found that the K-Nearest-Neighbours algorithm machine learning was the best ‘blob’ classifier for TA sensors, providing approximately 83 per cent accuracy with an RMSE of 0.304. Recently in 2021, [107] Chidurala et. al applied various preprocessing techniques including ‘blob detection’ to further improve the capacity for existing machine learning techniques. They were able to estimate human occupancy with 99 per cent accuracy. With continued improvements and commercialisation there was a wide application for these sensors.

2.7.6.2 Benefits of thermopile sensors

Thermopiles can also operate without regular maintenance for years depending on their power arrangements. Low-resolution thermopiles were incapable of identifying individual human characteristics. Thermopiles were relatively simple and based on mature technology and sound research. Privacy preservation was ensured using low-resolution thermopiles even if the sensor device was compromised by external actors. Therefore, thermopiles were appropriate for use in healthcare environments to understand patterns of occupancy. These devices sense infrared energy external and intrinsic to all humans. They remain the most viable of the commercially available sensor types to use in high privacy situations such as healthcare. Unfortunately, while the sensor itself is widely available, commercial distribution as part of an IoT device remains comparatively low.

2.8 *Machine Learning and sensor fusion*

Limited research has explored the use of machine learning applied to data from existing BMS sensors similar to Dey, et al. [82] in healthcare scenarios, such as the recent work of Saralegui, et al. [108] which explored the ability of such systems focused on monitoring occupancy patterns to detect potential symptoms of illness such as dementia. Typical BMS systems captured data on temperature, humidity and CO_2 concentrations designed to control HVAC systems. Saralegui combined data with various classifiers which included: C5.0, ctree2, SVMRadial, qda, rFerns, rpart and AdaBag among others. The latter four classifiers provided similar accuracy on binary occupancy values of approximately 80 per cent. Unfortunately, they encountered similar problems to Calì, et al. [85] in that accurate occupancy predictions were challenging if airflow between rooms was allowed. Such problems may have been minimised in the work of Dey, et al. [82] due to the self-contained nature of their HVAC systems. For occupancy values, the results could have been improved by adding PIR sensors in sensor fusion similar to Erickson, et al. [96]. Another approach to sensor fusion identified high occupant accuracy of more than 99 per cent. Other research combined data from CO_2, temperature, humidity, light level sensors plus occupancy using a photovoltaic infrared (PIR) sensor [109]. Similar results were found by [110]. However, it was unclear in both papers how they controlled for the CO_2 leakage from adjacent rooms/zones.

The techniques employed by these researchers may be effective in laboratory conditions. In many multidisciplinary clinics, these techniques have been less effective without consideration of air-transfer from adjacent rooms, or zoned air-conditioning systems. Researchers may have encountered challenges if these techniques were implemented in live built environments.

2.9 *Conclusion*

The above survey of literature sought to understand how IoT devices could support clinical space optimisation in outpatient clinics. The review found that few researchers had used sensor technology to explore their capacity to optimise clinical spatial assets. Those who did (RTLS and RFID) were challenged with the state of technology, or their high cost of implementation/maintenance. Most researchers focused on spatial aspects indirectly as a function of time, with their optimisation noted casually if at all.

This review has ranged across multiple distinct disciplines of research but had many common themes. Data acquisition on clinical space utilisation remains the primary challenge when attempting to optimise clinical space utilisation. Triangulating the results of such a broad spectrum of research suggested that in a multidisciplinary clinical environment:

- Sensors could be used to determine occupancy
- Data patterns could be determined through a variety of statistical analytical tools
- Gathering data on room occupation manually was resource intensive
- Thermal-emission-based IoT devices could remotely provide occupancy data in high privacy spaces on a room-by-room basis
- Machine Learning could be used to predict future occupancy patterns.

In the exploration of presence detection in clinical environments to optimise operational effectiveness, the literature suggested that significant performance improvements could be realised. Simultaneously, it may also be possible to reduce the cost of providing healthcare services by both improving patient-flow and reduced demand on building services. The most effective method of improving utilisation of clinical spaces found in the literature was not a single change. Concurrent changes in numerous factors holistically in the literature were found to have had the greatest impact. Without the ability to continuously measure the progress of improvement initiatives, the relative change (success or otherwise) cannot be demonstrated. Therefore, improved methods of data collection and monitoring were necessary. Introducing IoT devices in clinical spaces to determine occupancy provided an evidence-base upon which to propose improvement activities and demonstrate their effectiveness.

Spatial utilisation research using IoT sensor technology aligns with the emergent area of inquiry defined by Wiberg [111] as ‘Architectural Informatics’. Exploring these ideas through further works, Wiberg [112] aligns with the outcomes of Vahdatzad and Griffin

[63] in exploring *spaces as designed* versus *spaces as used* in healthcare environments. Currently limited research, data or even tools exist to provide the kind of data required for such an iterative process between designer and user.

The intersection of technologies combining the power of IoT and machine learning to study clinical space utilisation was presented as 'future research' by Stahl, et al. [27]. Refined information systems were required to make clinical resource utilisation data more readily accessible to healthcare workers, executive staff, architects and those performing quality improvement activities. These systems would use the power of technology such as IoT to transform sensor data into actionable information. Information would need to be presented in such a way that it can support evidence-based decision-making. Elevating the frontline data to a higher level of corporate knowledge would provide a new capacity for operational improvement to those who need it. Optimising spatial resources in multidisciplinary clinics would drive down the cost of providing healthcare services. Also, this improvement would allow the healthcare system to provide more healthcare services within existing resources. Further, the pressure to increase the physical and carbon footprints of the healthcare system would be reduced. Finally, access to healthcare services would be increased, resulting in reduced reliance on more intensive and costly downstream care activities.

The research projects identified in this chapter all contain some critical challenge. Common data gathering techniques are typically unsustainable (too expensive at scale or long term). Each technological intervention explored in the literature involved some form of ongoing management by healthcare staff, involving patient interaction. Technological gaps were identified with the systems themselves, such as the challenges of the various 'tag' systems. In many cases, the correct use of technology had to be explained to patients, and consent to collect data obtained, which introduced friction into the patient experience. To avoid these challenges, future researchers are recommended to employ technological systems that are low-power, low-cost, low-maintenance, privacy-preserving and do not rely on human interaction.

Sensor technology implemented in a live healthcare environments must be carefully selected for appropriateness. Many healthcare services involve highly sensitive medical equipment. Therefore, it is critical for new technology introduced into these spaces to avoid interfering with potentially life-saving processes by minimising electromagnetic noise. Sensors exclusively capturing passive environmental data are considered ideal. Signal transmission in all forms should be limited to technologies pervasive in the modern clinical environment (e.g. WiFi and cellular networks). Finally, if using exiting communication networks, adjusting transmission to non-peak clinical service delivery periods would avoid contributing to signal congestion. The experience of previous researchers was therefore invaluable in the selection of technology used in this research. A demonstration of decision-making informed by this review is presented in Section 3.2.2. The relative success and limitations of each body of research reviewed in the literature therefore shaped the direction of this research project.

This literature review has identified numerous gaps in the literature that the remainder of this research project has attempted to resolve. Untapped data sources within the built environment of our hospitals and other healthcare environments could support evidence-based decision-making on the optimisation of space utilisation. Well-structured feedback mechanisms using the tools of computer science could provide a much-needed feedback mechanism to planners and designers of future healthcare spaces. This field of inquiry has been tentatively referred to as 'Architectural Informatics'.

CHAPTER 3

METHODS

3.1 Introduction

This chapter explores three distinct features of using IoT devices to study clinical space utilisation in operational multidisciplinary ambulatory clinics, within a regional public tertiary teaching hospital. These features include the following, used to study clinical space utilisation:

- The effectiveness of IoT technology to gather/disseminate information
- The appropriateness of collecting human activity data using IoT devices
- The acceptability of IoT devices by staff working under continuous observation.

First, the primary hypothesis was that IoT technology was effective when used to improve the utilisation of clinical spaces within the THHS. This hypothesis was tested by the installation of IoT sensors within live clinical spaces. This type of data collection is referred to as 'new data' by Peacock [115] who defined several advantages and disadvantages of this data collection method. First the advantages were that the PI can ensure that the data collected is fit for purpose, and current. Next, the disadvantages listed by Peacock were the cost of undertaking research, the 'time to collect and process' the data and the 'possibility of unknown quantity of missing data …'. The first two disadvantages were considered offset by using IoT devices being allowed to run for a long period. The last was mitigated by having a third-party proprietary service monitor sensor health and battery life, notifying the PI if any action was required. Once the method of data collection was established, sensor choice, testing, and installation methods were explored, in addition to an account of device maintenance throughout the study period.

The second hypothesis was that the use of specific IoT devices to study human activity within high-privacy clinical outpatient spaces was appropriate. The restricted features of IoT devices installed for this purpose respond to the confidentiality of the activities undertaken within the target clinical spaces. Devices had to be incapable of disclosing personally identifiable information, even if compromised. Also, installed IoT devices must not instil the feeling that personally identifiable information was being recorded, regardless of their actual capabilities. Staff perceptions of IoT device ‘appropriateness’ were gathered through one-on-one interviews and a staff-wide survey.

The third hypothesis suggests that healthcare staff would be comfortable working under the constant monitoring of clinical spaces in their workplace by IoT devices. Comfort levels were explored across a range of increasingly dense data gathering on human activity. A theorised ‘threshold of acceptability’ common across staff would be established or disproved. Data was collected using the same sources of one-on-one interviews and staff-wide survey used to explore ‘appropriateness’ above.

Studying only the effectiveness of technological interventions within live-care environments without considering the effects of these interventions upon the occupants would have been irresponsible. Continuously monitoring clinical spaces with IoT devices/sensors may be considered wholly inappropriate in healthcare settings. If the latter was true, demonstrating the effectiveness of these devices was pointless. Similarly, if IoT devices were considered appropriate in clinical settings, but staff felt that working under their constant observation was unbearable, successful implementation would be unlikely. These three hypotheses structure the remainder of this chapter.

3.2 Exploring capacity of IoT devices

Collective references to ‘IoT technology’ throughout this research project refer to a suite of interconnected technologies. This term includes the local sensors and their container IoT devices, cloud-based middleware and client-side postprocessing software. The results presented in Chapter 4 would not be possible if one or more of the links in this chain of technology were broken. Underpinning this research was Hufner (et. al)’s behavioural science methods developed as a subset of design science in the field information systems research. The methods in this subsection aimed to:

> *…develop and verify theories that explain or predict human or organisational behaviour… [including]… interactions among people, technology and organisations that must be managed if an information system is to achieve its stated purpose, namely improving the effectiveness and efficiency of an organisation. [116].*

Current space management within the study setting used static spreadsheets with a fortnightly clinic usage scheduling. Daily load-shifting activities were undertaken by frontline staff with limited ability to *demonstrate* spatial capacity limitations. Executive decision-makers had little-to-no data to support evidence-based decision-making on space allocation/re-allocation. The intent of this research project subsection was to identify and test sensors and their associated IoT devices capable of identifying human activity within high-privacy spaces. The boundaries for ethically appropriate electronic data gathering were agreed in advance through the authorisation of the local Human Research Ethics Committee (HREC). Authorisation to proceed was received by the THHS HREC (HREC/17/QTHS/54). Summarising the 101-page HREC application, it was considered ethically appropriate to remotely gather nonoptical, nonaural, nonpersonally identifiable, ambient environmental data. Specifically, sensor devices 'such as infrared radiation, ultrasound or other similar technology' were referenced to reinforce the type of data being gathered.

3.2.1 Repurposing existing systems

The first attempt at obtaining space occupancy data involved the repurposing of an existing access control system employed by the Townsville Hospital and Health Service (THHS). This technology takes advantage of a combination of passive RFID tags, and access control via electronic door locking. Staff at the THHS were obliged to carry staff identification badges to identify themselves to and provide access to nonpublic spaces within the facility. Electronic access to restricted spaces across the THHS was provided by an electronic locking system using RFID chips embedded within staff ID badges.

The following section has summarised the functionality of these systems by combining hardwired, wall-mounted receivers with transmitters (badges). These badges differ from the battery-powered tags trialled by researchers in Chapter 2 as they are passive, near-field systems. Small antennae inside the badges are powered by proximity to readers and broadcast weak signals containing encoded unique identifiers (UIDs) to receivers. Once the UID was obtained, this information was transmitted via the intranet where a comparison was made against a list of authorised ID numbers assigned to the door in question. If the UID was authorised for the requested door, an 'access authorised' signal was sent to the receiver. This signal triggers the electronic lock for a predetermined interval, allowing the door to open. The UID number accessing the door was logged, along with the time, the result of the ID check (pass or fail), and the result of the electronic lock activity (open or fail).

Logs from these systems were proposed as one potential source of spatial occupation data to help understand patterns of occupancy within a clinical healthcare environment. CARDAX data was compared to a 'ground truth' recording of room occupancy (see 'calibration activity' below). The capacity of this system to understand room occupation was analysed. The technology underpinning these systems was mature. However, the literature contains lessons from the use of RFID and similar other 'tag' bases systems. Using these systems to explore room utilisation has known flaws, including:

- Resource intensive – may be appropriate for staff, with tags issued upon employment, but not appropriate for healthcare consumers who required tags issued/collected every visit [4, 7]
- Cost prohibitive – badges were expensive and often went missing, though the cost of these systems has reduced in time [7, 27]

- Data integrity – badges had to be ‘worn correctly’ by occupants, only one badge per occupant, and badges had to match occupants [5, 7].

1. locked door upon lock-side approach; locked status shown by red indicator on ‘reader’	2. proximate placement (10mm max) of ‘authenticated’ card electronically opens lock (green indicator) after hard-wired/powered sensor communicates with centralised security system	3. RFID coil contained within THHS staff ‘ID’ cards (similar), outer loops used for antennae, inner ‘chip’ contains data broadcast when excited by ‘readers’

Figure 7 - Radio Frequency Identification (RFID) Tags used at the THHS

In addition to some of the challenges above, doors could be propped or held open to allow passage by multiple occupants. Despite these known flaws, log data was gathered and compared with data obtained through the proprietary sensor units. Data was kept in spreadsheet format for direct comparison to the other ‘calibration activity’ sensors discussed below.

3.2.2 Commercial IoT sensors selection

A subset of commercially available sensors used in this research was chosen in accordance with an analysis of options seeking a balance between numerous factors, including:

- Occupancy Sensing
- Potential for collection of personally-identifiable information
- Ceiling Mounted
- Bi-Directional people counting
- Battery Operated
- Wireless networking
- Capacity for integration with other software (i.e. FMI)
- Node to network connection (no router)
- Cost for deployment across 20+ spaces
- Availability in Australia.

These criteria were applied to commercially available sensors identified through online searches to establish the decision matrix in Table 5, organised by vendor. Some criteria above were nonnegotiable. For example, if the sensor was affixed to movable objects, it was removed from further consideration (i.e., item #1 in Table 5). For optical-sensor-based devices, regardless of how the images were protected or how long they were kept in memory, these were not considered to progress to the next stage. Finally, if the 'count' sensor maintained a record only of single-directional travel, it was no longer considered viable for this research.

Table 5: Sensor selection decision matrix including taxonomy

			TAXONOMY																					
#	Vendor	Sensor Type	Primary Classification (I=Intrinsic, E=Extrinsic)	Secondary Classification (D=Dynamic, S=Static)	Type category (V=vibration, E=Ext. Motion)	Room Occupancy Sensing?	Bi-Directional?	Ceiling Mounted?	Personally Identifiable?	Battery Operated?	Wireless Networking?	FMI Integration Possible?	Node-Network Direct?	Identify Location in Room	Additional Sensor (value-add)	Proceed to Costing?	Cost per 'Sensor'	# sensors required	Cost Per 'Hub'	Number of 'Hubs' Required	Total Projected Sensor Cost	Proceed to Explore? ($40k max budget)	Proceed to Purchase?
1	Cowrkr	Vibration Sensor	I	D	V	N	N	N	N	Y	Y	Y	N	N	N	N							
2	Cowrkr	Optical Camera(s)	I	D	E	Y	Y	Y	Y	N	Y	Y	N	N	N	N							
3	Hella	Optical Camera(s)	I	D	E	Y	Y	Y	Y	N	N	Y	N	N	N	N							
4	Nortech	Optical Camera(s)	I	D	E	Y	Y	Y	Y	N	N	N	N	N	N	N							
5	Axis Tech	Optical Camera(s)	I	D	E	Y	Y	Y	Y	N	N	Y	N	N	N	N							
6	Cohera-Tech	Optical Camera(s)	I	D	E	Y	Y	Y	Y	N	Y	N	N	N	N	N							
7	Total Count	Single Thermal Beam	I	D	E	N	N	N	N	N	N	N	N	N	N	N							
8	Beonic	Dual Thermal Beam	I	D	E	Y	Y	Y	N	N	N	Y	N	N	N	Y	-	-	-	-	$61,315	N	
9	Occupeye	Optical Camera(s) (Occupeye 'flow')	I	D	E	Y	Y	Y	Y	N	N	Y	N	N	N	Y	$2,400	25	$1,000	2	$62,000	N	
10	Maxim Integrated	Thermopile Array (Panasonic Grideye)	I	D	E	Y	Y	Y	N	N	N	Y	N	Y	N	Y	$200	25	$150	2	$5,300	N	
11	Schnider	Thermal PIR	I	D	E	Y	N	N	N	Y	Y	Y	N	N	N	Y	$490	25	$481	5	$14,655	N	
12	Schnieder	Thermal PIR, Temp & Humidity Detection	I	D	E	Y	N	Y	N	Y	Y	Y	N	N	Y	Y	$490	25	$481	5	$14,655	N	
13	Cohera-Tech	PIR array (Irysis Gazelle 2)	I	D	E	Y	Y	Y	N	N	N	N	N	N	N	Y	$1,100	25	$0	2	$27,500	Y	
14	A-Beautiful-City	PIR array (Irysis Gazelle 3)	I	D	E	Y	Y	Y	N	N	N	N	N	N	N	Y	$1,600	25	$1,180	2	$42,360	Y	
15	Cohera-Tech	Dual IR Beam	I	D	E	Y	Y	Y	N	Y	N	N	N	N	N	Y	$420	25	$840	2	$12,180	Y	
16	Evolve Plus (door mount)	Dual Thermal Beam	I	D	E	Y	Y	N	N	Y	Y	Y	N	N	N	Y	$450	50	$1,840	2	$26,180	Y	Y
17	Evolve Plus	PIR array (Irysis Gazelle 3)	I	D	E	Y	Y	Y	N	N	Y	Y	N	N	N	Y	$1,650	25	$1,840	3	$46,770	Y	Y
18	Elsys	ERS-CO_2: PIR, CO_2, Light Levels, Temp., Humidity	I	D+S	E	Y	N	Y	N	Y	Y	Y	N	N	Y	Y	$342	25	$2,500	2	$13,541	Y	Y
19	Occupeye	Thermal PIR	I	D	E	Y	N	Y	N	Y	Y	Y	N	N	N	Y	$240	25	$1,000	2	$7,280	Y	Y

Once a subset of potential sensors was identified, their respective vendors were contacted by phone and/or email to better understand:

- the technology employed by the system
- the various technical requirements of the system, such as networking capacity/technique, requirement for/distribution of local 'hubs', etc.
- the cost per sensor device and if required, the cost per hub.

The resultant data was applied to the floor plan using computer-aided drafting (CAD) software to map out sensor and hub placement (Figure 8). The quantity of hubs required was calculated based on the published limiting distances of the system. Grant funding to purchase sensor equipment was provided by the THHS through the Study, Education and Research Trust Account (SERTA) funding scheme for this research project.

Once the quantity of hubs was established, the total cost of the proposed installation was calculated. As all sensor types except one were over the budget assigned for the purchase of technology, a budget change request was lodged to increase funds assigned for technology purchase, and an internal security review of the LoRaWan

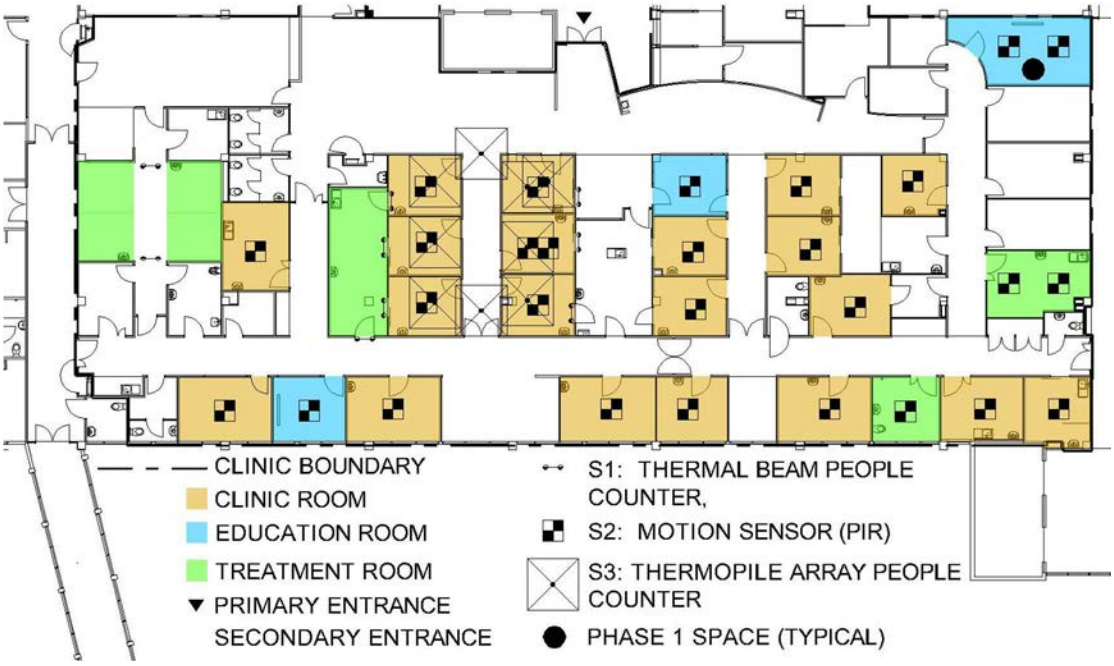


Figure 8 - Floor plan of target multidisciplinary clinic overlaid with initial layout of trial sensors to identify quantity of hubs required, from Figure 2, McNabb et al.[1].

technology commenced. These requests were under way while sample sensors of the 'top 4' sensor types were purchased through the THHS corporate financial system. The intent of this initial procurement was to test proposed units for effectiveness prior to committing the remainder of the budget on a single type of sensor device.

The sensors 'short list' (Table 6) showed the most appropriate sensors available on the market at the time of the research. While other sensors existed, such as the Grideye thermopile from Panasonic, existing fully resolved commercial IoT devices containing these sensors were not available. The shortlisted sensors were primarily limited in the first instance to variations on the theme of human thermal emissivity. With a 'privacy first' focus for use in live healthcare environments, most available commercial options at the time of the research had to be eliminated. This exclusion was due to the reliance on optical image processing to understand human activity patterns. These sensor manufacturers felt confident privacy concerns were addressed by not storing any video on the device. However, the presence of a camera in high-privacy clinical exam rooms, where patients frequently disrobe for a physical examination by a healthcare professional, was not considered appropriate. A brief overview of the shortlisted sensors types, the reason for their selection, and their

Table 6: Most suitable sensor short-list identified via Table 5 decision matrix

#	Vendor	Sensor Type	Comment
16 (S1)	Evolve Plus	Dual Thermal Beam	System exceeded budget, but represented the most common non-optical counting sensor, purchased for comparison
17 (S2)	Evolve Plus	PIR Array (Irysis Gazelle 3)	System exceeded budget, but is innovative technology unique in the market, purchased for comparison
18 (S4)	Elsys	ERS-CO_2: PIR, CO_2, Light Levels, Temp., Humidity	System exceeded budget, however, contained five sensors in one; additional funding re'd to purchase trial units; uses LoRaWan networking system, requiring approval
19 (S3)	Occupeye	Thermal Motion Sensor; Passive Infra-Red, or Photovoltaic Infra-Red (PIR)	Met budget at scale; used mature technology with long transmission distinct from units to hubs, which reduced the number of hubs required

functionality can be found in Figure 9 [1]. However, this summary has not provided detail on how the sensors function.

3.2.3 Thermal Motion Sensors – Photovoltaic/Passive Infra-Red (PIR)

Simplified, this type of sensor received infrared radiation on its detector surface and converted this radiation into an electric charge. Typically, these sensors were used in combination with a segmented dome (Fresnel lens) which broke the infrared energy received into distinct cells. The sensor device tracks activity in each of the cells, and triggers when the infrared energy levels, typically emanating from humans, passes through one or more of these cells. For sensors used in this research, the 'motion' event triggered a time-stamped 'occupied' data point. Once triggered, the device then went into low-power mode until the start of the next temporal increment with 10-minute intervals minimum. The middleware dataset consisted of collated 'occupied' or 'vacant' data points for variable temporal increments. Alternatively stated, data viewed filtered through one-hour periods would report any occupancy triggers in that time that the space was 'occupied' during that period. Refer to Figure 10 for an illustration of the basic functionality and networking structure.

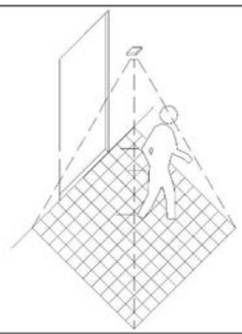
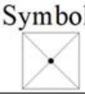
Sensor Type 1 (S1): Infra-Red Break-Beam Unit Cost: $450 AUD Installation: Low Impact Data Resolution: High Clinical Suitability: Low	**Sensor Type 2 (S2):** ***Photovoltaic Infra-Red*** (PIR) Motion Unit Cost: $250 AUD Installation: Low Impact Data Resolution: Low Clinical Suitability: High	**Sensor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

Figure 9 - Extract from McNabb et al. Figure 1 [1] illustrating shortlisted sensors trialled for accuracy and suitability for clinical environments

3.2.4 Thermal (passive or Photovoltaic infrared) array sensors

In contrast to the standard PIR identified in 3.2.3 above, this sensor used an array of PIR devices behind a proprietary lens. This lens focused each PIR on a distinct section of the target space. Data from the field of sensors was processed within the device using proprietary technology. The device display, when connected to a laptop computer, visualised the location of one or more sensed humans as they moved through the target space. The number of humans within the target space was logged by the sensor in an online data repository.

Infrared radiation was received at an angle of approximately 60 degrees from the sensor in all directions away from the device. The process of calibration was more labour- and infrastructure-intensive compared with the other shortlisted sensors. This was due to the cumbersome calibration process that must be repeated on each device, and the 240V power supply required for the ceiling-mounted sensor.

A laptop running proprietary software was connected via long, high-speed serial cable. While inside the sensed field, the sensors' boundaries were mapped by moving around and following the 'blob' on the screen. A threshold line was established for each direction in and out, and the device logged the number of count activities per set

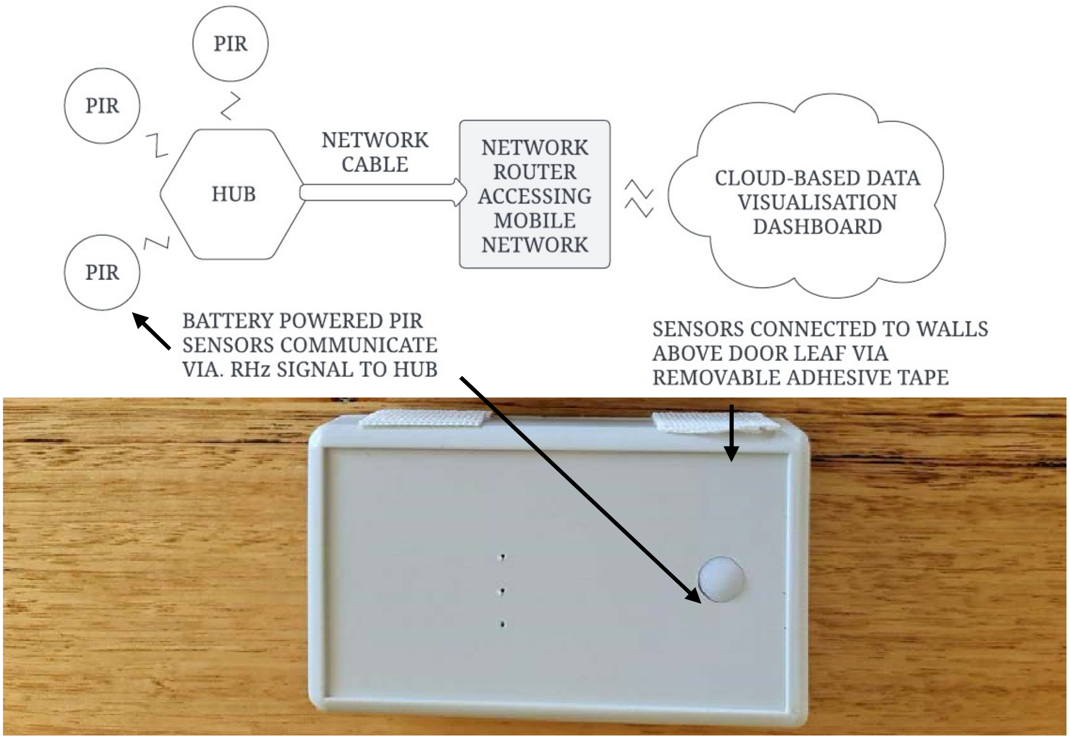


Figure 10 - Thermal (PIR) Sensors Functionality

period. With two thresholds, the entrance and exit activities of humans were able to be recorded. The latter statement assumed all paths leading to/from the entrance/exit were within the field of view, and thresholds were drawn accordingly. The result was an online spreadsheet of actions, but a total count was not provided. To maintain a running count total, the spreadsheet had to be downloaded and calculated by each client outside the vendor's system.

3.2.5 Thermal beam sensor

These sensors were based on relatively mature technology. The sensors used in this research used two thermal beam transmitter/receiver combinations: 'A' and 'B'. These two sensors were housed in separate units which mounted directly opposite each other across the desired threshold. When beam A was broken followed by beam B, an 'in' data point was recorded.

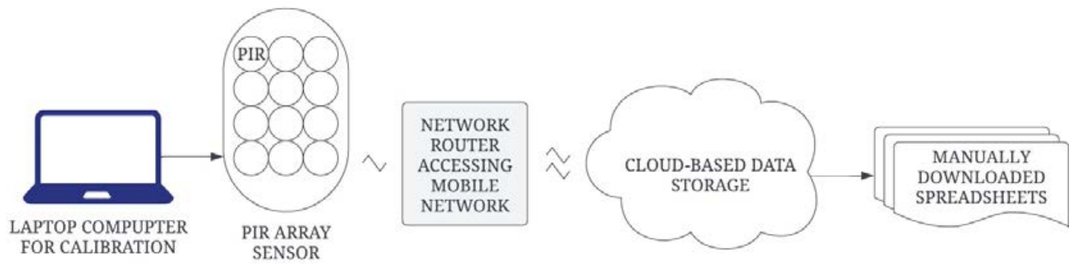


Figure 11 - PIR Array sensor illustrating basic networking functionality.

Similarly, when the reverse happened, an 'out' data point was recorded. Data was collated for fixed periods, and broadcast via RF transmission to the hub, then via mobile network to cloud-based middleware. A fixed minimum period between activities within the device attempted to minimise the number of false recordings.

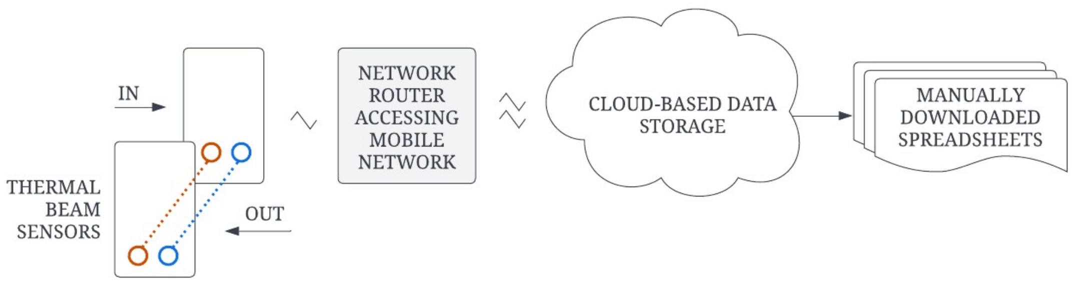


Figure 12 - Thermal Beam Sensor, basic networking diagram

Limiting their suitability and increasing the potential cost, the devices were not tamper-resistant without secondary encasement. Installed in the outpatient clinic, these sensors would have to be mounted on the corridor side of every space under observation. This requirement included the numerous clinical rooms with multiple doors, further increasing complexity and cost. The thermal beam sensors were manufactured by the same company that produced the PIR array sensor in Figure 11. Data collection was similarly challenging as it used the same exported spreadsheet process which recorded trigger events but did not provide running totals, meaning a manual count had to be completed by the end user. Once the detailed features of the sensors were identified, and their installation requirements known, detailed pre-planning was required.

3.2.6 Planning IoT sensors installation into operational clinical environments

Commencing 'human research' in an operational clinical environment required mandatory completion of several preliminary activities. First, a research proposal was prepared and submitted for assessment and authorisation to the HREC of the HHS. For this research project, this controlling body was the THHS HREC. Once duly authorised (HREC/17/QTHS/54) was submitted to the Research Governance Office (RGO) controlling research activities within the HHS. All activities associated with this research project were confined to the main Douglas campus of the THHS. Research commencing on different campuses would have required separate applications to the RGO. No research activities were allowed to commence until all internal authorisations were duly granted, and the ethics unit of James Cook University were equally satisfied. Beyond assuring the research project was ethically appropriate, the capacity of the PI to manage the research project effectively had to be demonstrated. From risk and data management to demonstrating realistic viability, the research project had to be meticulously planned and exhaustively stipulated.

3.2.6.1 Risk management

This research involves interventions in a highly dynamic, fully operational public healthcare facility. Consequently, the safety and wellbeing of staff, inpatients, visitors, contractors and any other occupants were the highest priority of this research project. This section outlines some known and known unknown risks, and the mitigation measures used to manage these risks if they cannot be designed out of existence.

As this research did not require consent from participants, no consent information was gathered for any participants attending the target spaces during the two-year observation period. Since consent was not required, the risks to THHS staff and service users from consent-related issues were considered negligible for the purposes of this research. No further work was undertaken with respect to the issue of consent through this stage of works.

Sensor devices were installed on the underside of ceilings, centred in target outpatient clinical spaces. When adhering devices to the ceilings of target spaces, only rated adhesion systems were used. A safety factor beyond twice the adhesive manufacturer's recommended power-to-weight ratio of individual sensors minimised risk to staff or patients from falling sensors.

No personally identifiable information was to be collected by sensor units. Data transmitted by the sensor units consisted of two primary pieces of data:

- whether a target space was occupied or vacant, and
- the time at which key observations occurred.

Sensors used for this research were like those widely used in both residential and commercial environments. Consequently, the sensors were not expected to alarm most individuals from a personal perspective. This position was a theory during the 'IoT installation' stage of research. Given the passive observational nature of this research, *adverse events*, *serious adverse events* and *suspected unexpected serious adverse reactions* were not expected. Any transmitted signals maintained to or from the selected sensors were within established tolerances already used within the host organisation, and common in the broader society. These signals included Bluetooth, 3-5G networks and other common radio frequency-based technologies. Consequently, the risk of interference with medical or other devices was not expected.

Several potential risks existed during this stage of research. These included:

- potential reduction or withdrawal of support within the THHS for the research

- high levels of discomfort from staff and/or patients
- the potential failure of the select IoT devices.

Funding from the THHS, plus approvals from both HREC and Research Governance, strongly suggested withdrawal of support was unlikely. However, had support been withdrawn, relocating the research project to clinical outpatient spaces on the adjacent JCU campus would have allowed the project to proceed.

3.2.6.2 Data management

Once sensors had been selected, the next step was procurement. Sensors were procured using grant funding from the THHS from an Australian distributor of products manufactured in England. Data was collected predominantly through internet-connected sensors mounted to the building fabric such as walls and ceilings over a period of two months. Also, the intent was to undertake 'spot checks' consisting of a single, full day of physical observational studies used for data-validation purposes. For this purpose, a bespoke application was written for the Android mobile operating system entitled 'Clinic Count 3000'. This app received user 'count' input for up to six separate user-defined fields and exports data to an Excel file. Each time the 'count' was increased or decreased, a new datapoint was created with a time stamp for when the associated 'count' changed. In the end, the full-day observation was not undertaken, and the app was not utilised.

The data was imported into third-party software vendors, such as Facilities Management Software (FMI), R, Occupeye and various open-source products. These software packages were chosen due to their suitability to the task of data analysis including integration with machine learning algorithms as required. In addition, they were both readily accessible to JCU students, with sufficient educational material available. Corrupted data, missing, unused and spurious data was removed from the dataset entirely. This consisted of erroneous preliminary installation data, or data after the formal close of the research period.

3.2.6.2.1 Data storage / data safety

Data was temporarily stored with the middleware vendor in England prior to being downloaded to servers behind the THHS corporate firewalls. Data was stored using standard data storage systems such as a database or spreadsheets. For purposes of visualisation and reporting, data captured by IoT devices was shared with and processed by external (non-THHS) service providers. Prior to distributing data, 'nondisclosure agreements' (NDAs) were distributed and agreed between JCU, the THHS and the PI. Service providers included:

- Advanced Spatial Technologies (AST): vendors of FM Interact, facility management software used by the THHS
- Mapspeople: developers of spatial visualisation and mapping software
- Livesense: middleware vendor providing general technical support
- Sensor manufacturers: vendors of deployed proprietary sensor systems.

For the study period, the data was analysed using numerous software programs, on numerous platforms. At no time was the data posted publicly or transmitted for analysis by third parties outside NDAs. Analyses by the PI were undertaken using software running on computers managed by three distinct parties: JCU, THHS and the PI. The PI's personal computer was in the sole possession of the PI, and continuously password protected.

Stored data was to be retained by the THHS for five years after the study period was finalised. This availability was retained for future recurrent analysis, stored on the internal eHealth file storage system. The THHS has advised the data was considered 'health data', and consequently was covered by strict data protocols limiting downstream availability.

3.2.6.2.2 Sample size

The size of the final dataset was expected to be substantial. The volume of data collected was dependent on the number of target rooms being studied and the duration of the study period. The following preliminary calculation was expected:

*25 (target spaces) * 6 (10-minute intervals per hour) * 24 (hours per day) * 7 (days per week) * 52 (weeks per year) * 2 (years) = 2,620,800 data points*

The 10-minute minimum interval was selected as the shortest realistic unit of time for a clinical consultation. Prior to initiating the data collection, consultation was undertaken with a JCU statistician. This consultant was available throughout the research project to ensure data was collected and managed to optimise potential for statistical analysis. The number of clinical rooms participating in the study was expected to be maintained for the duration of the study period with no changes.

3.2.6.2.3 Data integrity

The data was imported into and processed by third-party software vendors as noted in 3.2.6.2.1 above. Potential corrupted, missing, unused and spurious data was monitored through the data collection period. All data collected prior to or after the start/stop dates of the collection period were removed from the final dataset. No other data were added or removed from the primary dataset. The original intent was for multiple overlapping sensors to be deployed (Figure 8) however the reliability of sensors had not yet been determined. Once PIR-based IoT devices were demonstrated to be the only commercially available, viable option the proposed multisensor saturation was no longer feasible.

3.2.6.2.4 Data visualisation

Extracting knowledge from the data was a key aspect of this research project. Therefore, creating a dynamic human-centric interface to the data was considered critical. Following the Hervener et. al methodology of artefact creation as a design science within information systems, a blend of quantitative and qualitative data analysis was utilised. This combination of technologies bridged the gap between information technology and its application within complex organisations such as the THHS. As Hervener et al. note:

> *The rich phenomena that emerge from the interaction of people, organisations, and technology may need to be qualitatively assessed to yield an understanding of the phenomena adequate for theory development or problem solving [116]*

In addition to standard data visualisation, it was posited that a data ‘heat map’ overlayed onto relevant floor plans would provide intuitive insight to clinical managers. Therefore, data were initially imported into the THHS’ facilities maintenance software by linking spatial data such as room numbers, floor plans, etc., with a subset of sensor data. The intent of these activities was to utilise FMI's robust database querying interface and generate simple reports on the data to better understand patterns of clinic room utilisation. Unfortunately, the limited visualisation capability of this vendor's software within the budget of the research resulted in FMI's limited usefulness to the research. Postresearch implementation would require additional funding to develop a robust user interface. Plans to further integrate the dataset with FMI were subsequently cancelled.

3.2.6.2.5 Application of machine learning

To establish a prediction tool more efficient and effective than the above dynamic dashboard, the tools of machine learning were applied to a limited dataset. These tools were applied by third-year pregraduate students from James Cook University's Workplace Integrated Learning (WIL) program. These students worked under direct supervision of the PI and staff from the THHS Data Research Lab. A proposed subproject was presented to potential WIL students, in competition with numerous other potential projects. Six students chose to participate in the project supporting this research project. Students were divided into two teams based on their interests. One team worked on applying established machine learning techniques to the dataset, while the other created a visualisation dashboard. Both teams combined their work into a containerised package hosted behind the THHS corporate firewall. The intention of this site was to act as a nonproprietary, internal front-end to the dataset. Data was imported from the primary database hosted by the sensor vendor, which received data directly from the sensors. Once daily, data was downloaded and the database was updated.

One month of the most recent data was removed from the training dataset to use as a test dataset to gauge the predictive accuracy of the machine learning algorithms. The remainder of the dataset was used to train a series of trial-and-error machine learning models to see the effects of the different approaches. This method was chosen due to the limited experience with machine learning of the WIL students, combined with the advanced state of many algorithms. This 'scatter gun' approach resulted in a relatively quick feedback loop, limited primarily by the capacity of the available computer systems to run the algorithms. Though rudimentary in nature, this approach yielded considerable results, despite lacking an in-depth knowledge of how the tools functioned. Algorithm predictions were applied to the test dataset, and the accuracies were compared to identify the most optimal approach based on the tools and experience available.

3.2.6.2.6 Data analysis

The data was subjected to descriptive statistical analysis to identify occupancy patterns, repeating trends, outliers, etc. The proprietary software used to undertake this analysis was provided by the sensor manufacturer. Occupation data was also subject to machine learning algorithms to explore how well historic usage patterns can be used to predict future occupancy. Data was analysed via standard statistical techniques in conjunction with JCU statisticians.

3.2.6.2.7 Project setting / location

All sensor-based IoT activities took place within THHS facilities, on the Douglas campus in Townsville, Queensland, Australia. The THHS was a tertiary teaching hospital, part of the Queensland Health healthcare network. Data logging for clinical outpatient areas (see Phase 3 in 3.3.3 below) took place within the Primary Care Building on Level 1 of the Townsville University Hospital. Further, the location of the clinical IoT implementation was limited to the multidisciplinary medical outpatient clinic within the Primary Care Building on the Douglas campus. Select spaces within the outpatient suite were studied during the research period including offices, consult, education and treatment rooms (**Error! Reference source not found.**).

Table 7: Space types and quantities within the participating multidisciplinary outpatient clinic suite, modified from Table 1 by McNabb et al [1]

Type	Description	Typical Images	Qty
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		20
Type 2: Education Room	Rooms where diagnoses or procedures were explained to healthcare services consumers through either interaction with healthcare service providers or via multi-media presentation, and appear as a typical office space		2
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		4
Type 4: Offices	Offices in the target clinical space were like standard commercial offices	n/a	2

3.2.6.2.8 Project population

The population targeted by this research were all occupants of the 25 targeted spaces during the target observation period. Data was continuously gathered by IoT sensors in the target spaces 24 hours per day, 7 days per week over two years. The quantity of occupants to these rooms varied by necessity; collectively this total population was considered sufficient to provide meaningful analysis.

All attendees of the target spaces were treated uniformly. No differentiation was made between humans based on race, age, education, profession or gender. Due to this equality, the research data was indiscriminate to any features other than ambient features associated with human presence. All humans that did not attend the target clinical outpatient spaces during the study period were excluded from this research.

3.2.6.2.9 Privacy preservation

Maintaining the privacy of patients and staff was critical to success in answering the research questions of this project. Privacy protection was a legal obligation for healthcare service providers. As well as ethically and morally appropriate, demonstrating how participant privacy would be maintained was critical to receiving the approval of the HREC to proceed.

No personally identifiable images or any other information was captured, processed or stored through any sensor units placed in clinical areas. No optical cameras were used as part of this research as noted earlier. Advances in the field of computer vision have made these devices scalable, low power and low cost to retrofit into existing systems. Despite the efforts of both sensor vendors and researchers to preserve privacy such as optical defocusing in the work of Baccelli, et al. [84], several researchers in the field of computer vision and occupancy sensing/counting including Akkaya, et al. [79], Erickson, et al. [117] and numerous others had acknowledged the privacy issues associated with the use of optical cameras in human activity detection. Conversely, privacy issues emergent from the use of cameras to study human activity were not mentioned by other researchers such as Kirchner, et al. [118]. Consequently, if optical sensors such as cameras were embedded into sensor devices, regardless of protection measures, privacy could not be guaranteed.

Designated healthcare spaces in Australia were obliged to protect patient confidentiality including acoustic and visual privacy. The Australian Health Facility Guidelines (AusHFG) [119] present best-practice specifications for the design of healthcare spaces. The use of the AusHFG was not mandated in Australia. Regardless, these guidelines had been designed to satisfy minimum obligations for healthcare spaces, and to meet industry best practice and had been based on iterative clinical and consumer input. The measures identified in the AusHFG had been designed to provide visual and acoustic privacy while making the patient journey as comfortable and stress-free as possible. Beyond the patient journey, a workplace free from excessive observation supports a positive working environment associated with higher levels of job satisfaction [120, 121]. In summary, the perception of cameras in high-privacy healthcare spaces may cause undue stress in both the healthcare providers and consumers. The use of optical devices, including devices that appear to be optical devices but were not, had been expressly omitted from the scope of this research.

An information sheet identifying the nature of the research project was posted in multiple locations within the target clinical area studied through the Phase 3 sensor installation (see 3.3.3) These information sheets were also included in multiple staff-only and public-access spaces. The purpose of this information sheet was to inform occupants of the nature of the research. Information included the aims of the research, the research questions being explored, and specifics on the sensors including information recorded and excluded. Participants were provided with contact details of the PI which allowed the capacity for occupants to ask additional questions. The information sheet as distributed is shown in Appendix 1.

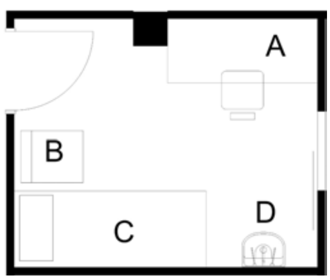
3.2.6.3 Expanding the concept of 'optimal utilisation'

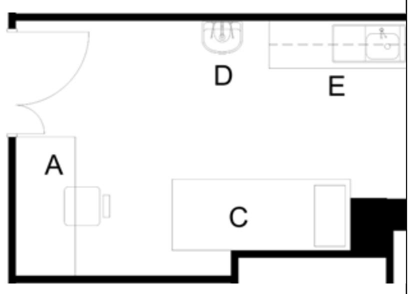
'Optimal Utilisation' was necessarily different for the various classifications of rooms, defined as *Consult Rooms*, *Treatment Rooms* and *Education Rooms* – see **Error! Reference source not found.** and Table 8 for a more detailed breakdown on each room type. For example, a *treatment room* was required for medical treatments such as wound care and other clinically intensive physical interventions. Therefore, occupation of *treatment rooms* was not scheduled in the same way as *consult rooms*.

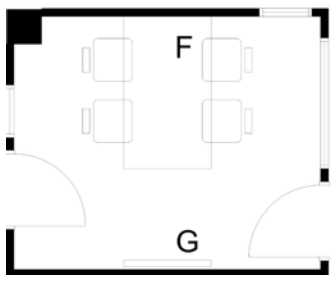
The former was treated and were used in a more ad hoc manner on an ‘as needed’ basis on a case-by-case basis. Similarly, *education rooms* were used ad hoc to explain recent diagnosis or treatment options to consumers of healthcare services by healthcare providers in a less formal setting.

The use of both *treatment rooms* and *education rooms* stems from the day-to-day activities being undertaken within the *consult rooms*. Therefore, demands on these two spaces change depending on the kind of healthcare services being provided. However, while suitable for certain kinds of clinical consultation (e.g., social work) in the context of this research, they were not used for consultation. Perhaps the greatest distinction between a *consult room* and *education room* in the context of this research was the finish and service support within the room. *Consult rooms* were floored with vinyl, contain a sink and often a patient bed. *Education rooms* were typically carpeted, do not contain a sink, and typically involve discussions sitting around a common table.

Table 8: Typical healthcare space for provider/consumer interactions in outpatient clinic settings







Consult Room	Treatment Room	Education Room

LEGEND:

A: Write-up desk (Healthcare Practitioner)

B: Chair (Healthcare Services Consumer)

C: Patient Bed (portable)

D: Hand Basin

E: Fixed bench with under-bench storage and cabinetry over

F: Table / chairs for face-to-face discussion

G: Wall or table mounted telemedicine facilities

Data was collected, stored and analysed in a similar way for the space types above, though judgement of *optimal utilisation* was unique for each. If the location, model of care or numerous other precursors change, how the space was operated would similarly change. Any operational change could also have changed the perception of what *well utilised* means.

For example, rural clinics containing the same space type under the same model of care may be 'well utilised' with lower occupancy rates as the demand for space was lower. Finally, it would be unlikely that clinical rooms in the context of this study could be 'optimally utilised' at 100 per cent utilisation. High to very high levels of occupancy may not allow for the ad hoc flexibility that a dynamic modern outpatient facility requires. More likely this space would have been considered 'over-utilised', which was as important to know for facility managers as 'under-utilised' spaces. In summary, each healthcare facility needs to establish parameters for 'well utilised' for each space depending on location, services delivered and model of care among other factors.

3.3 IoT sensor installations

Sensors appropriate to install in healthcare spaces had been identified, purchased and experimented with. The latter was required to understand their unique installation requirements and to establish the PI's overall familiarity with the devices. The sensors were subsequently installed into healthcare spaces in three phases:

- Phase 1: Preresearch sensor calibration activity
- Phase 2: Sensor installation in a nonclinical, reservable healthcare space
- Phase 3: Operational multidisciplinary outpatient clinic sensor installation.

3.3.1 <u>Phase 1: Preresearch sensor calibration activity</u>

Though clinical spaces were plentiful within a public healthcare facility and represent the highest value spaces relative to area, they were also high-risk spaces from a public and staff safety perspective. The suitability of these sensors in sensitive clinical environments had not been proven prior to their installation in a live clinical environment. To demonstrate the accuracy of these three units, a trial was established at the entrance to a nonclinical space using all three sensor types simultaneously

(Figure 13). The calibration activity was undertaken in a low-risk environment that was designated for 'nonclinical' functions. A partial floor plan of the singular entrance to the target space and the sensor layout can be seen in Figure 15. This floor plan illustrates the placement/configuration of sensors and video recording equipment used.

Figure 13 – Three sensor calibration activity layout (1: PIR array, 2: PIR, 3: Thermal beam) trialled for accuracy against a video camera (4) along a defined threshold (5) at the entrance (6) to a 3-room, non-clinical suite.

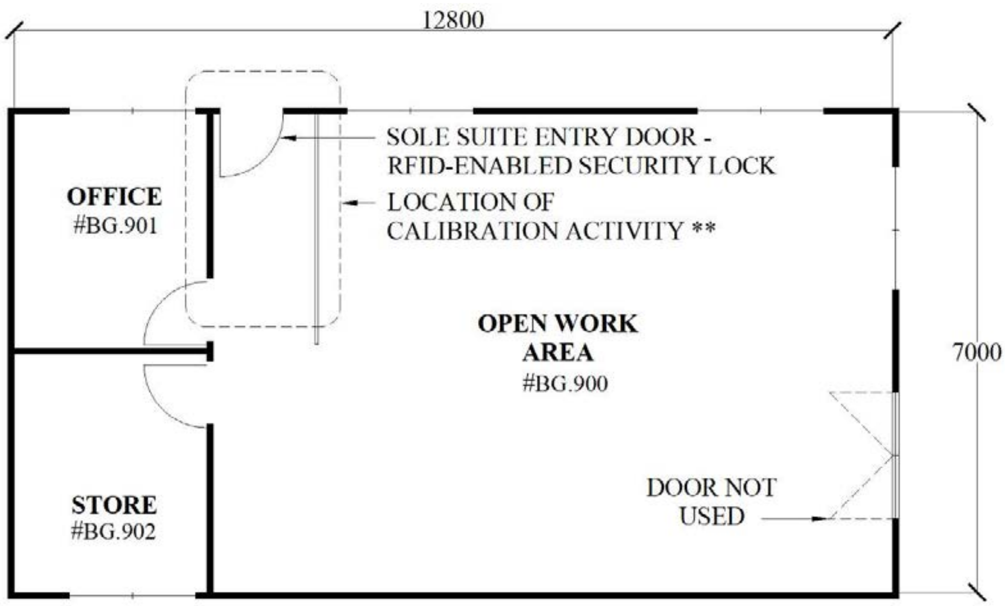


Figure 14 – Target Space for Calibration Activity

First, three battery-operated ‘PIR sensors’ were placed in the space. One sensor was placed at approximately shoulder height in each of the two small offices, and one above the target threshold, adjacent to the PIR array sensor. The data from all three PIRs was manually combined into a single three-room, suite-wide dataset. Then, a line of visible tape was placed on the floor parallel to the entrance, to act as a designated threshold. Next, a ceiling mounted ‘thermal (PIR) array sensor’ was placed directly above the tape threshold. This large sensor had an ‘optional’ camera which required the most infrastructure, as mains power was required. A power supply and extension lead were run from a local wall-mounted plug to the sensors’ transformer.

The ‘PIR array sensor’ was calibrated using a serial connection to a laptop computer running the manufacturer’s proprietary software. The ‘incoming’ and ‘outgoing’ thresholds were set to count these activities along the line of threshold. The final ‘thermal beam sensor’ was placed in two parts across the entrance corridor, directly above the tape, mounted 700mm above the floor. Lastly, once all sensors were confirmed operational, the camera was directed to capture only foot traffic across the threshold, and the ‘ground truth’ was filmed. Occupants were recorded on video entering and leaving the space over a 24-hour period, from 6pm to 6pm the following day. The intent of the video was to compare ‘ground truth’ to the three sets of sensor data. Data from the PIR remained on the sensors, which were sent via the postal system back to the Australian distributor for data download. The PIR array and thermal beam devices were connected to a shared proprietary hub, which transmitted data to cloud-based middleware.

The use of a video camera was confirmed acceptable with the HREC to use for the purposes of this experiment in the target nonclinical space. The 'nominal' threshold established by the tape was approximately 1.5m inside the target nonclinical space. The purpose of this offset was to allow for the swing of the door which would otherwise have at least obfuscated the thermal beam sensor. The video was then watched by the PI, and all occupant entrances/exit activities were time-stamped and logged. Once the data analysis was complete, the PIR sensor was selected as the sole sensor type accurate and appropriate enough to proceed to the next stage.

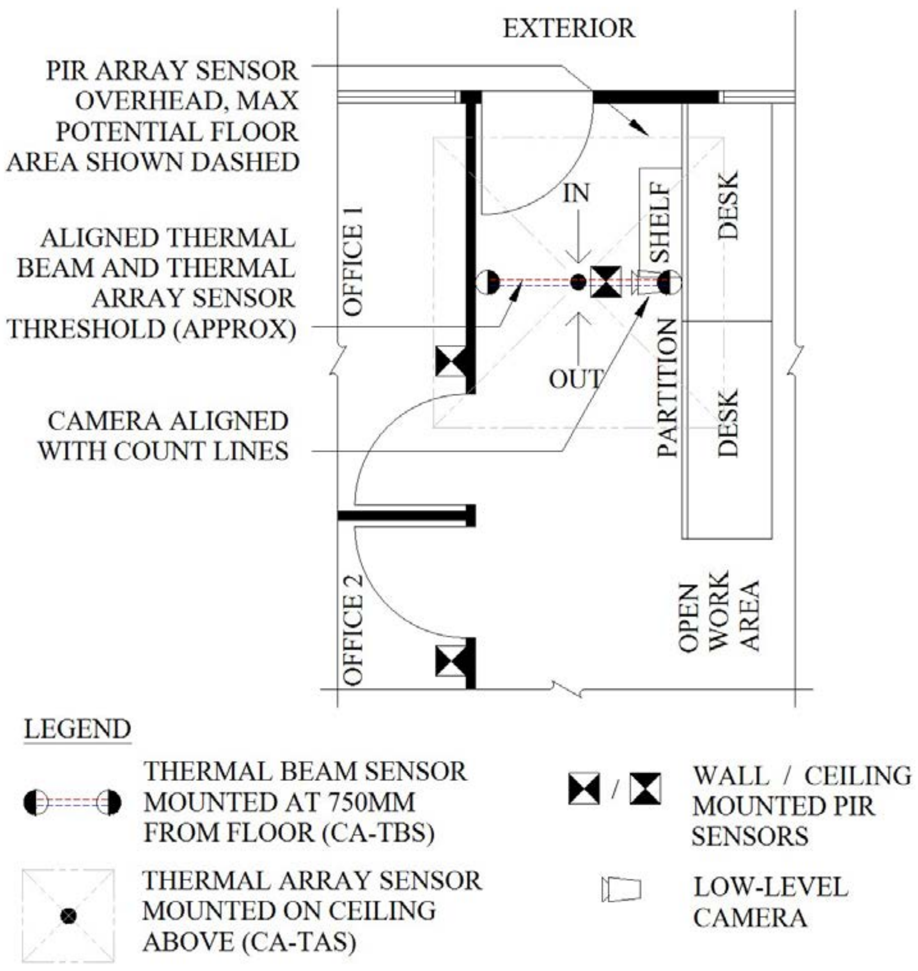


Figure 15 – Calibration activity – trial installation of three sensor types within a small non-clinical space within the target healthcare system, accessed by a single entrance.

3.3.2 Phase 2: Sensor installation in a nonclinical, reservable healthcare space

The intent of the next installation was to demonstrate the capacity of these devices to support a comparison of nonclinical spaces 'as used' versus 'as reserved'. The study period was one full work week from 8am on Monday to 5pm on Friday. This timeframe was chosen to gauge effectiveness of the PIR sensors over longer periods than the initial experiment. As per the previous installation, wall-mounted PIR sensors were installed at shoulder height in the target space (**Error! Reference source not found.**).

Two PIR sensors were used to compare the stated sensor range of 7 metres. With the technical success of this trial, planning began for the wider installation of PIR sensors in a large multidisciplinary outpatient clinic in the THHS. Data was recorded on the PIR sensor units' on-board memory and the devices were physically shipped back to the vendor for data download. Data from sensors were compared with the target space's reservation system to compare data 'as used' versus 'as reserved', and their suitability for use in live clinical environments was determined. Once the latter had been confirmed, planning commenced to expand installation into an operational clinical environment.

3.3.3 Phase 3: IoT installation in operational multidisciplinary outpatient clinic

Since PIR sensors had been demonstrated as effective, it was appropriate to install them in the primary clinical target area. Sensors were installed in the evening of 4 November 2018 commencing after the close of operational business. Installation of

IoT sensor installation took place in several 'subphases'. The main installation of PIR sensor devices formed the bulk of the data collection period. This main phase has been identified in this section as the subphase 'Phase 3, Part A' (A). Further trial installations involving different types of sensors were also undertaken. These secondary trials have been described as 'Phase 3, Part B' (B), and 'Phase 3, Part C' (C) respectively, the latter of which contains two parts (C.1, C.2). The latter two parts (B-C) were the final IoT sensor installations undertaken during this research project.

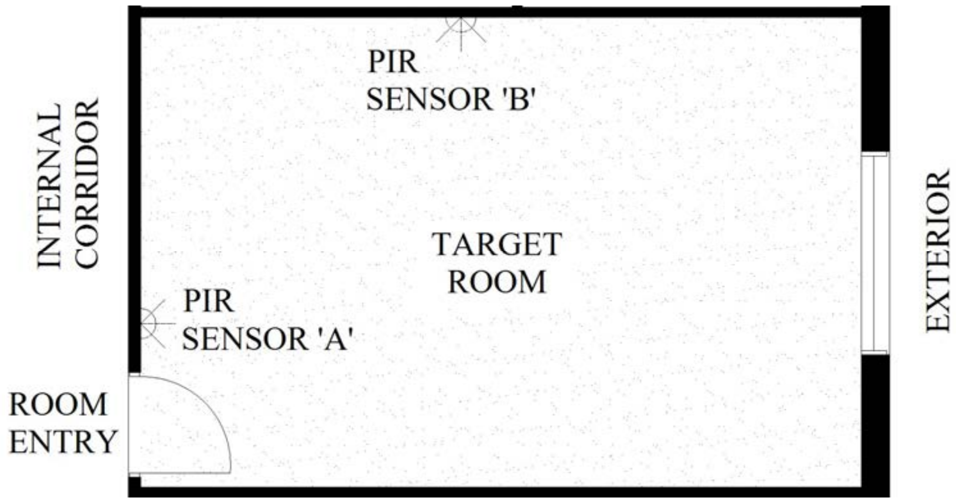


Figure 16 - Installation diagram for PIR sensors in a non-clinical space, managed through an in-house room reservation system.

3.3.3.1 PIR sensor installation (A)

For each PIR sensor installed, target surfaces were cleaned with isopropyl alcohol prior to applying half of the hook-and-loop style mounting system with adhesive tape. To ensure proper alignment and thorough adherence, the removable strips were adhered according to manufacturer's instructions: pressure for 1 minute minimum, no weight-bearing for 1-hour minimum. Hubs were placed to ensure coverage of all sensors across the clinic with a 15-metre maximum range, and sensors were placed in each target room (Figure 17). Sensors were installed with two new AA-size batteries each and initialised to the hubs in coordination with the manufacturer's Australian representative via mobile phone. This coordination ensured connectivity of all sensors through the hubs and routers, to the middleware database prior to recording any data. Each sensor had a unique identifier, which was matched to the room number and floor plan provided to the sensor manufacturer to incorporate into the data dashboard. Once the data dashboard was confirmed operational, the sensors were left to begin the long data gathering process.

Figure 17 - Final layout of PIR sensors within the target multidisciplinary clinic including hub location and radius of hub influence.

3.3.3.2 PIR sensor re-positioning (A)

After initial installation, the sensors collected data for a period of two weeks, after which the data was examined. The resultant test data showed very high occupation rates for all rooms during operational hours, which seemed inaccurate. It was suspected that the ceiling-mounted sensors, despite being mounted according to the manufacturer's recommendations, were being triggered by corridor pedestrian traffic.

To test this theory, the clinic was attended after hours, and a series of tests was undertaken while the target clinic was effectively vacant. All internal doors were opened, and the PI briskly walked through the clinic corridors continuously for 10 minutes without entering any target spaces. Sensors in all target spaces recorded 'occupied' status during this trial period, thus confirming the previous suspicion.

All sensors were removed from the ceiling and re-mounted to the walls directly above the door leaf. The after-hours 'corridor walk' was repeated with no sensors triggering during the 10-minute period. For confirmation, for an additional 10-minute period, while all doors remained open, every other space was entered by the PI during the walkaround. Finally, during the following 10-minute period, the opposite rooms were entered during the walkaround. Each room entered showed 'occupation' during their respective 'occupied' test periods, and vacant when vacant. Sensors remained in this position above the door leaf for the remainder of the two-year study period. When the study period was completed, all adhesives were removed from the walls, with no recorded wall-surface damage.

3.3.3.3 PIR sensor maintenance (A)

Maintenance interventions were required for the PIR sensors 19 times across the 25-month study period. Transmission strength was received by the hub as part of each transmission, so this allows remote oversite of the operational capacity of the installation. The sensor vendor monitored the system remotely via service contract, and contacted local staff, such as the PI, when interventions were required. These interventions typically required either replacing batteries, restarting sensors and/or hubs, and obtaining new SIM cards.

On each occasion, the requested intervention was undertaken, and the operational status of the system was confirmed. If sensors were powered through existing building power systems, new power points would have been required for each sensor location at least. This additional cost would have exceeded the project budget, despite the forecast reduction in intervention.

3.3.3.4 Alternative sensors trialled (B & C)

The PIR sensors had been proven capable of safely delivering data on room occupancy in clinical environments. As noted in section 3.2.2, the three selected IoT sensors were chosen in part due to their cost and commercial availability. At that time, a process of further exploration and authorisation was undertaken to consider expanding the selection. Once the potential budget for technology purchase using the previously awarded SERTA grant funding was increased, additional sensors could be explored. Consequently, multiple Elsys 'ERS-CO_2' sensor devices were ordered, and experiments began with a raw thermopile sensor.

3.3.3.4.1 Elsys ERS-CO_2 sensor trial (B)

These sensors contained five separate sensors: PIR, CO_2, Light Levels, Temp., Humidity, and transmit to any generic 'hub' using long range, low power (LoRaWan) networking technology. This technology has been demonstrated as capable of transmission distances of up to 10km for line-of-site installations [122]. Internal transmission distances were identified as 'variable' depending on materials and quantity between transmitter and receiver. An outdoor rated LoRa gateway (IP67) was installed inside a mechanical plant room, two storeys above the target clinic in 3.3.3.1 above. Transmission tests occurred within the target clinic and within a remote building on campus. IoT devices in the clinic were approximately 12 metres away from the receiver. These signals however travelled through two steel-reinforced concrete slabs, two ceilings, several HVAC systems and various steel/plasterboard internal walls. Sensors in the remote building were approximately 350 metres from the transmitter, and there were two exterior walls between them.

The intent of installing these sensors was to learn more about human activities in these spaces, seeking *count* data (Figure 2). This intent hinged on the documented accuracy of CO_2 sensors in closed spaces, and the potential of sensor fusion. The target clinical spaces had no operable windows, and all activities were undertaken with doors closed to limit communication of air with the corridor. Hence it was theorised that these sensors may provide an accurate way of understanding more about human activity within closed-door, high-privacy clinical spaces.

Sensor devices were adhered in the clinical environment using the same method as described in 3.3.3.1 above, in the relocated position described in 3.3.3.2. They were placed adjacent to the existing PIR sensors. Installation took place on 27 March, 2019 approximately four months after the initial PIR installation.

3.3.3.4.2 Thermopile sensor – IoT device development (C)

Thermopile sensors were the most promising from the literature review, with abundant research demonstrating their capacity to count humans via their infrared radiation, or heat emissions. Despite this initial success, few market-ready solutions existed. Those that did, such as the ERS-Eye, used the thermopile only to confirm occupancy, reinforcing the PIR data. Two proof-of-concept experiments were undertaken using a thermopile sensor in a live clinical room.

The first proof-of-concept set-up was to determine whether thermopile sensors recording heat signatures could identify human presence, and whether the data could be visualised sufficiently to understand anything about human activity beyond *occupancy*. A basic thermopile sensor connected to a proprietary circuit board was purchased online. This serial breakout board contained the resistors and other circuitry required to power the sensor and obtain data from it (Figure 19). The breakout board was mounted by the PI in a generic plastic enclosure into which a hole was drilled to capture each sensor's full 60-degree viewing angle.

Placing the sensor in a separate housing to the main computer was intentional to reduce the visual presence of the IoT device in the clinical space. Using the Universal Asynchronous Receiver Transmitter (UART) protocol, the breakout board continuously transmitted data at 115200 bits per second when powered. Sensor data was streamed via a modified 5-metre-long serial-to-USB cable/converter to a laptop housed in the ceiling space and connected to the existing building power supply (mains power). The laptop ran demonstration software provided by the UART breakout board manufacturer which visualised the sensor data as a moving heat map of activity.

Demo software was run on the PC, which was configured to remain on and active for the duration of the study period. A small section of the computer screen containing the visualised data was then recorded using proprietary software (Bandicam) purchased for this purpose. Once completed, the streaming video was overlayed on to a floor plan of the room. This combination was intended to help humans observing the video identify occupants and infer activity patterns within the clinical space based on location. Recordings six hours long were taken 24-hours per day over two different periods. First, a typical long weekend was observed when the clinic was typically empty to confirm baseline data, confirm logistics and detect the PI moving about the space. Second, the period between and including Christmas and New Year holidays incorporating one week of clinic operations. Video data was time-stamped and saved

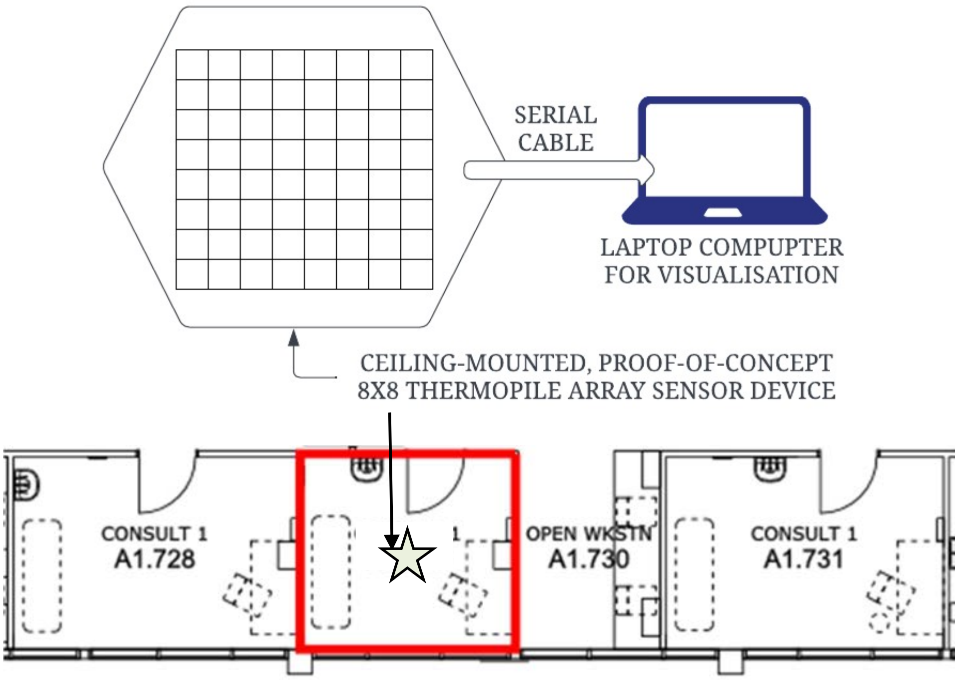


Figure 18 –Setup of proprietary 'breakout board' in off-the-shelf enclosure connected from USB port on the board to USB port on the computer using 'Serial to USB' converter cable/hardware to serial port on laptop computer mounted in the ceiling space of the the target clinical room (highlighted red)

on THHS servers.

The second version of the thermopile sensor experiment, conducted after the 'demo software' screen recording above, was a data-driven method which used an internet-connected, nonscreened computer. A more sophisticated breakout board was purchased using I2C protocol rather than UART for data streaming and control. Like the UART board, this I2C breakout board was mounted into a generic enclosure, then connected to a proprietary minicomputer (Raspberry Pi), powered by a 5V generic power supply. The minicomputer and power supply were placed above the ceiling, and the housing was secured to the underside of the ceiling tiles approximately the middle of the space. The PI then used virtual private network (VPN) software to transmit sensor data at 1-minute intervals to middleware vendor LiveSense for downstream processing. Data was transmitted from the Raspberry Pi through Wi-Fi to the same SIM-enabled router used for the PIR sensor-hub, and from the mobile networks to the internet. Including the minicomputer, three volunteers simulated activity within the target clinical space for approximately one hour, outside clinic operational hours. The target clinical space was in a different location from the initial proof-of-concept in this section (above) due to the requirement to co-utilise the PIR SIM-enabled router. To facilitate the manual count, a new tool was required.

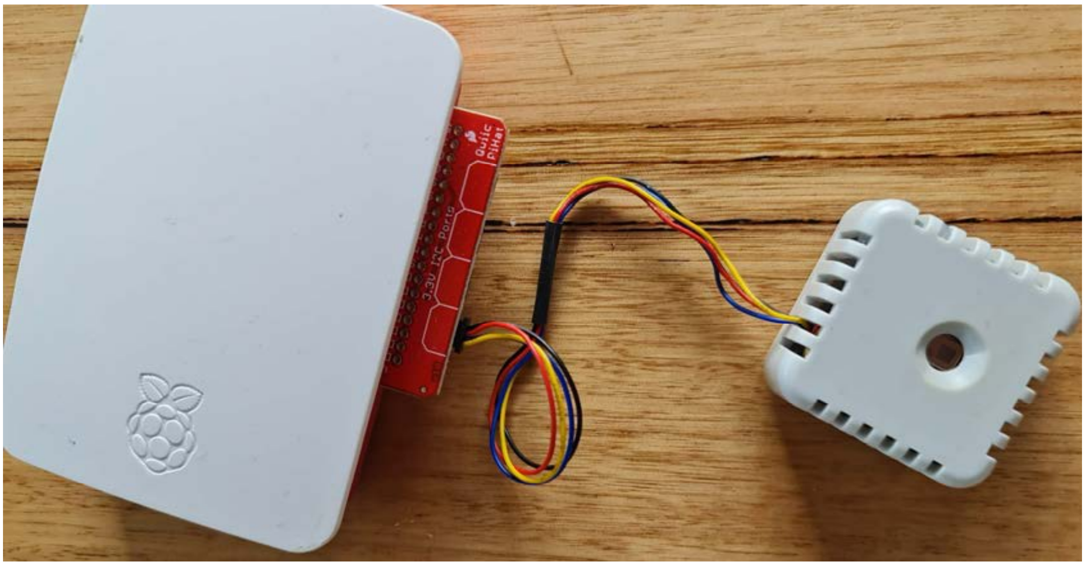


Figure 19 – Panasonic 'grideye' thermopile sensor on proprietary circuit board (right), connected through 'Quiic Hat' pin connector to Raspberry Pi, powered by 5-volt adaptor

3.3.3.4.3 Counting Timeseries events

The capacity of electronic tools to collect data on human activities within clinical spaces has been central to this research project. As noted in Chapter 2, the predominant form of data gathering in the literature was based on human observation. Despite this majority, few tools existed to support researchers in recording customisable timeseries data into standard formats. A search of potential offerings in July 2019 for Android operating system applications (apps) identified many counting apps with various functions. Few apps had the capacity to log data in standard data storage formats, and none was identified that suitably recorded timeseries data. Consequently, a simple app named *Count n Time 3000* (CT3K) was created by the PI using the development platform 'MIT App Inventor' to meet the demands of researchers creating timeseries counting data (Figure 20). This app allowed for the comparison of *count* data received by the thermopile sensor with observed 'ground truth' over a simple 1-hour demonstration of the accuracy and flaws of the thermopile

Basic User-Interface

Sample file output (dummy data)

Label	Count	Date	Time	am/ pm
staff (AM)	1	2019/25/05	10:51:57	am
staff (AM)	2	2019/25/05	10:52:03	am
consumer (AF)	1	2019/25/05	10:52:09	am
consumer (AF)	0	2019/25/05	10:52:15	am
staff (AF)	1	2019/25/05	10:52:20	am
consumer (AM)	1	2019/25/05	10:58:20	am
consumer (AM)	0	2019/25/05	11:13:15	am
consumer (AF)	1	2019/25/05	11:22:01	am
consumer (child)	1	2019/25/05	11:22:03	am
staff (AF)	2	2019/25/05	11:28:52	am
consumer (AF)	0	2019/25/05	12:10:13	pm
consumer (child)	0	2019/25/05	12:10:15	pm
staff (AF)	1	2019/25/05	20:52:26	pm

Figure 20 - 'Count n Time 3000' mobile application interface (left) and sample output (right); custom labels identify time/date-stamped count events; table data is illustrative only.

sensor's in-built 'count' data. During this period, three volunteers walked into and out of the space and the two data streams were compared with different numbers of participants entering/exiting the room. Thermopile sensor data experienced a time lag of up to two minutes due to residual human heat from vacant seats, which was mitigated in C.2 above by increasing the minimum period studied to one-hour.

The interface was basic by design, but functional to match the app development skill-level of the PI. The app consisted of a user interface with customisable labels between green and red buttons denoting addition and subtraction of observed elements. When either of the latter buttons were pressed, a new entry line was created locally in a comma separated value (csv) file, and associated 'label' cell was filled, along with the current 'count', and time stamp information from the devices' current time. The potential applications for the CT3K app were many.

This app allowed researchers to automate the task of manually counting individual items along with count-specific timestamps. For example, it could be used to survey the timing of various vehicles parking in a specific zone, fish swimming into/out of a video feed, primates in a specific tree, etc. There was no intention to publish CT3K due to the ongoing maintenance required.

3.4 Predicting future utilisation

The bulk of this chapter thus far has been about the collection of clinical space utilisation data generated by IoT devices. These datasets represent aspects of activities that had occurred in the past. To explore the actionable value extractable from these datasets, their capacity to support predictions of future optimisation opportunities for clinical space utilisation was considered. To support the PI in the application of machine learning tools to undertake these predictions, external resources were sought.

Through a WILs program, four third-year computer science JCU undergraduate students were hosted by the supporting HHS for a two-week period in November 2019. These students undertook the planning, data cleansing, user interface research, algorithm modelling and final instantiation of the work underpinned by the methods presented in this section and associated publication. Students were provided with oversight from two experienced data scientists employed by the host HHS.

Daily meetings and close communication through online collaboration tools (i.e. Trello), allowed staff to provide real-time support to the students. They demonstrated their process and learnings through daily logs and provided extensive documentation inside written computer code. The methods covered in this section took place over two weeks in November 2019. In April 2023, the *THHS Research Data Lab* (RDL), a work unit of the host HHS, was asked to review technical aspects of the methods previously documented by the students. Text in the following section was provided by the RDL based on the documentation written by the students in 2019. This text has been reformatted and edited to support readability, while the intent has remained the same.

3.4.1 Research data laboratory methodology review

3.4.1.1 Occupeye code review

The RDL has been approached by the PI to aid in reviewing a machine learning project assessing the occupancy of clinical rooms within the Townsville University Hospital.

This section presents the common data science project methodology used (CHRISP-DM), outlines the methodology established through the Occupeye Python code, and assesses the model evaluation. This documentation was prepared by Rudolf Schnetler and reviewed by Benjamin Crowley of the THHS RDL.

3.4.1.2 High-level process

IoT sensor data streamed into the cloud service contained, (1) the sensor ID, (2) room number, (3) datetime (EPOCH), (4) meridian and (5) occupied status. Therefore, a timeseries database showed whether the location was occupied (5), at certain time (3) with additional metadata (1-2, 4).

3.4.1.3 Methodology review

The methodology used by the research team closely follows the CHRISP-DM [123] methodology for data science project management. The following steps were undertaken [124] in applying the above model:

1. Business Understanding: The business situation should be assessed to get an overview of the available and required resources. The determination of the data mining goal was one of the most important aspects in this phase. First the data mining type was clarified, and the data mining criteria for success defined. A compulsory project plan was created.

2. Data Understanding: Collecting data from data sources, exploring, describing it and checking the data quality were essential tasks in this phase. To make it more concrete, the user guide describes the data description task with using statistical analysis and determining attributes and their collations.

3. Data Preparation: Data selection should be conducted by defining inclusion and exclusion criteria. Bad data quality can be handled by cleaning data. Dependent on the model used, derived attributes must be constructed. For all these steps, different methods were possible and were model dependent.

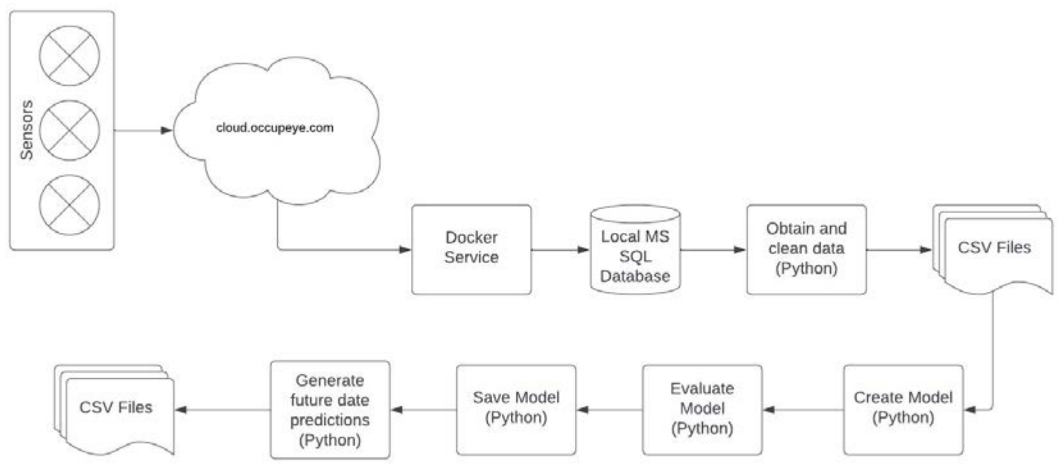


Figure 21 - High level process diagram linking sensors through the process of obtaining and cleaning sensor data, followed by creating, evaluating, and pre-populating the user interface with prediction data.

4. Modelling: The data modelling phase consists of selecting the modelling technique, building the test case and the model. All data mining techniques could be used. In general, the choice depended on the business problem and the data. More

important was how to explain the choice. For building the model, specific parameters must be set. For assessing the model, it was appropriate to evaluate the model against evaluation criteria and select the best ones.

5. Evaluation: In the evaluation phase the results were checked against the defined business objectives. The results must be interpreted, and further actions had to be defined. Another point was that the process should be reviewed in general.

6. Deployment: The deployment phase was described generally in the user guide. It could be a final report or a software component. The user guide describes that the deployment phase consists of planning the deployment, monitoring and maintenance.

3.4.1.4 Directly from code

Step 1: Create Historical Data

5) Load data from SQL database
    a. Consult rooms only
    b. All weekdays
    c. 8am to 12pm data
    d. 1pm to 5pm data
6) Clean and Format Data
    a. Convert datetime data to readable format (from EPOCH)
    - Split datetime data into multiple features (weekday, month, day of month, hour)
    - Create final clean dataset containing multiple data points (sensor ID, room number, weekday, month, day of month, hour, meridian and occupied status)
7) Save historical data

Step 2: Create Training Model

1) Instantiate algorithm (using K-Nearest-Neighbours Classifier)
2) Load clean historical data (From step 1)
3) Resample data evenly
    a. Select all positive (occupied) observations and randomly sample equal amount of negative (empty) observations

b. Append dummy dates in January and December
  - Create 12 months of data to predict a 12-month period
  - The dummy data was empty observations for both January and December

4) Preprocess data
   a. Remove room number
   b. Convert day, month, and meridian to integers
   c. Min-max scale hour and minute (-1, 1); this was to ensure the variables contribute equally to the model fitting
   d. One-hot encode features (convert each categorical value into a new categorical column and assign a binary value to those columns)
   e. Data split into 80-20, training-test split (80 per cent of the data was used for training, 20 per cent of the data was used for testing)
5) Fit model on train data
6) Test model on test data
   a. Produce evaluation report and confusion matrix
7) Save Model

Step 3: Create Predicted Data

1) Load model (from Step 2)
2) Generate future dates
   a. Generate future dates in 10-minute increments for a 12-month period
3) Clean generated future dates
   a. Remove any dates that were not weekdays
   b. Remove any increments not inside operational hours
4) Preprocess prediction data
5) Write prediction data
   a. Using trained model (Step 2) on historic data, predict whether a room, by increment, would be occupied or not
   b. Write prediction data on future dates to CSV file

3.4.1.5 Methodology Notes from development team

6) When a script updates the database, no more than seven days of data can be pulled at one time

7) GradientBoost and RandomForest machine learning (ML) models can be used, but kNN was hardcoded
8) Prediction data was saved to a csv file currently, could be changed to save into a database if need be.

3.4.1.6 Methodology Review summary

In summary, the methodology document by the WILS students in November 2019 was rigorous and scientifically robust. By following the methodology above, these students created the suite of tools presented in the relevant results section of this research project (see 4.2.7 below). The tools may have changed but the methodology employed would remain largely the same if redone with improved tools. Suggested improvements to the methodology for future researchers have been covered in Chapter 5. The application of ML was the final activity in the collection, presentation and processing of IoT data for the purposes of optimising clinical space utilisation.

3.4.2 Sensor installation conclusion

This subsection has described the selection, testing, and installation of various 'smart' building sensors to record aspects of human activity in healthcare spaces. The sensors were tested for their effectiveness in determining human occupancy patterns. Selected sensors were installed in a single space attached to a nonclinical reservation system to compare occupancy *as planned* versus *as used*. The sensor installation was increased to study occupancy patterns in an operational multidisciplinary outpatient clinic over a two-year period. Occupancy data alone however was insufficient to resolve whether spaces were well utilised or not. Seeking to move up the 'data density ladder', a proof-of-concept IoT device was developed. This device was based on a thermopile array sensor and the occupancy patterns in a single room were studied over a one-week period. Results from the technological interventions above are documented in the next chapter, however after these 'works', burning questions remained. Were sensors monitoring human activities within sensitive, operational clinical environments appropriate for the purposes of improving their utilisation? Were staff comfortable under the constant observation of these electronic devices in their workplace? To answer these questions, the opinions of staff were elicited through a series of one-on-one interviews and an all-staff survey.

3.5 Interviews

Understanding staff sentiment was critical to the long-term effectiveness of any technological solutions proposed in previous sections of this chapter. If staff considered sensor devices appropriate for use in a clinical environment but were strongly opposed to workplace monitoring of any kind, sensor installations were unlikely to succeed. Similarly, if staff were comfortable working under electronic observation but considered the use of space monitoring sensors in healthcare environments extremely inappropriate, sensor installation was similarly doomed. Due to a clear need to understand staff opinion on both appropriateness and acceptability, interviews were conducted with selected staff within the THHS.

3.5.1 Participants

Participants were selected using either one of two categories. Either they had directly participated in the research as workers in the multidisciplinary outpatient clinic, or they had direct experience in the operational aspects of managing the use of clinical spaces. Within the research, due to the limited number of participants, the precise role of each participant was not recorded as this could have led to participant identification. Potential participants were initially contacted via email, followed by scheduling an appropriate time in their calendar if amenable. In this introductory email, participants received both an interview information sheet and a participant acceptance form. A sample of this form has been included as Appendix 6. Participants were encouraged to review the information sheet, and if they remained agreeable to return the signed consent form in advance of the interview. Ten staff agreed to take part in these research interviews, however timing was inappropriate for one staff member. Consequently, nine interviews were conducted.

3.5.2 Preparation

Proposed interview questions were submitted to and authorised by the THHS HREC in accordance with the host organisations' standard operating procedures. This submission included statements from the PI assuring that the submitted questions were the only allowable formal questions to be asked in the interviews. The questions were written in full and submitted in electronic form through the Ethical Review Manager website.

To maximise potential for high quality research outcomes, practice interviews were undertaken over videoconferencing software. Three volunteers gave mock interview responses to familiarise the interviewer (the PI) with the experience of interviewing. Interviews were recorded and played back for personal assessment. General feedback was sought on the interview process from the participants after the conclusion of each interview. Based on the experience of the interviews, the questions were extensively modified and resubmitted for final authorisation. The resultant THHS HREC authorisation (AM/2020/QTHS/35376_3) was tabled with the JCU HREC.

Technology proposed for use in the interview, such as recording devices and the use of automatic transcription software, was trialled in advance and considered appropriate for use prior to undertaking any interviews. Three separate recording devices were proposed, one of which used Google Live Transcribe, two personal phones and one laptop computer. The purpose of using multiple devices was for redundancy, and the use of autotranscription software was intended to reduce postinterview processing times. The latter was considered appropriate prior to conducting the first two interviews but was abandoned after final transcriptions were compared to audio recordings and were found too inconsistent to prove useful. For the remainder of the interviews, transcription software was abandoned and the third device used to reinforce recording redundancy.

3.5.3 Interview location

All interviews took place on the main campus of the host regional hospital. Participants worked either on or within walking distance of the campus in multiple buildings. A central, quiet, dedicated interview room was reserved to host the interview process. The selected interview room had been recently constructed, so was known by the PI to contain certified acoustic dampening systems appropriate to suit the process of conducting interviews. Inherent acoustic treatment included carpet tiles on the floor and acoustic tile ceilings to minimise reverberation and other audio distortions in addition to in-wall and on-ceiling treatments. This location was selected to minimise external interruptions or distractions. Physically, the selected space was relatively small (approximately 9 square metres) and contained a small round table and several comfortable conference room chairs. Suitable air-conditioning and lighting systems were considered appropriate to maintain the comfort of both the interviewer and interviewee. The space contained sensors in the ceilings to inform and control building systems, which were used as ambient electronic sensor reference points during the interview.

A detailed digital map was prepared and distributed to each participant the day before their scheduled interview via email. This email also contained a reminder to bring signed participation sheets or submit via email before the interview. Despite the detailed map and verbal instructions, several participants were delayed due to their inability to find the meeting room. Sufficient time was allotted for each interview session as contingency, so this did not appear to reduce the quality or fullness of the interviews.

3.5.4 Visual aids

To help orient participants within the body of the interview, visual aids were created to reinforce the types of technology being discussed. Also, these aids anchored their placement on a spectrum of increasingly dense data gathering, stylised as 'the data density ladder' (Figure 22). These mnemonics were used to simplify concepts inherent to the categories of human-sensing spatio-temporal properties (Figure 2) for the purposes of the interview.

In addition to providing context, visual aids were created to focus participants' minds to specific technologies at relevant sections of the interview. Each visual aid contained references to the 'data density ladder' as well as several other visual cues about the technology being considered (Table 9). Visual aids were displayed and changed to represent the changing types of data collection: human observation versus electronic observation, being discussed during the interview. For the entirety of the 'human observation' interview (Part 1) the 'human observation' A4 sized card remained in place. For the duration of the 'electronic observation' interview section, no preformatted visual aid was used. Instead, direct reference was made to the ambient electronic observation currently in place to control the lights, monitor temperature and sense smoke. The purpose of this was to reinforce the nature of the ambient data gathering devices being discussed in the relevant interview section.

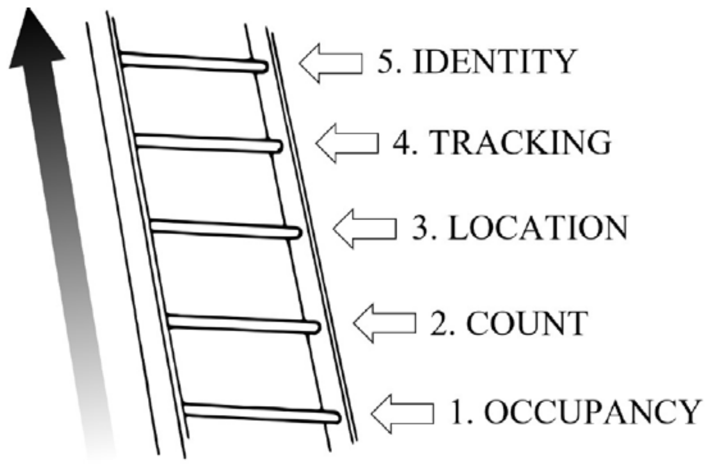


Figure 22 – Mnemonic created to support interviewees during the interview: the 'data density ladder'; this device simplified the 'categories of human sensing' as shown in Figure 2, with each rung containing the attributes of those below it

Table 9: Visual aids used during the interview, printed on A4 paper, backed by black, A4 card stock, and laminated together.

3.5.5 Interview structure

Each interview was structured around two formal interview sections with a break in the middle. There was an informal preamble and postinterview discussion recorded for each session. Each of these has been explored in greater detail below. This structure provided the framework to:

- transition into the interview from demands of the workplace, and introduce the subject matter (preinterview introduction)
- explore staff perceptions about human observation gathering increasingly dense data, (Part 1)
- present the capabilities of the data dashboard to explore research data (break)
- explore staff perceptions about electronic observation gathering increasingly dense data (Part 2)
- ensure all participant questions were answered (postinterview discussion).

Questions asked in Part 1: Human Observation, were repeated verbatim in Part 2: Electronic Observation, to enable response comparison. The questions asked in Parts 1 and 3 were as follows, noting question 8 has several subsections:

1) How do you feel about clinical spaces within the Townsville Hospital and Health Service (THHS) being monitored for occupation using this method of data collection?
    9) Can you describe how you think access to this data would influence your daily activities?
2) How useful do you think this data would be to the THHS?
3) How would you feel if data was continuously collected like this in each space in your workplace, every day?
4) What factors do you think influence or support these feelings?
5) If you received any feedback from either colleagues or healthcare consumers about their experience of being observed by this data collection method, can you please share it?
6) What recommendations would you make to future researchers looking to use this data collection method?
7) How would you feel if the data collected by this method was instead focused on:

a. ‘count’ data: identifying the number of people in a room?
b. ‘location’ data: identification of the location of occupants?
c. ‘tracking’ data: identifying the location of people in a room over time?
d. ‘identity’ data: collecting personally identifiable information on each occupant?

3.5.6 Preamble

The preamble did not constitute part of the formal interview but was used as a ‘settling in’ opportunity for the interviewee. Receipt of a signed authorisation to participate was confirmed in each case. This was the first face-to-face opportunity interviewees had to ask questions of the interviewer in a one-on-one setting, and they were encouraged to do so in this section. Interviewees were informed that the preamble did not form part of the interview, but that the recording devices were currently recording. An ‘interrupted flow’ was noted during preliminary interview sessions by the PI. Consequently, the commencement of recording prior to the interviewee’s arrival was intentional to check sound levels, recorder placement, etc. was intentional. Then, the structure of the interview was explained, and the visual aids were introduced. All visual aids were laid flat on the table with a black card facing up to reinforce the pending commencement of the interview. Finally, another opportunity to ask questions was offered prior to commencement of the formal part of the interview. When there were no further questions, interviewees were advised that the interview would commence upon asking the first question.

3.5.7 Part 1 – Interview Section 1: Human observation

Orienting the interviewer in this section was considered critical to the success of the chosen interview. The visual aid referring to the ‘human observation’ data collection technique from Table 9 was visually prominent, propped against the left side screen of a laptop computer. The data-collection-type aid remained in place for the duration of Part 1 of the interview (left in Figure 23). A second visual aid referencing the type of data being collected (right in Figure 23) remained in place during questions 1-7. This second aid reflected the type of data gathered, remained the same for questions 1-7 and was changed for question 8a through 8d. Regular verbal and physical references

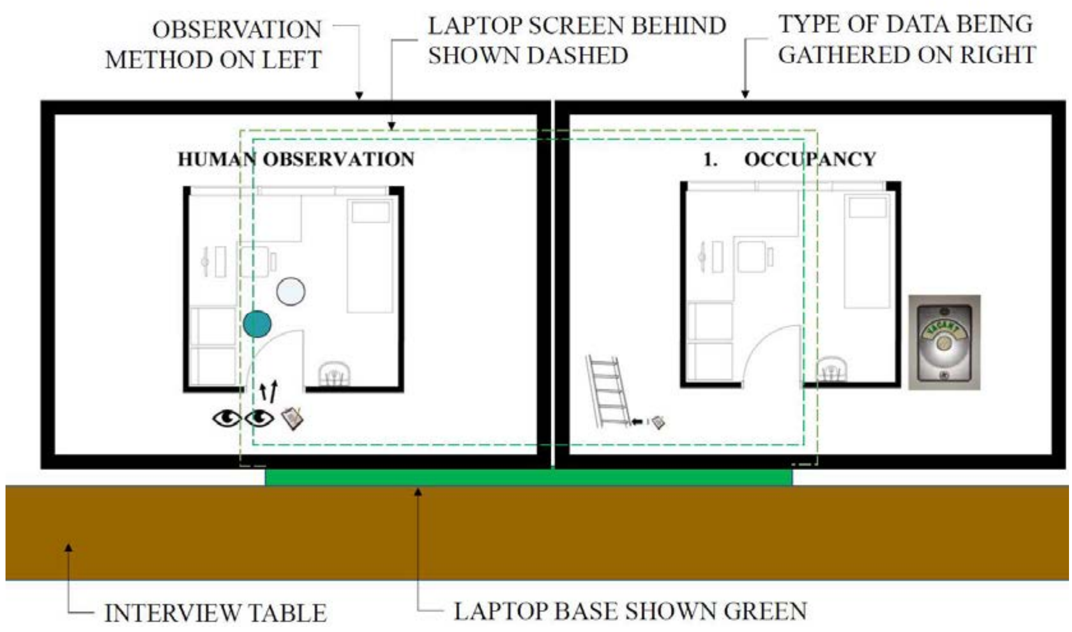


Figure 23 - Visual aid presentation style during Part 1 of the interview, for questions one through seven

were made to the visual aids through the interview to help orient the minds of the interviewee as the context of the questions changed. Once the answer to question 8d was provided in Part 1, the interviewees were advised that the formal Part 1 of the interview was over. Further, participants were advised that Part 2 of the interview was about to commence. Visual aids were simultaneously removed and placed face down on the table.

3.5.8 Part 2 – Data presentation

During the informal 'Part 2' of the interview, attention of the interviewee was directed to the screen of the laptop computer, where a prerecorded video was played. The interviewer spoke in person overtop of the video which was paused at relevant points for further elaboration as required. The purpose of the video presentation was to provide the interviewee with the experience of exploring the dataset collected by the electronic devices identified in Figure 17. The video was a recording of the PI filtering the data for an identified period using the proprietary data visualisation software, which dynamically responded to the filtering selected. Starting from an average utilisation of c.19 per cent the data from all rooms for 24-hours per day, seven days a week, the percentage utilisation changed in response to each filter applied. An average utilisation of c.51 per cent was demonstrated by filtering data to consult rooms, five days per week, clinic hours only. Further, the data exploration continued to identify a peak load of c.95 per cent utilisation on one of the days in the target period. Finally, the video exploration filtered data to look at afternoons only and identified several rooms with historically low occupancy on Friday afternoons. Upon conclusion of the video, the opportunity to ask any clarifying questions was offered, prior to the commencement of Part 3 of the interview relating to electronic observation.

3.5.9 Part 3 – Interview Section 2: Electronic observation

Again, visual aids were critical to re-orienting the focus of the interviewee to the context of Part 3: electronic observation after the data presentation in Part 2. The same questions were asked as identified in 3.5.5 within the context of electronic observation. Again, the visual aid on the right of Figure 24 was changed for each subsection of question 8. As noted above, the left side visual aid was removed and instead reference was made to existing ceiling sensors like those used in the multidisciplinary clinic ‘occupancy’ study described in 3.3.3.1 above. Upon conclusion of the final response, participants were advised that the formal interview was now complete. In all cases, postinterview discussions took place of varying lengths. This exchange was recorded but was not considered part of the formal

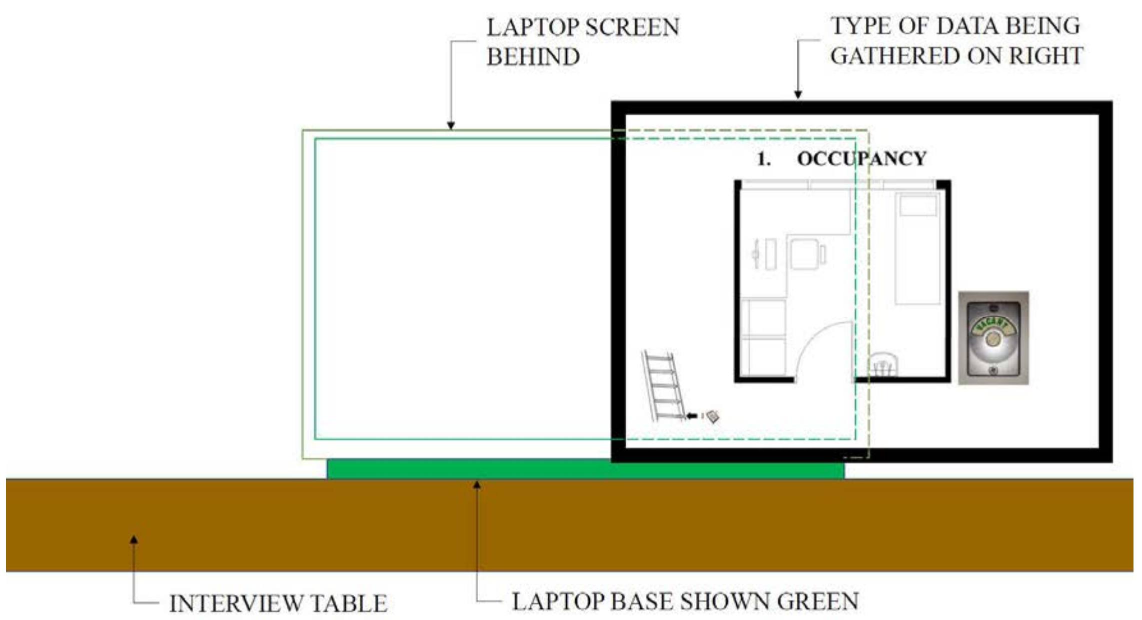


*Figure 24 - Visual aid presentation during **electronic observation** section, intentionally with no visual aid to represent this observation method, instead referring to existing sensors in the room for context*

interview. Interviewees were then thanked and escorted back to the main corridor by the interviewer.

3.5.10 Postinterview data management

Immediately after the conclusion of each interview once interviewees left, recording on each device were stopped. Files were saved from all three recording devices and saved in accordance with the data policy established in 3.2.6.2 above. A naming convention was established to maintain participant confidentiality. Original participant names were obfuscated to gender-neutral first names only for reference in the results chapter (Table 10). Once files were appropriately saved behind THHS firewalls from each device, files were deleted from the recording devices.

The intention was to use Google Live Transcribe on one of the recording devices. However, the quality of the transcription was insufficient given the speed of discussion and the multiple accents involved and the use of live transcription software was abandoned after the second interview. Transcription software (FTW transcriber) was purchased to facilitate the PI creating interview transcriptions for later text processing in NVivo, however the process of transcribing was slow and cumbersome by the PI as a first-time transcriber. Free use of a professional transcription service was offered from a colleague at JCU as part of an existing transcription grant. An

Table 10: Obscured, non-personally identifiable names and numbers assigned to each interviewee to maintain confidentiality.

Interview Number	Interviewee Name
11	Jamie
12	Sam
13	Quinn
14	Casey
15	Kai
16	Akira
17	(not used)
18	Jessie
19	Pat
20	Kerry

amendment to the standing ethics approval to utilise the transcription service was submitted to the THHS HREC and subsequently approved (AM06). Files were transmitted via proprietary secure upload link and returned within several weeks. Transcription files were in Microsoft Word (MSWord) format on the template of the transcription service, separated into 'facilitator' and 'interviewee' sections.

Transcribed files were then reviewed twice word-for-word against the original recording and any corrections made. Another listening of each full interview was undertaken while the text was reformatted into a standard numbered format created by the PI. To facilitate data analysis within NVivo, embedded stylistic coding within MSWord was used to:

- Colour code all transcribed text associated with the facilitator (interviewer) and interviewee. Facilitator text was changed to red, and interviewee text to green.
- Number each interview according to the file name assigned as per this section above, obscured in such a way as to ensure interviews were de-identified (e.g., Interview #21).
- Number each question as a separate section header (e.g., 21.1 Part 1 – Human Observation).
- Number each question as a separate section header (e.g., 21.1.7).
- Preamble and postinterview discussion sections were not numbered.

The above template system was used to format each interview in separate files to import separately into the qualitative data analysis software NVivo.

3.5.11 Interview analysis

Extracting meaning from the complexity of qualitative data can be challenging. To strike the appropriate balance between 'flexibility on the one hand, and consistency and coherence on the other' [125], a thematic analysis approach as defined by Braun and Clarke [126] was used. Six phases of thematic analysis undertaken by the PI have been identified *underlined and italicised* through this subsection, in reference to the latter work on this type of qualitative analysis [127].

All re-templated transcriptions were imported into the NVivo software. The text of each interview was reviewed word-by-word three times in different ways. In this way the PI became 'immersed in the data' [128] as per phase 1: *familiarisation with the data* [127] in preparation for thematic analysis of the transcribed interviews. Relevant sections of text were reviewed many more times and were associated with unique code as per phase 2: *coding* [127] Codes were defined by the PI based on the transcribed text. These codes became the variables under which like sentiments, thoughts, feelings or other expressions by each interviewee could be organised across the entire transcribed dataset. Over time, some codes were split into nuanced subsections, while others were combined in an evolving and iterative process. Ultimately through management and grouping of like codes, themes emerged forming the primary concepts emergent from the analysis as per phase 3: *searching for themes* [127].

The above process was repeated through three consecutive iterations through all the interview text. Once one full pass through the dataset was completed creating, combining and splitting codes, a second pass through the dataset was completed. This second pass ensured all relevant data in earlier texts could be captured by codes emergent from the later textual examination. During the second pass, a further review of the codes allowed the separation of nuances in the text, and the re-combination of like ideas in alignment with the steps of thematic analysis [126, 129] [130]. These iterative passes through the data constituted the fourth phase of analysis: *reviewing themes*.

A mind-map of all codes and their interrelationships was created to support the visualisation and organisation of the analysed data which produced clear themes within the dataset [131]. Finally, an overarching 'grand theme' was established based on all underlying data. The mind-map created also identified contributing elements within each code to capture the nuance of each and determine that new codes were or were not required. For reference, this mind-map has been included as Figure 25, Figure 26, and Figure 27. The creation of the mind maps in turn formed phase 5: *defining and naming themes* [127]. Finally, an overarching grand theme was established based on all of the underlying data after this exploration of clustered patterning across the dataset [130].

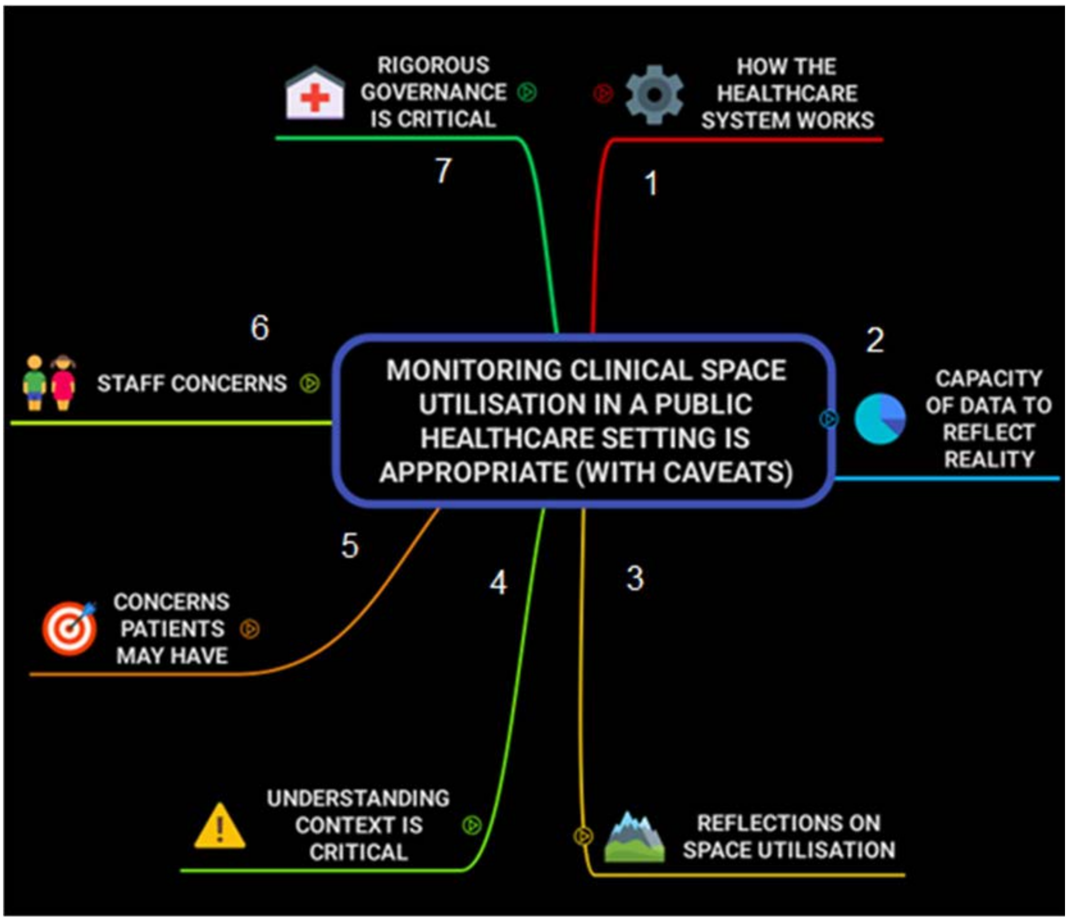


Figure 25 – Mind map detail showing central grand theme, and all themes (one through seven); refer to Figure 26 and Figure 27 for associated codes

A third and final pass through every word of the dataset was undertaken, using reformatted transcription text. Instead of passing through the data linearly for each interview as for the first two passes, the qualitative data was re-organised using the rigorous templating described above. Using the software's capabilities, all data was re-organised as datasets unique to each question. Each question-based dataset contained all answers to that question provided during each interview. The use of styles and colour coding allowed the extraction of only the interviewee responses identified per respondent, while also acting as a double-check to confirm no transcribed text from the interviewer was being considered. Reorganising the data in this way allowed a different perspective on the responses by being able to quickly compare 'like' responses. This cross-section of data allowed analysis to be conducted to a given question without having to scroll through the text of each individual transcription file. As one of the files was more than 11,000 words long, this process helped supported comparison of each interviewee's responses without having to wade through extraneous verbiage. This method was considered highly successful and provided confidence all relevant data had been extracted from the transcribed text.

Once the PI was satisfied all relevant information had been extracted from the qualitative data, the results of the final phase: *writing-up* was commenced [127], and is presented in Subsection 4.3.1. The interviews provided abundant information on staff feelings comparing IoT versus manual data collection, however the number of interviews was limited. Though the validity of qualitative data obtained through interviews is reinforced most strongly by the presence of the PI, triangulation would 'corroborate and analyse the data being collected' [20]. Consequently, an all-staff survey was designed to explore key staff sentiments emergent from the interviews and

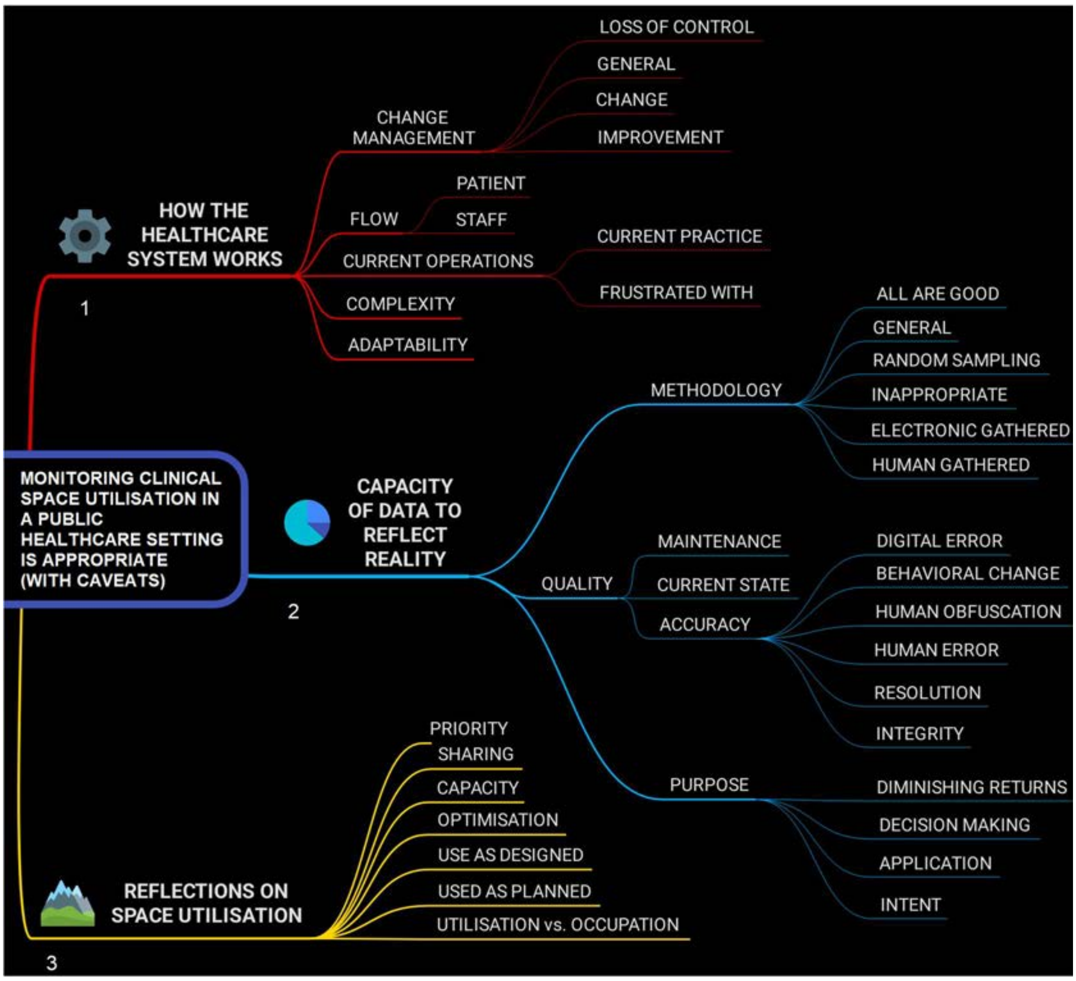


Figure 26 – Interview data analysis mind map detail, showing themes one through three, including both code and formative sub-codes.

try to understand the boundaries of both appropriateness and acceptability for collecting increasing levels of data density.

3.6 Survey

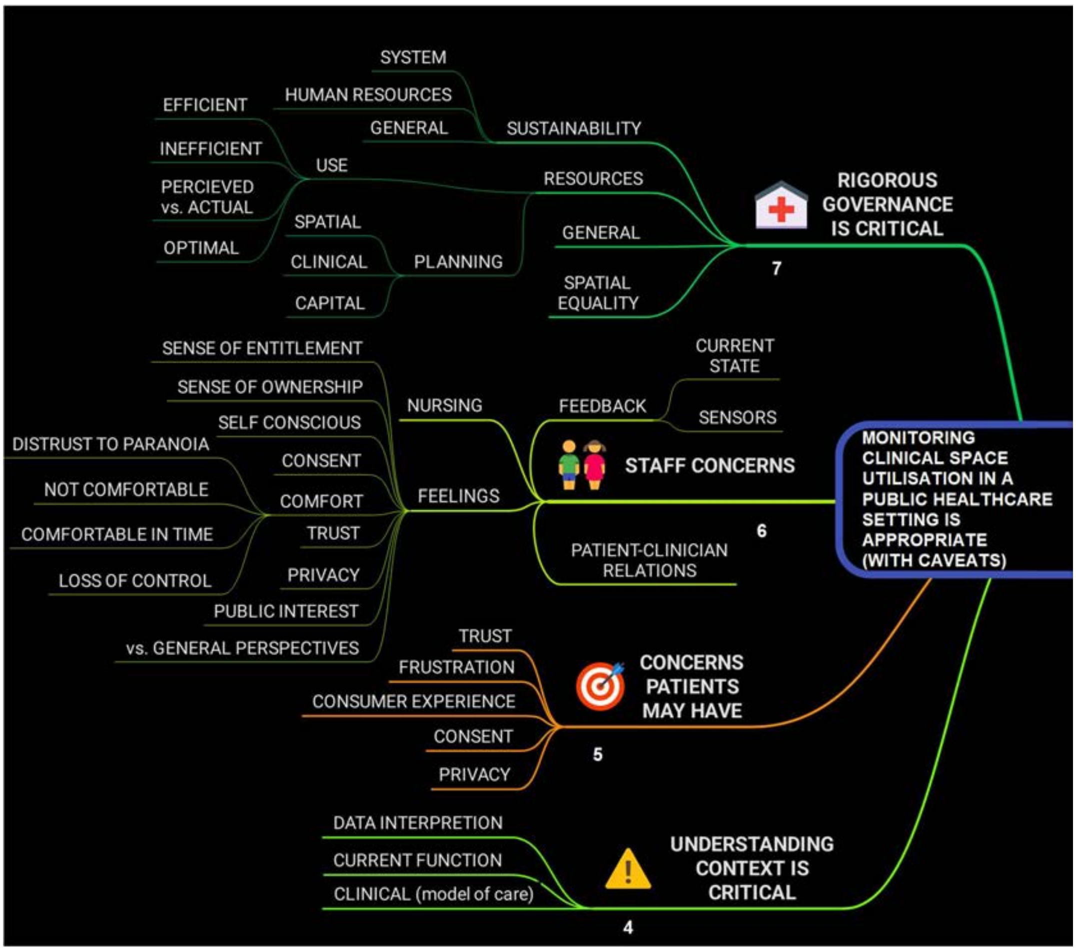


Figure 27 – Interview data analysis mind map detail, showing themes four

All aspects of the survey including the questions proposed, length, duration, distribution method, etc. were written down and submitted to the THHS HREC for review and approval. Key to this approval was ensuring that all potential participants were aware of the nature of the research project, its purpose, and that their participation was nonmandatory, unpaid and anonymous. This survey information sheet was distributed as an attachment to a broadcast email to all staff. Also, this sheet was copied onto the title page of the survey. The first and most important question was: ‘do you agree to take this survey?’ which asked potential participants to consider their options and register their consent.

3.6.1 Survey preparation

The questions for the survey were developed in an iterative process to ensure they accurately reflected the core research questions:

- Were electronic sensors appropriate for use in a clinical environment?
- How comfortable were people working under IoT sensor observation?

Techniques employed in the development of suitable questions for the survey included the use of visual aids, repetition and predominant use of a 5-point Likert scale. These scales are defined by Peacock as *'discrete scales where respondents have to tick one of a number of replies to describe their degree of agreement with a statement'* [115]. Strict use of Likert scales limited the potential of measurement error [132] and allowed an accurate comparison across responses. Potential responses in 5-point Likert scales used was considered appropriate to allow a neutral position for both acceptability and appropriateness questions. This neutral position was considered important because the introduction of electronic sensors monitoring clinical spaces was considered a sufficiently new concept that respondents may not have had previous opportunities to form an opinion.

Also, a neutral position was intended to facilitate a theorised shift from positive to negative responses as the level of data density increased. This expected shift of opinion from positive to negative was also facilitated by the repetition of survey questions. Finally, removing the neutral position 'may annoy (respondents) and may not uncover the truth about their views' [133]. These questions repeated across increasingly dense data gathering designed to capture the subtleties of shifting opinions as the density of data gathered by electronic means increased. A 3-point scale was considered inappropriate as the barrier between positive and negative sentimentality was considered insufficiently subtle to facilitate the expected shift in opinion. Similarly, a 7-point Likert scale was considered onerous for the reader and overly complicated.

The survey was designed to be as accessible as possible. As an internet-based survey, the site could be accessed by a variety of hardware and software. Using 'preview' sites from several different devices such as handheld phones, and laptop computers, the survey graphics were deigned to remain easy to read and relate to the questions being asked. Pilot testing [133] of the survey was undertaken by the PI and three other volunteers on multiple devices confirming technical aspects of the survey. Regardless of the technology the survey was viewed through, the survey was automatically re-sized to maintain the design intent of the PI.

3.6.2 Survey participants

Initially, the staff survey distribution was limited to only staff on the campus where the target multidisciplinary clinic was located. The intended purpose of this delineation was twofold. First, the intent was to limit the survey to staff who may have had some exposure to the target clinic. Second, responses were to be restricted to the location where clinical space was most scarce within the HHS: the main campus. Upon review prior to distribution however, this delineation was considered insufficiently logical and ultimately unobtainable through the corporate email system. An amendment was made to the THHS HREC (AM06) to extend the survey to all staff employed by the THHS. The approval for this amendment was also tabled to the JCU HREC. This change also minimised *coverage* and *sampling* errors across all staff demographics to ensure results were as representative as possible of 'all staff' [132].

3.6.3 Survey questions

The survey was hosted by a third-party corporation Qualtrics (XM) under licence from JCU. The survey was designed using the corporate proprietary system through an internet-based user interface behind a username and password on a site dedicated for this survey. Access to the survey was limited to the underlying corporation, and two research advisers of the PI.

After arriving at the survey site, potential respondents were first presented with a presurvey 'front page' which again invites participants to take part in a survey. The purpose of the survey was identified on this page, as were the PI and his advisers, affiliations and contact details. Potential respondents were advised that the research was being conducted in accordance with the boundaries of a designated HREC approval. Also, the entry page advised potential respondents that no personally identifiable information was collected through the survey, and that the aggregate data provided by responses may be used in publications and other means of distribution such as conferences. Finally, after providing contact details of the PI, potential respondents were presented with the first question in the survey: ‘do you agree to participating in this survey?’. A ‘no’ response sent users to a ‘thank-you’ page which ended their survey session, while a ‘yes’ response allowed respondents into the remainder of the survey.

3.6.3.1 Survey preamble

Once the survey commenced, the first page presented to respondents was a preamble further reinforcing the aims of the research. This page introduced the concept of data density like the ‘data density ladder’ presented to interview participants previously. The mnemonic of the data density ladder was not used on the survey, instead referring to five categories like 2.2.2 above. The questions were stated to reflect the kinds of data gathered:

1) Was the room occupied or vacant? (presence / occupancy)
2) How many people were in the room? (count)
3) Where were the people in the room? (location)
4) How did people move in the room? (tracking)
5) Who were the people in the room? (identity)

Respondents were then further advised that each category (from 1-5) contains data from all previous categories, like Figure 2. The last element of the preamble introduced the two primary streams of sentiment the survey was designed to collect data on:

- How appropriate did staff feel the sensor technology in each category was for use in clinical environments?
- How comfortable were staff working in clinic rooms being monitored by each category of sensing technology?

The final elements of the preamble introduced two visual aids to the viewers. The first visual aid was a photograph of a standard consult room within the THHS. Next, a standard consult room floor plan overlayed with graphics was presented which served as visual aids to help reinforce the category under consideration. The floor plan and graphics were effectively identical to the visual aids used in the interview, which have been represented in Figure 28 below. Further, the initial juxtaposition of a typical consult room photograph with a typical consult room floor plan was intended. The purpose of this juxtaposition was to support respondents unfamiliar with the abstract format of a floor plan representing space, so the floor plan alone could be used for the remainder of the survey.

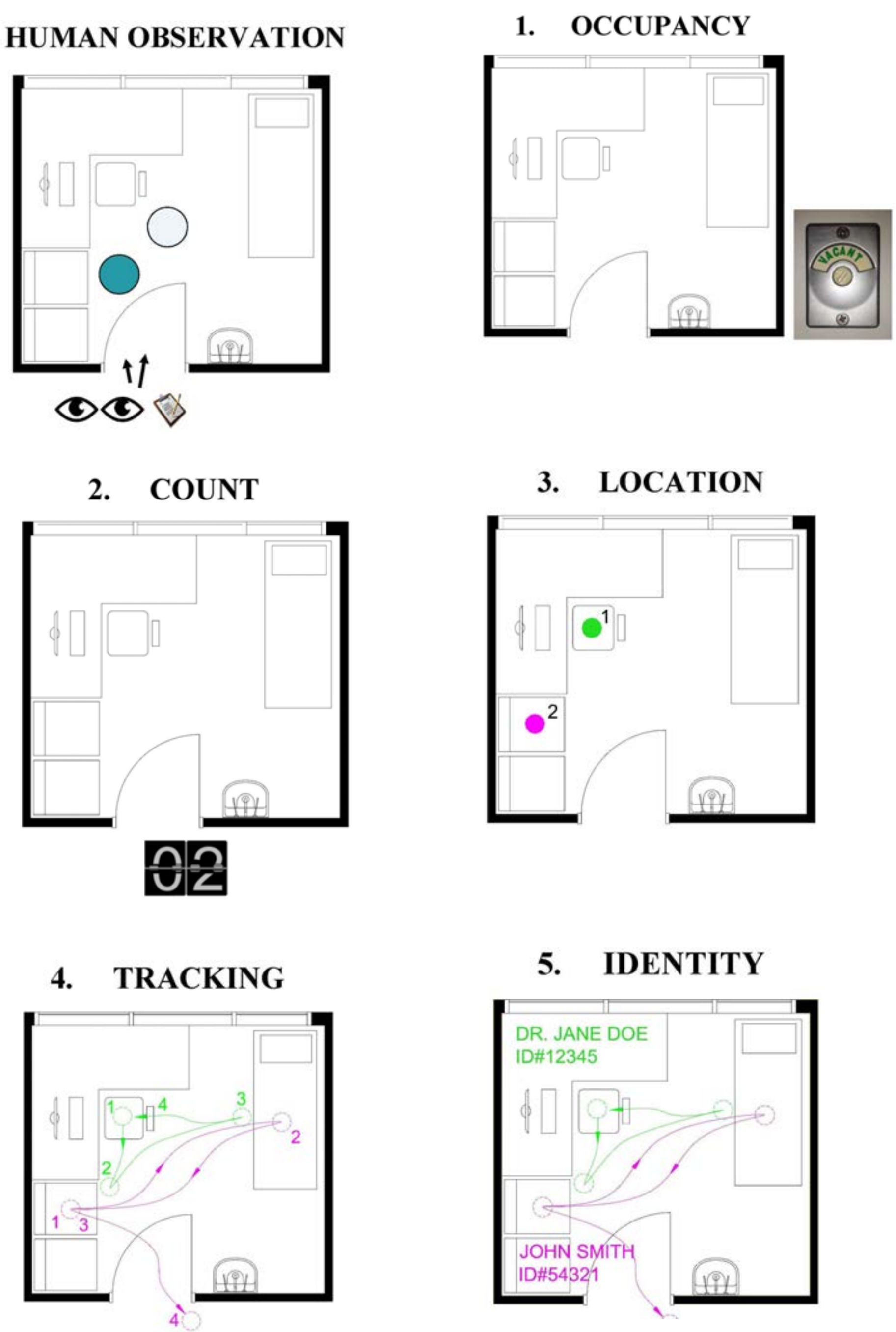


Figure 28 - Visual aids used in all-staff survey were adapted from those used in staff interviews, originally presented via Table 9 above

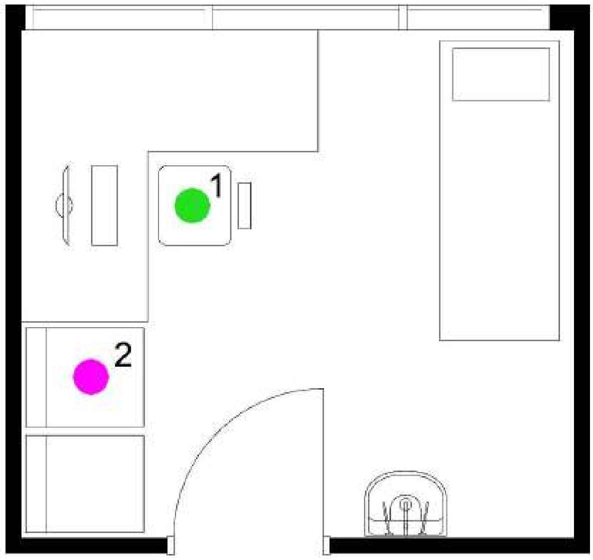
These aids provided context for the upcoming questions in a clinical outpatient environment. This singular floor plan was repeated, overlaid with a series of graphics representing the five numbered categories in the introduction section through the remainder of the survey. In summary, visual aids adapted from those presented during staff interviews (Figure 28) were presented on individual pages for each category. Two questions were asked on each page, relating to opinions on either the acceptability or the comfort level of staff respectively. For reference, the survey has been included as Appendix 8.

As noted in 3.5.6 above, a 5-point Likert scale was used for each subquestion for each of the five categories of data density, as per the survey extract in **Error! Reference source not found.**. For each question, an attempt to visually distinguish similarly worded potential responses such as comfortable and uncomfortable, was made by bolding the prefixes **un** and **in**. This style of question was repeated for each category of data density, altering the text of each to reflect the category in focus.

LOCATION

Location sensor technology can identify where each person is in the clinic room.

(eg. There are humans in this room at locations 1 (green) and 2 (purple.))



How appropriate do you feel it is to use location sensor technology to determine how clinic rooms are used?

Extremely appropriate

Somewhat appropriate

Neither appropriate nor **in**appropriate

Somewhat **in**appropriate

Extremely **in**appropriate

How comfortable would you be working in clinic rooms that are being monitored by location sensor technology?

Extremely comfortable

Somewhat comfortable

Neither comfortable nor **un**comfortable

Somewhat **un**comfortable

Extremely **un**comfortable

Figure 29 – Typical survey question including sensor description, graphic and two questions

The survey contained one set of questions per category, such as: *occupancy*, *count*, *location*, etc. Questions in each were slightly altered to reflect their respective sensing category. For example, the following alterations were made for the ‘appropriateness’ Category 2 question regarding count: ‘How appropriate do you feel it is to use counting sensor technology to determine how clinic rooms are used?’. Each question proceeded this way until the end of the main survey. Demographic questions were asked at the end of the survey to explore potential association between the demographics of age, role, gender and education.

3.6.4 Survey distribution, timing and reminders

The survey was released via email from the THHS public affairs unit via all-staff broadcast email midmorning on Wednesday 05 October, 2022. Public affairs were the only staff unit with authorisation to distribute staff-wide broadcast emails after authorisation from the relevant executive authority. A midweek release was considered optimal to avoid high postweekend workloads and avoid preweekend distractions. A midmorning release was chosen to maximise engagement at the most common break times and allow lunchtime discovery for staff with moderate email access.

To maximise participation for staff with limited access to email such as ward staff, operational officers and landscaping crews, information posters were distributed across the HHS. Regional managerial staff for campuses outside Townsville were provided with survey information posters via email to post in staff common areas. Posters were personally delivered by the PI to reception staff on buildings on all campuses within the Townsville area. Additionally, posters were hand delivered to all ward and clinic reception and common areas on the main campus including ancillary buildings. The posters contained a quick response (QR) code for staff to access the survey via smartphone cameras. Potential respondents clicking either on the link in the distributed email or following the QR code from the posters were sent to the same ‘live’ survey.

Survey reminders were distributed on two occasions by the THHS public affairs unit. An email reminder was sent one week after the initial survey release on Wednesday 12 October, 2022. The text of the email was identical to the original distribution except for minor wording changes to reflect its purpose. A second reminder was distributed on Wednesday 19 October, 2022, reinforcing the survey close date on Friday of the same week. These reminders were introduced to minimise potential nonresponse errors from the dataset and ensure a sufficiently representative sample of staff responses was obtained [132]. Finally, the survey was closed on the Qualtrics (XM) site at 4:30pm on Friday 21 October, 2022. Final data was downloaded and stored as per obligations stated in 3.2.6.2 above.

3.6.5 Survey analysis

Data from the online Qualtrics (XM) software the data was downloaded to a secure location as per the data management section in this chapter above. Data was imported into MS Excel (Microsoft 365 edition) spreadsheets. Graphs were created using MS Excel pivot tables, and basic descriptive analysis was undertaken with numbers and percentages from the pivot tables. This type of analysis is used *'to describe and synthesise data'* [134]. Results from the survey emergent from this analysis are presented in Chapter 4, where graphs summarising the various data have been provided. Graphic presentation has been used as they 'represent a visual image of the data all at once, which not only helps to describe the interrelationships among the data but also allows the viewer to retain this image.' [135].

Demographic survey questions allowed a free text 'other – please explain' option. This inclusion allowed for flexibility should certain individuals feel their demographic category was not represented in the original list of question options. Introducing a free-text option also introduced potential for measurement error [121], however this potential was mitigated through the following postinterview data processing:

ROLE: various changes to 'role' demographic data were made to reflect responses provided in free text:

- Converted numerous 'Allied Health' related role responses to new primary occupation category 'Allied Health'
- Converted all 'Midwife' role responses to new primary category 'Midwifery'
- Converted all 'Student' type responses to new primary category 'Student'

- Converted ‘Nurse’ role into ‘Nursing’ to capture responses aligned with nursing
- Converted all ‘Management’ responses into ‘Administration’
- Converted the 11 remaining responses into ‘Other’ category
- Removed ‘Role – Other’ column from dataset, since the column was empty
- Combined ‘Engineering and Maintenance’ with ‘Information Communication Technologies’ and ‘Operational Services’ into nonclinical ‘Operational Services’.

GENDER: combined noncisgender responses including ‘prefer not to answer’ and one ‘other (please describe)’ response into a single noncisgender category: ‘other’

AGE: converted individual ‘Age’ responses into ‘Age Bracket’ categories to facilitate comparison across age groups – this could have been avoided by asking age-group questions initially, however it:

- Introduced a novelty slider response mechanism for variety, and
- Allowed for the postsurvey creation of age groups based on the responses.

EDUCATION: converted various ‘Other’ education level responses related to workplace education into ‘Vocational Qualification’, and single free text based ‘Education’ response converted to ‘Other’

The above changes were made to improve and facilitate the analysis of survey data. Also, the free-text option allowed a sense of representation outside of strict demographic categories defined by the PI. This inclusive approach was an attempt to maximise demographic responses. As per the description above, merging data into ‘like’ categories also minimised data skew that may otherwise be emergent from too fine-grained demographic categories.

3.7 Conclusion

Preparing to undertake this research in a live operational healthcare environment required meticulous advanced planning, and authorisation by several governing bodies to proceed. This research project required numerous steps in attempting to resolve the following distilled research question: *are IoT devices effective in* *supporting optimised clinical space utilisation and are they appropriate and acceptable?* First, sensors were selected from the commercial marketplace and trialled for effectiveness. Then, occupancy sensors in a nonclinical space were used to compare intended use using reservation system data, with actual usage data from IoT sensors. Next, the same IoT sensors were then applied across 25 rooms in a multidisciplinary outpatient clinic and data was recorded for 25 months. Clinic occupancy data was presented in a dynamic online data dashboard, including novel grid-matrix user interface with machine learning space utilisation prediction capability. Beyond sensors, one-on-one interviews were conducted with THHS staff. These interviews were conducted to obtain a broad understanding of their feelings towards increasingly dense data gathered by both human and electronic observation. Finally, to compare interviewee responses with the sentiments of a cross-section of staff across the broader HHS staff population, an all-staff online survey was distributed. Each activity result formed the foundation of each subsequent activity in a logical chain of events. Detailed results of each activity outlined above can be found in the next chapter, which follows the same order as presented above.

CHAPTER 4

RESULTS

4.1 Introduction

Research activity results presented in this chapter follow the same logical flow as the methods section from Chapter 3. For clarity, this flow is represented here, adapted to the purpose of this chapter:

1) IoT sensor installation results
    a. Phase 1: Preresearch activities
    b. Phase 2: Sensor installation in a nonclinical reservable healthcare space
    c. Phase 3: IoT installation in operational multidisciplinary outpatient clinic
2) Predicting future utilisation results
3) Interview results
4) Survey results.

This flow formed out of necessity, as each result formed the basis of the next activity, which repeated until the last activity. The list of publications in the preamble to this document naturally reflected this same flow. All data described in this chapter has been stored in accordance with the data management plans established in the previous chapter.

4.2 IoT sensor installation results

Results from the introduction of IoT sensors are presented in this chapter in the same order as they were introduced in the previous chapter to facilitate cross-referencing. Where applicable, results had been published, presented at conferences or both. Multiple publications listed in this subsection can be found in the appendices for reference. Findings that may be useful for future researchers were included in this chapter despite suboptimal outcomes, such as the use of staff RFID cards.

4.2.1 Phase 1 – Preresearch activities: staff RFID card results

The process of selecting an appropriate IoT sensor for use in fully operational, live clinical environments has been described in detail in 3.2 above. Though these results were preliminary and therefore unpublished, they may be useful to future researchers in this area. Utilising existing staff RFID card access-control data was the first thought of the PI and many others when approaching the issue of studying patterns of occupancy in healthcare spaces. Technically, this was the combination of multiple technologies: RFID cards, electronic door locking and remote access systems. All the HHS's staff carry these cards, and each card allows access to a limited subset of doors and spaces, typically organised into categories. The same doorway used to study purchased IoT sensors in the next section was used to explore the capacity of this technology to understand patterns of clinical space utilisation. Data logs recorded by this door's security system are presented in Figure 30, noting personally identifiable information has been removed. The logs present data on 'door access granted/not granted' activities only. For the 24-hour target duration, entry was not refused for any presented RFID tags. The logs provide a general understanding of entry activities for staff in this nonclinical area, but cannot provide insight into:

- staff access to the system using their own ID cards or someone else's
- how many staff entered the space when door access was granted
- when staff left the target space as it was unrecorded and therefore
- the number of staff in the space at any point in time.

The door access data has limited usefulness in supporting an understanding of space utilisation beyond a very general sense. The logs loosely reflect patterns of entry, and not patterns of occupancy. In addition to the above, security access doors must be closed, and accessed only by staff or other visitors granted temporary RFID cards. In clinical areas within the target HHS, electronic access-control doors form part of the secure after-hours access perimeter. Typical clinic primary entry doors were held open during operational hours. This form of access control uses magnetic locks connected to fire safety systems, supporting patient flow during operational hours, and no data was recorded. Placing electronic locking mechanisms at every target clinical outpatient space has a high capital cost plus ongoing maintenance costs for the life of the doors and was therefore not considered feasible at scale. This cost was approximately $5,000 per door. For these reasons and more, electronic access-control door logs were not considered useful in supporting an understanding of clinical space utilisation. Use of these logs has therefore been disregarded for the remainder of this project.

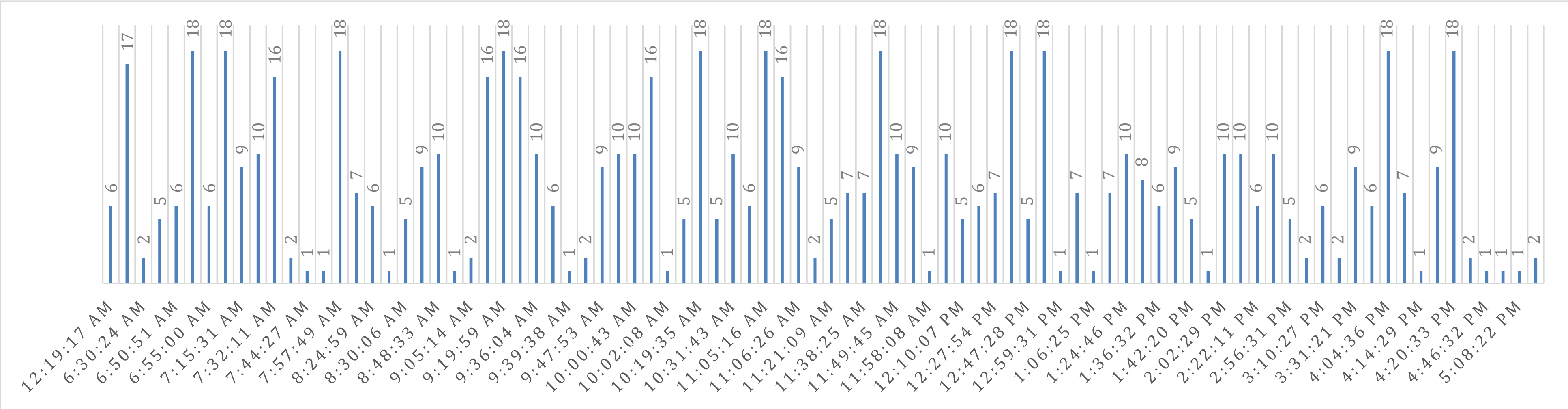


Figure 30 - RFID logs from electronic locking system for the sole access door to a non-clinical space over 24 hours

4.2.2 Phase 1 – Preresearch activity: sensor calibration activity results

Select human activity sensors were installed simultaneously in a nonclinical space. Results from the sensors were compared with a video recording of foot traffic into/out of the single-entry door in a healthcare administrative space. This study period was 24-hours long as described in 3.2.3 to 3.2.5 above. This section presents typical results from the three sensor devices tested. Excerpts from the video recording illustrating sample time-stamped entry and exit activities has been presented in Table 11. Much of the video recording was dark as the target nonclinical space was operational for nominal business hours only. Between sunrise and sunset however, the video was effective in allowing the identification and precise timing of entry and exit events. The entry and exit events were logged for the entirety of the video, and results compared with data output from the three sensor systems.

Extracts from the collated data from the three sensors and the video recording have been presented in

Table 12, with 10-minute intervals used as a common denominator. These results demonstrate that both the thermal sensor and beam sensors were inaccurate, but in opposite ways. The PIR array sensor had an inward bias. This sensor reported there were seven staff present in the space at 6pm when the video count was zero. Similarly

Table 11: Video stills from the 'ground truth' recording of entry (top row) and exit (bottom row) activities across a nominal entry threshold

inaccurate, the thermal beam sensor had an outward bias, reporting negative six staff in the space at 6pm, with the video confirming the human count was zero.

The PIR sensor, in contrast to the other two sensors, was accurate for 98.6 per cent of the video recording data obtained. There was approximately 1.5 metres from the door threshold to the 'nominal' threshold established to facilitate the video recording. The two counting sensors were deemed insufficiently accurate for the purposes of the proposed research. Consequently, the PIR sensor based IoT devices were the only commercial sensors used for the remainder of the research.

Table 12: Data extract from first/last occupied 1.5 hours of the target 24-hour period in a non-clinical space; green/red cells indicate data equal to/not equal to video recording data

TIME (over 24-hrs)	Video Count	PIR Sensor (0=vacant, 1= occupied)	PIR Array Sensor (count)	Thermal Beam Sensor (count)
6:00:00 AM	0	0	0	0
6:10:00 AM	0	0	0	0
6:20:00 AM	0	0	0	0
6:30:00 AM	0	1	0	0
6:40:00 AM	2	1	2	1
6:50:00 AM	3	1	4	3
7:00:00 AM	5	1	6	5
7:10:00 AM	5	1	8	6
7:20:00 AM	5	1	8	4
7:30:00 AM	6	1	8	4
(Data extract for the first 1.5 hours above, the last 1.5 hours below)				
4:30:00 PM	4	1	11	0
4:40:00 PM	3	1	10	-2
4:50:00 PM	1	1	8	-5
5:00:00 PM	0	0	7	-6
5:10:00 PM	0	0	7	-6
5:20:00 PM	0	0	7	-6
5:30:00 PM	0	0	7	-6
5:40:00 PM	0	0	7	-6
5:50:00 PM	0	0	7	-6
6:00:00 PM	0	0	7	-6

4.2.3 Phase 2 – Sensors in nonclinical reservable healthcare space results

Data from PIR-based IoT devices explored in the previous section were demonstrated to be highly accurate over the 24-hour period, as expressed in the previous subsection. This level of accuracy was considered sufficient for the purposes of this research; however, the trial period was brief. Consequently, the capacity of these sensors to accurately detect human presence over a longer period needed to be determined prior to the installation of these devices into clinical spaces. Sensor accuracy was verified by installing multiple PIR sensor devices, which correlated highly against one another. The target nonclinical space selected to undergo 24-hour observation over a longer period using the PIR sensors was managed through a room reservation system. Data from this system was readily available for comparison against the sensor data at the end of the trial.

Results were presented in person at the Health Information Science and Systems International Conference in Cairns, Australia, in December 2018. As part of conference proceedings, this paper was published in 2018. Results from this research are published with the title: '*Optimising spatial healthcare assets with Internet of Things*'' [1] (Appendix 2). This research paper has been reproduced with permission from Springer*Nature*. Authorisation to re-publish the paper noted above has been included in the appendix.

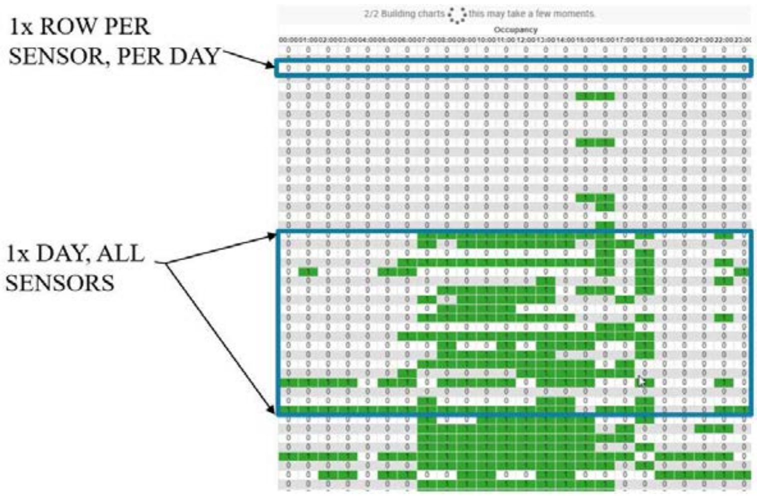


Figure 31 - Green cells indicate the target space was occupied for the selected interval (one hour in this case) from left to right; data is presented in one row per sensor; sensors were grouped in rows, visualising occupancy data for one day across all sensors in the clinic

This paper presented data on how the target space was used according to the sensors. One outcome was that one well-placed sensor was sufficient for the size/shape of the target room, implying sensor placement was critical to quality data. Another outcome was a demonstration of a variety of actual uses which differed from the planned use according to the reservation system. A longer study period for these sensors was suggested, leading to the next research activity in an operational clinical environment.

4.2.4 Phase 3a) - IoT installation in operational multidisciplinary outpatient clinic: preliminary results and the anomaly

Preliminary sensor results presented some mildly interesting results but suggested an alternative interface to the data was needed. To explore the preliminary results, data was downloaded directly from the proprietary cloud-based repository on to THHS computers through encrypted transmission. A brief introduction of the data format was required prior to a presentation of findings (Figure 32).

The downloaded repository was received in the form of a MS Excel database consisting of rows and columns of data. The rows each represented a single day of data, which presented a period of data selected prior to download, up to the full 24-hour cycle. As the full capacity of the room was under observation, 24 hours of data

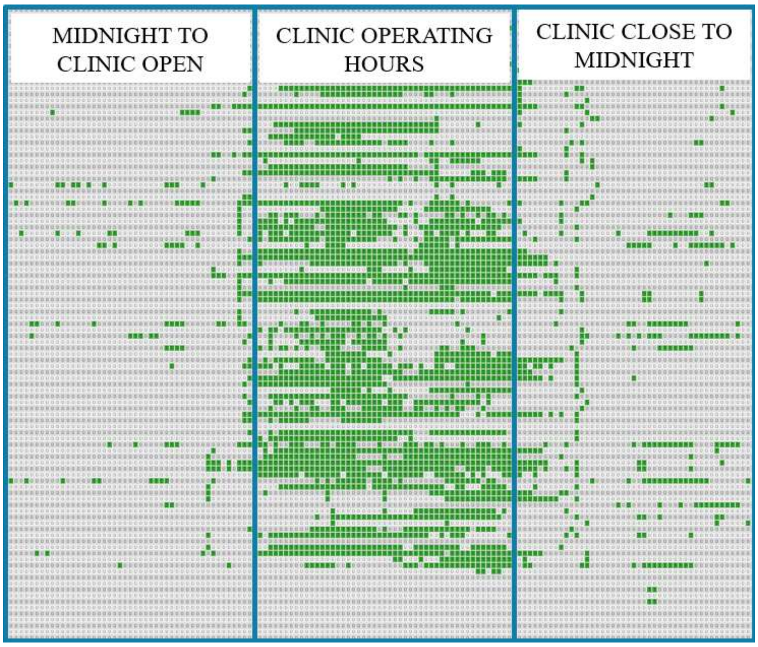


Figure 32 – Typical data structure visualised for one week in the clinic, demonstrating typical clustering of occupation data across 24 hours (left

was selected. The columns present occupation data for the period selected. In Figure 32, one-hour time periods were selected to illustrate the structure of the visualised data. A typical week was shown in Figure 32 with a data resolution of 10-minute periods. The latter illustrates high-level occupation patterns for all sensors in the clinic, across a full week. In the raw data, this pattern was typical.

In limited cases, when the target clinic was known to be closed, such as public holidays, an anomaly appeared. This data anomaly initially suggested that one target space was occupied continuously from after close of business on a Friday until hours prior to the next clinic operational period. Queries with THHS maintenance and the sensor vendor did not identify any known activities that may have tripped the sensor so completely for this period. To illustrate this data anomaly, two typical weeks of occupancy data were contrasted (Figure 33). Both weeks contain sensor recordings of sleep study patients occupying their respective spaces all night long. In both cases, periods of restless sleep trigger the occupancy sensors, and periods of motionlessness reflecting sleep activities which have been visualised as ‘white’ spaces. In no sleep

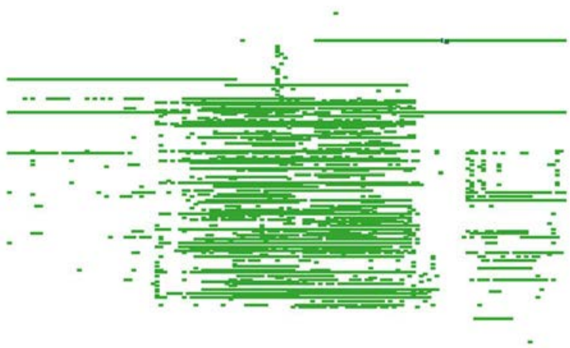
	← a) week showing high levels of overnight activity when select spaces were used after hours to accommodate overflow sleep studies; breaks in evening occupancy patterns represent times of consumer stillness (i.e. asleep)
	← b) week including a public holiday with unusual activity commencing after clinic close and continuing until just before next clinic opening; the clinical space associated with the anomaly was not used for sleep studies

Figure 33 – Comparison of two high-level patterns of occupancy accross the target clinic showing high-levels of continuous activity during known clinic shutdown times

study rooms were occupants awake and moving all night, and all morning long. Week b) (Figure 33) contains a public holiday when the clinic was closed. Despite the entire clinic scheduled to remain empty, a continuous occupancy pattern occurs during the public holiday and through the weekend.

Two findings emerged from this preliminary data analysis. First, that an improved method of data analysis was required as the raw data made detailed analysis challenging. The format of the database was challenging to navigate in any way except at a very high level. The period of data was selectable, however only a broad overview could be visually observed at one time. The timeseries nature of the data created challenges for running descriptive analytics. Most influential in coming to this conclusion however was the volume of data. At 10-minute intervals, six months of data produced 604,000 data points which became unwieldy in the current format. Extrapolating to the full study period of 25 months, this 2.25 million data points push the limits of Excel to handle the data. A better method of visualising and exploring the data was needed (see 4.2.5 below).

The second finding was triggered by the anomaly. Insufficient data was being provided by the sensors to understand anything beyond when the room was occupied, and when it was vacant. The sleep studies demonstrate that the anomaly was not reflective of a sleeping activity for a single person. Also, the spaces recording continuous activity were not used for sleep studies and the anomaly occurred on multiple occasions when the clinic was known to be closed. To understand patterns of human activity beyond, more information was required. IoT sensors collecting category 1 occupancy data (see 2.2.2) provide a limited understanding of utilisation. The information the occupancy sensors do provide however, was a significant improvement over the limited space utilisation data studies in existence. As suitable 'count' sensors were not commercially available (Table 5), or were insufficiently accurate (see 4.2.2), a proof-of-concept trial using a thermopile sensor was initiated (see 3.3.3.4.2).

In summary, the preliminary data download guided the research activities towards their inevitable conclusions below. This exploration suggested that a more intuitive method of data exploration was needed, capable of handling large volumes of data. Also, this preliminary investigation identified an anomaly which could not be resolved with the current level of clinical space utilisation data being limited to ‘occupancy’ status.

4.2.5 Phase 3b): IoT installation in operational multidisciplinary outpatient clinic: the data dashboard

To improve usability of the raw data, a proprietary ‘data dashboard’ was utilised as a user interface to the data. The dashboard drew from the full cloud-based dashboard. Beyond the capacity to change the study period, such as changing from 10-minute intervals to 1-hour intervals, this front-end provided several other filters to increase the functionality of data exploration. Selecting these filters caused the data to change dynamically, which informed whether additional filtering was required. These filters included:

- Start date and end date, e.g. limiting scope to examine a specific time period.
- Start time and finish time within a day, e.g. limiting scope to operational hours.
- Day of the week to exclude weekend data.
- Space type, such as education room, consult room, treatment room, etc.
- Room number, to focus the dashboard on a specific space.

In addition to the filters above, numerous other filter types were available. For example: building ID, floor ID, sensor location, etc. These filters existed but were unused as part of this research as the research scope was limited to a single clinic, with one sensor per room. The data dashboard contains numerous visual feedback elements that dynamically reflect the settings of applied filters. Results from the implementation of the user interface was published as an ‘open access’ publication under the title ‘Optimising clinical spatial resources with IoT’ [136](Appendix 3). This paper was the first of two outcomes from looking at the raw data. The second was confirmation that more information was needed if the utilisation of clinical space was to be understood beyond occupation status.

4.2.6 Phase 3c) – IoT installation in operational multidisciplinary outpatient clinic: from occupation to utilisation

From the IoT device interventions identified in this section, an extensive understanding of the occupation patterns across multiple clinical spaces has been demonstrated. Though this confirmation was a significant advancement over manual data gathering, the PI was still not satisfied. Results from the *occupancy* study still felt incapable of fully answering the generative research question sparking this research project. This generative question was: were we using our clinical spaces optimally? Knowing patterns of occupancy, or more importantly vacancy, was a significant improvement on state of the art. This knowledge clearly answers questions about when a target space was used, but says little about what it was used for, or for what purpose was it used. Data supporting the latter question was key to understanding the efficiency of clinical space utilisation, beyond simply being occupied.

Inspired by the anomaly (4.2.4 above) to understand more about patterns of human activity within clinical spaces, one final IoT sensor intervention was trialled. A thermopile sensor producing an 8x8 grid of temperatures at a 60-degree angle was installed in the ceiling of a consult room. This installation was intended to confirm the capability of these sensors to provide additional information on the utilisation of clinical spaces beyond occupancy status. The initial proof-of-concept sensor trial installation was made capturing a video recording of the changing temperatures in a live consult space hosting a typical week of clinic activities. Results from this initial experiment were sufficient to support a more resolved installation of the sensor, digitally extracting 'count' data produced within the sensor from the temperature data it receives. This second iteration was also placed above a consult room to observe a week of live clinical activity.

The result of this intervention has been presented in the paper 'Occupation versus Utilisation of Clinical Spaces Using Internet of Things Devices: Are Consult Rooms Well Utilised?' [137] (Appendix 4). This publication contains additional data visualisations. The proof-of-concept utilisation of a thermopile to both count occupants and provide data on patterns of activity contained therein was still subject to error, however. The algorithms on the selected sensor providing 'count' data were still somewhat simplistic. The sensor data represented an approximation of utilisation at specific points in time. This approximate count may be appropriate for obtaining a general understanding of occupancy patterns, for example in a retail store. These sensors would not however be appropriate for use in life safety applications which would require a high-precision occupancy count. For example, precise occupancy sensors could be used to determine whether all building occupants have evacuated in an emergency, avoiding dangerous human canvasing of unstable spaces. Regardless of the sensor's algorithm, with stated accuracy within temperatures within 2 degrees Celsius being received from the thermopile at a rate of 115200 bits per second, others had produced accuracy rates of 84.5 per cent in densely crowded spaces using these sensors' raw data [138]. As research continues to improve the accuracy of extracting human 'count' data, the recordings of visualised data as reported in this subsection suggests these devices have the capacity to capture data up to category 4 'tracking' data, should this be required.

What remained unclear however, was whether the deployment of IoT devices capable of continuously tracking humans was suitable for deployment in healthcare settings. At some point up the 'data density ladder', the collection of increasingly dense data on clinical space utilisation was likely to produce diminishing returns and become an increasingly oppressive environment in which to work. Prior to increasing the level of data density gathered however, maximum utility must be made of the data that has been collected. To that end, the tools of ML were applied to the extensive IoT dataset. This work was undertaken to explore the capacity of ML to predict future clinical occupancy patterns supporting the development and initiation of improvement activities.

4.2.7 Predicting future occupancy

Historical occupancy data gathered through IoT devices allow frontline and executive decision-makers to identify clinical spaces that remained vacant during previous operational hours. Though previously unidentifiable by conventional means, these vacancies represent lost opportunities. Results in this subsection demonstrate the capacity to predict future vacancy rates based on historical occupancy pattern. These results were accepted for publication titled 'Predicting optimisation opportunities for clinical space utilisation' (Appendix 5), which contains additional data visualisations.

This section has demonstrated that future utilisation of clinical spaces can be predicted with an F-score of 0.82, or 82 per cent accuracy based on historical data. Using the power of ML tools, decision-makers can take advantage of these spatial opportunities before they become lost in time. Also, with iterative prediction based on continuously collected IoT occupation data, an iterative loop was formed. In addition, continuous iteration can demonstrate the effectiveness of future improvement initiatives. Beyond predicting future optimisation opportunities, this predictive capability also supports assessment of the relative success or failure of intervention strategies in an iterative process.

The demonstrated capacity of low-cost IoT devices to continuously collect ambient data on previously un-discoverable patterns of clinical utilisation has answered the original research question. This capacity to predict future improvement opportunities makes the data generated by these IoT devices actionable. The research question with respect to the capability of IoT devices to support improvement in clinical space utilisation has now been favourably demonstrated.

4.2.8 IoT sensor installation: results summary

This subsection of the results chapter presented findings from 25 months of occupancy data gathering by IoT devices in a live clinical environment. In addition to the extreme duration of the observation period, this research provided a continuous collection of utilisation data 24 hours per day, seven days per week. Results presented demonstrate that IoT devices were an effective means of collecting this data. This chapter also demonstrated that a dynamic data dashboard can be used by human operators to make sense of the abundant data these devices produce. A proof-of-concept IoT device which extended the possibilities of understanding human activity within high-privacy clinical spaces was presented. IoT data was then used to train a ML algorithm to predict future opportunities for improved clinical space utilisation with an accuracy rate of 82 per cent.

One critical element was missing on top of the mountain of data collected through the research thus far. Though the research was conducted in accordance with the strict ethical boundaries established by the local HREC, questions remained. These questions included:

- How did staff feel about these devices continuously collecting data on all occupants of these spaces, including themselves?
- Was there any preference for this type of data gathering over the most common alternative in the literature, human observation?

- If they were comfortable with the level of data collected, were they comfortable with additional data being collected?
- Was there a point at which they no longer felt comfortable as the density of data collected increased, or did the benefits of data collection outweigh any negatives?
- Did they consider the collection of this data in their workplace oppressive?
- Did staff agree with the premise of having electronic space monitoring technology installed for the purposes of observing patterns of activity within a live healthcare environment?

An answer to the original question about the capacity of these senor devices to support the optimisation of clinical space utilisation has been provided thus far. To explore where the balance exists between the need for space utilisation data collection and the personal sense of oppressive surveillance, more information is required. As this exploration of the potential for IoT's to support the optimisation of clinical space would not be complete without exploring the human elements, the results from one-on-one staff interviews and an all-staff survey are presented in the next section. This research had demonstrated that IoT devices were effective in supporting the optimisation of clinical space utilisation. Put simply, the quantitative sensor research to this point had answered the question: 'Could it be done'? Remaining questions were now about 'Should it be done?' To explore the remaining questions, qualitative data from staff was needed.

4.3 Interviews

Interviews were conducted with a small number of staff to understand various perspectives on gathering data for the purposes of optimising clinical space utilisation. Previous results demonstrated the capacity for IoT devices to collect a wide spectrum of human activity data inside high-privacy clinical spaces to support optimal utilisation. IoT devices have been demonstrated to be effective in providing actionable information to both frontline and executive managers. It remained unclear whether these technologies were considered suitable for continuous operation in clinical environments from a human perspective.

Interviews were conducted in person, in accordance with the methodologies identified in Section 3.5 above. Recorded data was transcribed and saved in accordance with the data management procedures. Raw transcriptions were organised in a common template designed to facilitate analysis.

4.3.1 Interview results

Interviews were conducted with the intent of answering specific research questions emergent from the sensor exploration and implementation stages of the research. These questions were as follows:

1) How do staff feel about clinical occupancy data being collected by two different types of data gathering: human observation and electronic observation?
2) How do staff feel about increasing levels of data density being collected in clinical spaces to optimise clinical space utilisation?
3) These two questions form the foundation of the interviews, and are re-examined at the end of this chapter.

Prior to addressing responses to these research questions, a summary of qualitative data emergent form the text of the interviews is provided. After this extended exposition, these questions are revisited. First, an overview of the importance of clinical space as represented by the interviewees is provided to establish context for the remainder of the interview results.

4.3.1.1 Clinical space's value and the need for utilisation data

Clinical spaces play a critical role in the delivery of healthcare services. Without clinical spaces to perform clinical services in, an HHS' capacity to deliver healthcare services becomes fundamentally compromised. Consequently, an understanding of the importance of clinical space and previously unobtainable data on its utilisation is presented prior to going into additional detail.

The topic of clinical space utilisation elicited passionate responses from most interviewees. For example, on the topic of scarcity Akira said: 'we've got very limited resources and we should be using them to our best advantage to see people'. This sentiment was echoed by Pat: 'We all know space is hard to come by and expensive to create. So, having it idle is not a valid usage.' Casey provided similar commentary, that 'real estate is number one in everybody's mind now. We've got limited space, and so greater utility of space is important'. Essentially, all interviewees responded with something similar. The value of clinical space within the healthcare system was clear by these responses. Perhaps because of this acute awareness clinical space's value, perceptions of inequality were apparent. This awareness may support suspicion and speculative behaviour about the efficiency of other groups' use of space, and the allocation of additional capital resources. Alternatively, it may be human nature to judge the needs of others more harshly than our own. Regardless of the drivers, a transparent clinical space utilisation system common across all service groups would mitigate many of these concerns.

The above are just some examples of the clear value that was placed on clinical spaces by healthcare staff. A broad perception of inequality appears to permeate respondents' views of the healthcare system at their HHS. Against this backdrop of spatial scarcity in the healthcare system, qualitative interview data can now be framed.

4.3.2 Interview outcomes

The analysis section identified numerous codes using the steps of thematic analysis codified by Braun and Clarke [126]. These codes formed the most basic elements of emergent interview data. Similar elements were collated together into categories, each of which belonged to one or more themes. In order that 'the reader can "hear" the intended meaning in the speech' [139], verbatim transcript material in some cases within this chapter has been made more readable. Themes emergent from the interview analysis resolved into a unifying grand theme: 'IoT devices are acceptable and appropriate for use in clinical workspaces, with notable caveats.'

4.3.2.1 Interview question review

Reviewing the interview questions expanded in 3.6.3 above, interviewees' perceptions were elicited about two kinds of data gathering techniques, each gathering one of five levels of increasing data density. This spectrum was referred in the interview as 'stepping up the data density ladder' (Table 9, *a* to *e*). This 'ladder' concept is inverted (Figure 34) for the remainder of this dissertation to simplify sequential data presentation through this linear text-based format.

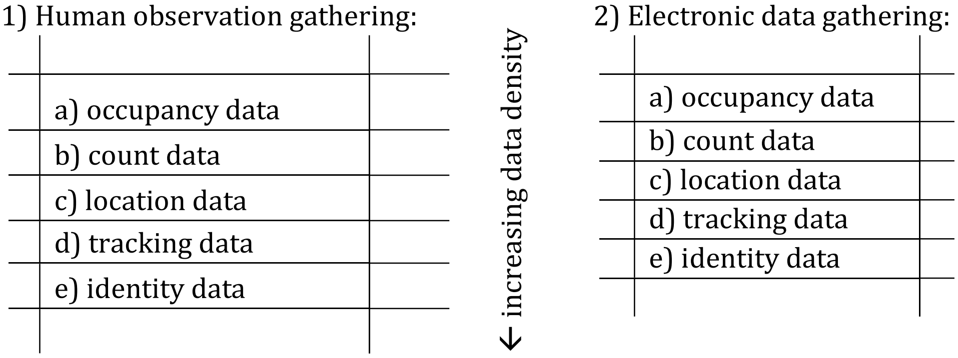


Figure 34 – Inversion of data density ladder mnemonic to facilitate discussion for the remainder of this thesis.

4.3.2.2 Interview analysis introduction

Main themes emerged from analysis of the interview data. These themes were supported by subthemes, categories and codes. Together these elements support a nuanced understanding of interviewee responses. For brevity, these seven themes have been introduced here noting they have been reordered from the mind-map in the analysis section to improve 'flow'. These themes have been expanded in subsequent subsections:

1) Systemic healthcare issues
2) Clinical space as a resource
3) Capacity of the data to reflect reality
4) Concerns consumers may have
5) Concerns staff may have
6) Context would be critical to accurately interpreting sensor data
7) Rigorous governance would be required.

4.3.2.3 Theme 1: Systemic healthcare issues

Modern healthcare systems are dynamic, complex entities. In many HHS, business as usual (BAU) requires reducing the complexity of this highly dynamic system into more manageable disciplines. This organisational structure helps manage the complexity of day-to-day healthcare services delivery through a multitude of modalities to eager consumers of healthcare services. While providing flexibility within disciplines, this 'siloed' structure limits flexibility across an HHS to manage clinical space holistically. Also, this structure limits transparency between disciplines, which makes managing change across service groups difficult. Without sufficient flexibility, the capacity of organisations to adapt to the needs of emergent challenges would be restricted. Restrictions in turn add friction to the flow of patients and staff through the system and reinforce inflexibility. Respondents felt that each of these systemic organisational issues may frustrate the implementation of any system to optimise clinical space utilisation by whichever method of data collection, if not addressed or allowed for in these complex systems. These issues form the framework for the remainder of this subsection.

4.3.2.3.1 Managing complex healthcare systems

The complexity and subtleties of providing healthcare were identified by respondents as challenges of clinical space utilisation data gathering. Clinical disciplines were aligned into 'siloes' to compartmentalise the complexity and control the dynamic nature of day-to-day service delivery. Positives of clustering healthcare service delivery include increased quality control and reduction of systemic complexity and allowing operational flexibility within the siloes. Negatives of clustering include reduced intersilo communication and the establishment of an 'us and them' mentality with respect to resource utilisation. Interviewees felt this organisational structure naturally establishes competition between clinical service delivery groups, and limits incentives to share spatial resources.

Further reductions in flexibility reinforce challenges experienced by service groups that rely on the capacity for self-management. When reflecting on humans gathering location data on the occupants of clinical spaces, Sam said: 'I think that would be quite an inflexible approach for a health service and the way that the health service works’. Maintaining as much operational flexibility as possible was key to managing complexity within the healthcare system.

4.3.2.3.2 Managing clinical spaces

Operationally, the management of clinical space falls to the leadership teams in each service group with limited coordination across the HHS. Casey noted the criticality of ‘space’ as an issue early in the interview: ‘it is one of my biggest problems’. Further, reflecting the consensus of the interviewees, Casey added that an improved system to manage clinical space utilisation through understanding space utilisation data would be appreciated. Casey said: ‘this is something that I deal with on a daily basis, arguments about rooms, so I think personally this data will harbour huge utility for me’. Obtaining space utilisation data, in any form, was considered a significant improvement by Jamie: ‘I think to have the information available for me in this role would be invaluable’.

As a point of comparison, Kai noted that the way space was managed at the host HHS was not the same for healthcare delivery universally. From their experience delivering healthcare in another country, they advised that alternative methods existed. Kai identified the alternative in this case required a space-centric approach, which:

> *... looked at which outpatient rooms were occupied and to what level and then it removed the disciplines ... and it made the room the centre of the process and it made occupancy the centre of the process.*

Consequently, a space-centric approach may be worth investigating through future work. Reflecting on the current HHS’s approach, Kai added ‘spaces seemed to be owned by people for different periods of time, which puts the occupancy onto the person, not onto the room.’

Beyond immediate need for spaces by individual units, perceptions about how space was used across service groups were mentioned numerous times. Jamie provided the following example: ‘somebody explained to me an area of theirs was in use 98 per cent of the time throughout the day, every day of the week. At various points of walking through that department, it’s completely empty’. Also, feelings of inequity were noted by Quinn on several occasions ‘I cannot understand why a department can say that they’re utilising space appropriately, when I am of an understanding that might be different to that …I’m trying to be a bit … nice here’. Finally, concerns were not just raised across service groups, but within them as well. Internal concerns were noted by Akira: ‘So, (location redacted) is a good example. My team would say it’s full. I go in there on a Friday, and I can’t find anyone there, and there’s a lot of clinic rooms free to me.’ Jamie also commented on spaces within their own service group: ‘Anecdotally we hear that it’s not a particularly well-used space’.

4.3.2.4 Theme 2: Clinical space as a resource

A siloed structure establishes competition between service groups and makes the comparison of similar activities in different groups challenging. Competition for limited resources can create perceptions of unequal treatment without hard data to support decision-making. Without a transparent method for data collection and sharing between the siloes of a modern healthcare system, inflexibility and perceptions of inequality both across and within service groups were likely to continue. Maintaining BAU also maintains the inflexibility of sharing spaces across service groups, which was reinforced by a lack of data and tools to manage clinical space utilisation. In the next section, staff reflect on ‘BAU’ practice within the health system and how it could be improved.

When demand increases within fixed constraints, improvement options were limited. Constraints in this case could be quantity of clinical spaces, for example. Despite known limitations across the HHS, Jessie advises that this doesn’t stop staff from striving to make continuous improvements. Jessie said: ‘We all try and tackle things for improvement and how to increase process flow and making things better for the patient.’ Pat felt that utilisation data was critical to overcoming some of these limitations in future: ‘Data like this becomes extremely valid. Where was the usage? Where did people go? How do we redesign it, so we make sure that all rooms (are) equally usable? So, it’s got some clear markers for the future.’. Kerry reflected that improved clinical space utilisation would be positive for both the HHS and consumers: ‘... that’s now getting our waitlist down and getting people through the health system.’

When reflecting on BAU, several interviewees acknowledged the inherent capacity for flexibility (see previous subsection). Jessie reflected: ‘our rooms are basically all generic, so anyone can use them; yeah, we can shuffle people around'. This capacity was reinforced by Kerry: 'why can't we run some of our other clinics out of this space?' Later Kerry went further, offering: 'I look at occupancy of any room as being potential for doing other things.' Beyond increasing flexibility of operations, and therefore efficiency by sharing spaces, Akira suggested expanding the use of clinical spaces beyond traditional operating hours, and perhaps beyond traditional function. If by collecting utilisation data, spaces were demonstrated as operating efficiently: '… we can then talk about in a much more informed way about staff using it after hours'.

4.3.2.4.1 Efficient use of space inside consult rooms

Another consideration in the use of clinical space was how efficiently clinical spaces address the needs of clinicians. Quinn spoke about how the space within consult rooms may not be optimally utilised, saying: 'if you can collect activity data inside rooms, then you know the specialist never used the bed and never used a sink'. They were suggesting it was more cost-effective to build spaces without reticulated water and drainage if that met the need of the clinical service delivery. Also considering the efficient use of space inside consult rooms, Kerry suggested that tracking data could enable more efficient use of space depending on the function within a speciality. They advised: '… it'll confirm that you're doing more procedures or consulting. I imagine people are more stationary during consultation. People that are moving around, from chair to bed are likely being examined. That difference in time tells me about turnover.' Unfortunately, studying the efficient use of space inside consult rooms was beyond the scope of this research. However, this line of thinking may be worth pursuing in future research.

As a critical resource in an environment of growing demand, limited access to clinical space creates friction within the flow of patients and clinicians. This friction becomes a bottleneck for the efficient delivery of clinical services within a healthcare system. Interviewees each considered how existing spaces were currently utilised. To varying degrees, each sought improvement opportunities taking advantage of the latent capacity within the existing system to improve healthcare service delivery. The first step in improving space utilisation was to realise that the resources were finite, and that oversight on utilisation was required. Casey encapsulated this concept well with the comment:

> *... if you don't know what you don't know about the utility of your space, how can you manage it?*

Next the capacity of the space needs to be fully understood, and systems need to be developed to optimise the use of this capacity. To utilise these spaces to the best of their ability however requires the sharing not only of space. To break down barriers established through siloes, data on how spaces were utilised needs to be collected and shared both within and between service groups. Beyond the capacity of existing spaces to improve utilisation, to realise these improvements, data on utilisation needs to be collected. However, there was limited point in collecting data on clinical space utilisation if the data does not accurately reflect how services were being delivered through them both individually and collectively.

4.3.2.5 Theme 3: Capacity of data to reflect reality

Some staff were concerned about the ability of IoT device data to accurately reflect operational reality. How was the data being collected and why? How accurate were the data? How was the context of the data understood? These questions reflect some of the concerns of the interviewees with respect to the data these devices collect.

4.3.2.5.1 Reflections on human observation

Concerns or feedback regarding the purpose and method of data collection ranged across the spectrum of data density. Sentiment on human versus electronic data gathering permeated all responses. With few exceptions, electronic data collection was considered superior to human data collection for the purposes of optimising clinical space utilisation. An overview on sentiments on human versus electronic observation was followed by comments on the inaccuracy of human observation and their counterpoints in electronic observation. As mentioned elsewhere in this chapter, these electronic devices could be compromised in the data they collect, and the accuracy of the data they record in reflecting reality. Most of these however were summarised as concerns with the capacity to provide context, or the capability of the sensors themselves to sense human motion as they were designed to do.

4.3.2.5.2 *Accuracy of human data gathering*

Sam was concerned about the accuracy of human observation and data gathering. This concern was demonstrated by his comment on humans gathering occupancy data: ‘I think there’s probably a lot of room for misinterpretation and error … it’s just human nature’ referring to the challenges humans experience with long periods of concentration and repetitive work. Another perspective on the accuracy of human observation and data gathering on clinical space utilisation relates to behavioural shift. Quinn felt that direct human observation changes occupant behaviours to skew the data: ‘so straight away staff want to change behaviour knowing that someone’s coming to observe them’. Concerns of human behavioural change due to human observation was repeated multiple times by Quinn and echoed by Sam: ‘If somebody wants to look as though they’re using the office because they know somebody is watching, so you probably – the degree of accuracy would wane, I think.’

Accuracy due to human intervention was also mentioned by Kerry with points both for and against. On the negative side, Kerry said, ‘like any data collection, it can always be skewed’, suggesting humans could alter data to suit an agenda, which may happen unconsciously. Similarly, Pat expressed similar feelings for the capacity of humans to accurately record the volume of data required to properly track multiple humans in a space continuously. Pat offered: ‘I think you wouldn’t necessarily capture all that information accurately because one person can’t potentially observe all the movements of that space.’

4.3.2.5.3 *Consistent* human data gathering considering aspects of time

Aspects of time or timing were other considerations underpinning accuracy concerns. For example, Jamie suggested that careful management of human observation would be necessary to ‘ensure that it’s done to meet varying times of the days and days of the week to ensure your sample is robust and reflects not just a point in time but a broad trend’. This sentiment about human data gathering over time was echoed by Sam: ‘I think it would become wearisome. I think it would become ad hoc and haphazard, and I don’t think you would get an accurate overview over time.’ Finally, Akira suggested that human observation would not be accurate due to the lack of continuous observation through time. Akira considered the continuity issues human observation would encounter that could be avoided with electronic observation: 'Sensors are triggered, it's measured, and you get the data and you're not relying on someone not to have gone to the loo and to come back and you've missed counting people.' The above considerations of timing were compared with the understanding that electronic data gathering was continuous for as long a study period as was required. Therefore, in the consideration of timing, electronic data gathering was superior.

4.3.2.5.4 Positive aspects of human data gathering

Despite the broadly negative perceptions of human data gathering expressed by the group as demonstrated by Sam, Quinn, Kerry and Pat's comments above, there was a minority of opinions providing potential positive outcomes of human observation. Jessie provided the most supportive opinion on human data gathering when suggesting the two forms of data collection were equal: 'I don't think it's any different to electronic data gathering'. Both Pat and Kerry providing a modicum of support for human capacity for understanding context. Kerry offered his positive opinions on human observation and data collection: 'Humans can judge the difference between a curtain moving in the breeze or a person being in the room. I suppose back to the age-old story of human versus machine.' This was followed by a second reflection from Kerry on the human capacity to provide context: 'I think human observation is probably going to be a little bit more accurate in what information you get than a digital device.' Also, Pat felt human observation could provide context to the data that the sensors by themselves could not: 'human observation is good, because they can gather context and context is critical from what I see.' The human capacity to apply judgement through understanding context was considered the sole support for the superiority of human observation in comparison to its electronic counterpart.

4.3.2.5.5 Sustainability of both kinds of data gathering

Finally, some commentary was collected on the sustainability of the two kinds of data gathering. Jamie felt that the application of human labour to the collection of clinical utilisation data was unworkable: '… It's just not a sustainable option'. Sam suggested human data gathering might have provided some functionality, but only for snapshot studies: ‘while it might have its uses within for a small area, and for a very limited time, I don’t think it’s one that you would want to use for a large area over a long period of time. It’s useful as a snapshot’.

Focused on the cost of human resources, Quinn reflected: ‘you’re going to employ someone to sit there doing this exercise for a long period of time that’s a costly exercise to do that versus electronic data gathering’. Kai added that human-based observation and data gathering was ‘very person heavy, whereas there’s probably other mechanism you can use that would be easier’. Summarising most interviewee opinions on human data gathering Kerry offered: ‘The obvious point from a human resource point of view is cost. It’ll be by far easier to have a digital device than it is to pay multiple people roaming around.’ It became clear from the interviews that relying on human labour to gather clinical space occupancy data was not feasible. This collective response explains the lack of mid-to-long-term studies on clinical space utilisation in the literature. Since as human labour was previously the only known method of collecting this data. including all associated flaws, it stands to reason that only ‘snapshot’ studies previously existed.

4.3.2.5.6 Reflections on electronic data collection

Concerns about data persist when considering electronic observation and data gathering, mostly as supporting points or counterpoints to responses provided above. For example, Kerry felt there were diminishing returns starting at gathering ‘location’ data by electronic means. However, Kerry’s sentiment ‘So, what I think we’ve got to a point now where I don’t see the electronic data actually helping too much now.’ This was the same point at which signs of discomfort were noted by Kerry with human observation gathering increasingly dense data. This observation was common across interviewees.

Sentiments towards increasingly dense data being collected tended to be the same regardless of electronic or human observation. If they were uncomfortable with humans gathering tracking data for example, they were either equally uncomfortable or slightly more comfortable with the same density of data being gathered by electronic means. It is possible in both cases that sentiment was predominantly influenced by the data density in question 8 as the data density increased, and the utility of gathering this data rather than the method of collection.

A poster on the preliminary sentiments on increasing levels of data density was accepted and displayed at the *2022 TropiQ Townsville Research Symposium* on the 15th of November 2022. In designing this poster, principals of effective poster design were used [140]. The poster was on display for two months (Appendix 7). The title of this poster was:

> *Preliminary Interview Results About Working in Smart Health Buildings - How do health staff feel about electronic and manual data gathering in healthcare spaces?*

Summarising the poster, staff sentiment generally progresses linearly from positive to negative as the level of data density increases with one exception. At the highest level of data density, the collection of 'identity' data within category 5, there was a weak increase in sentiment from the previous 'tracking' data from category 4. During the preamble of each interview, it was made clear that each rung of the 'data density ladder' contained all categories below it. For example, if *location* data was obtained on all room occupants, the 'count' of occupants was known, and the room was occupied (see 3.5.4). The design of the survey was intended to confirm this unexpected result across a wider selection of staff. Survey results are presented later in this chapter.

Interviewees' responses associated with the quality of data produced varied widely. These responses broadly related to the accuracy, integrity and continuity of the data over time. Concerns were raised about data quality regardless of whether the data was collected by either human or electronic means. However, most sentiments indicate a moderate to strong preference for electronic data gathering over human data gathering for a variety of reasons. Sentiment generally progressed from positive to negative as the data density increased regardless of data gathering method. Broadly speaking, sentiments associated with data quality and data density were also intertwined with a myriad of other concerns that staff or patients may have. These two categories of concerns are expanded in the following two sections.

4.3.2.6 Theme 4: Concerns consumers may have

Providing healthcare to consumers is the primary purpose of a healthcare system. It stands to reason then that one of the themes emergent from the interviews was about how the observation of activities in clinical spaces could affect patients. Responses in this theme all relate to aspects of the consumer experience, ranging from privacy and trust concerns to the operational matters of obtaining consent from each consumer.

Underscoring the primacy of patient care, the second response in Casey's interview was about how any human observation would require negotiation prior to commencement '... it's up to the individual clinician and patient whether they would be willing to have someone in that room, so I can't answer that question for you'. After some follow-up discussion Casey said: 'it takes time for a clinician to build a respectful and trusting relationship with an individual, and if there's suddenly someone else in there, that will make all the difference'. These two sentiments were reflected in the responses of others. For example, Pat provided a more direct response: '... having someone in the room is not feasible due to privacy'. Finally, Jessie cautioned that there may be legal issues to explore before commencing any kind of blanket monitoring: 'you've got the whole human rights issue around the fact that we're monitoring the public as well'.

The above two responses from Casey aptly illustrate the issues of patient privacy and trust under 'third-party' human observation. When considering the corollary of electronic observation, Casey noted that some services like mental health already use motion sensors to understand patient movements in wards. Casey said: 'Generally patients do not have an awareness that there are motion sensors in rooms, it's not something that we would necessarily point out'. In addition to direct concerns about the consumer experience, there were operational considerations as well.

4.3.2.6.1 Human observation impacting healthcare service delivery

Reflecting on the impacts of human observation on the delivery of healthcare services, Pat said: '... to gather this data by observation alone without gaining approval beforehand from each patient and physician is challenging'. Further, Pat also commented about the subtle interaction between provider and consumer within healthcare spaces which would be disrupted by the presence of a third party. Pat said: '… you're now partaking within the cone of silence within that space, which is hard enough for some clinicians to get into, let alone someone nonclinical sitting in'. The suggestion was that if the patient does not feel comfortable, they were less likely to volunteer highly personal information about their condition to their healthcare provider. This sentiment was later re-iterated by Pat, who continued:

> *Where somebody is in the room in relation to the doctor has a lot to do with interpersonal communication. Do they feel free to communicate with the doctor? Are they defensive? Is there something blocking them in the way? Which usually is a barrier to communication.*

Not all interviewees raised consumer-centric concerns, but those that did were significantly more comfortable about electronic data gathering, to the point of negligible concern. In addition to issues of trust, consent, and comfort, interviewees were less concerned about gathering increasing levels of data density with respect to patients. In all but extreme cases, the healthcare system already knows which patient was in which room at any one time and much of, if not all, their intimate medical history. If this was not true, something has gone wrong. The challenge was in recording the data without impacting the staff.

4.3.2.7 Theme 5: Concerns staff may have

Beyond their concerns for the consumers of healthcare services, the healthcare providers and the multitude of support staff may feel differently when the observations were of them. Broadly speaking, interviewee responses on how they feel about being observed varied as expected. Generally, electronic observation was considered more favourable compared with human observation. Staff-focused concerns aligned with patient-centric responses in the previous subsection, such as patient-clinician trust, privacy and consent. Given these issues have been discussed previously and were highly similar, discussions on the latter would not be repeated. One element that repeats with patient-centric concerns but bears a more nuanced understanding was staff comfort levels as individuals being observed in the workplace. Also, noting the host HHS was a public health service, interviewees provided their perspectives on their obligations as public servants. Several felt comfortable 'being monitored by the government' as an appropriate trade-off allowing public entities the capacity to demonstrate appropriate management of publicly funded resources.

4.3.2.7.1 Feelings about being observed

As it was a direct question, each interviewee provided their personal comfort levels being observed by both types of data gathering techniques. There was a range of responses from Akira being happy with both kinds of observations gathering whatever information was necessary to improve utilisation. In response to human observation collecting 'count' data, Akira responded: 'what, someone standing there counting? I have no issue with that'. This sentiment was repeated for each level of data density, and both kinds of data gathering, both human and electronic. There were caveats about communication and governance however, that are addressed later in this chapter. In contrast, Kerry and Pat both offered a more nuanced perspective.

Context has been discussed further in this document, however Pat suggested staff comfort may be tied with understanding the purpose for data collection. Reflecting on high-density electronic data collection, Pat offered: 'without systems in place as to why we're doing it, it starts to feel like 'overseer' watching, big brothers keeping an eye.' Under electronic observation, high data density collection would not be appreciated outside the strict confines of a research project. Extrapolating to others, Pat reflected: 'if you frame something to be nonresearch then people start jumping'. Needing to understand the purpose of data collection was critical to Kerry's comfort level:

> *As a public employee, I don't really see an issue with Big Brother watching me. I'd like to think that there's outcomes to that. I don't want to think that's nothing more than Big Brother making sure that we do the right thing, and if not, being reprimanded and called into offices or what not else.*

The interview questions were focused primarily on what data was being collected and how. Kerry's comment suggests that staff understanding why data was being collected was also highly significant.

4.3.2.7.2 Public sector employee obligations

Kerry also introduced a sense of obligation as an employee of a government. Akira acknowledged the unique role and responsibilities of public-sector employees: 'I always think I'm here on the good grace of the public. I'm a public servant to serve'. Kai also reinforced public servants' responsibilities in the use of publicly funded facilities: 'we have to remember we're public servants, so these buildings cost money.' As entities operating within the machinations of government, the spectre of 'big brother' may be closer for public sector workers, as this Orwellian concept was introduced several times by the interviewees [141].

Issues of trust between staff and unknown entities receiving observation data was different from the patient-clinician trust discussed in the previous subsection, though both may border on paranoia at the extreme. For example, when asked to consider how it would feel to work under direct human observation 'continuously collected in each space in your workplace, every day', Sam was unimpressed. Sam felt that working under constant human observation would be uncomfortable: 'I think you would feel that 'big brother' is watching, and I think it wouldn't give an accurate reflection in terms of what was happening in that room.' Under continuous human observation, interviewees' wariness of excessive scrutiny manifested at lower data-density levels than it did at data gathered by electronic means.

4.3.2.7.3 Proximity to the government and sensitivity to observation

The responsibilities of public servants directly reflect their role as government workers. Their proximity to government oversight may influence feelings of oppressive scrutiny, or it could just be human nature. More research would be required to explore these subtleties. Regardless, many of the public servants interviewed felt their role obliged them to use public-funded facilities to their maximum efficiency. Beyond individual responsibility, Kerry extended an obligation for efficient use of facilities to the entire sector: 'As a taxpayer, I want greater utilisation of my dollars if I'm going to be taxed $0.33 in the dollar.'. This sentiment underpinned Kerry's responses throughout the interview beyond the method or density of data collection. The passion in Kerry's voice was clear when expanding on this subject:

> *Being done in any format, doesn't really matter, but this is exactly what we should be using it – certainly what I want to hear for my tax dollars. I want to hear politicians standing up there going, we're getting the best value for our dollar. ...Any information you can gather on a particular activity can only lead to greater utilisation. It wouldn't matter if it was a beach, or police, health or education.*

Beyond their roles as public servants, how staff felt personally about being observed may depend on their role and their sense of ownership of a space. Quinn suggested that: '... for clinicians being observed, they are specialists and they're too busy to notice'. Conversely, Quinn's perception of the experience of nursing staff was the opposite: '… nursing staff external to the rooms will be more cognisant of observation happening'. Quinn's suggestion was that the nursing staff were present in the clinic constantly and therefore had a sense of ownership in the space, while clinicians come into the unit at their scheduled time, do their work and leave.

Understanding staff concerns was critical to the outcome of these interviews. Their concerns about potential implications of clinical space utilisation monitoring were important to informing answers to the core research questions presented at the outset of this section. There was a general preference for electronic monitoring over direct human observation in their workplace. More than expected, staff were open to the broad concept of monitoring clinical spaces for utilisation. Interviewees' responses indicated a nonlinear progression of positive to negative sentiment as data density increased for both methods of data collection. Staff felt the public service had an obligation to use taxpayer funds as efficiently as possible at both the corporate and individual levels. In several cases interviewees indicated they took their role as public servants very seriously. Finally, a sense of ownership established through functional roles in clinical spaces would influence how they would feel about monitoring clinical spaces to optimise utilisation.

4.3.2.8 Theme 6: Criticality of context

Interviewees generally felt that understanding the context of data being collected was critical to the success of any data collection activities. This sentiment was woven through responses across both methods of data collection and all levels of data density. Previously in this section, the issue of context was brought up several times, which speaks to the relationship of this concept with many others. For example, Jamie noted that the application of this technology could be applied to bed occupation in wards. For the data to reflect the dynamic reality of providing healthcare services however, a significant amount of context would be required. The following extended quote from Jamie reflects this concern:

> *to an analyst or a finance officer, they might say: 'this bed is utilised 73 per cent during the day', or 'It looks like there's a delay between someone leaving and someone arriving', or if it's over six months, 'it looks like this bed is vacant a quarter of the time' … but actually it's due to mobilising the patient in the day. So, I think if we're going down that route, that would be the risk.*

How the data would be contextualised by an accurate reflection of 'appropriate' utilisation was critical. Quinn felt the assigned function of the room was key to understanding whether a clinical space was well utilised or not. Paraphrasing, Quinn suggested that to interpret utilisation data accurately, the interpreter needed to first understand the type of clinic being operated, the design intent of a given space, and the nominated function of each clinical space. Also, critical to establishing the parameters of *optimal utilisation* was the model of care for each space, which might change within any given day.

4.3.2.8.1 Context supporting decisions on optimal utilisation

Similarly, Kerry extended Quinn's position on context to the activities being undertaken in each room. Kerry felt that to judge efficiency of a given clinical space, knowing the clinical service type being undertaken in each room was important, asking: '… how many people can you book into a procedural clinic, as compared to how many you can book into a consultation clinic?' Other respondents also suggested comparing efficiencies across different functionalities may be problematic in judging utilisation. For example, though data may report spaces were repeatedly unoccupied, one model of care may specifically keep a proportion of rooms at low vacancy rates to allow for spontaneous attendance by certain vulnerable patient cohorts. This contextual consideration was supported by Akira's response: 'if clinic rooms sit empty for 60 per cent of the time but it's available when we need it for that family in need and that crisis meeting, then that's what the resource needs to be able to accommodate'. In other words, low-utilisation rates may be considered optimal utilisation based on the clinical drivers. Other clinical services may utilise rooms that were solidly reserved, but the specialty has irregular, high levels of nonattendance.

Pat made similar observations about context when judging optimal utilisation, '… sometimes, the data might not show true evidence of utilisation because a room or a piece of equipment might need to be set aside for a clinic, that doesn't mean it necessarily would be used. But it's important that it's sitting there available for different reasons.' Another example may be a resuscitation trolley that sees very little use but was critical to be present and available when needed, like other critical infrastructure (i.e., fire extinguishers). The quality of any interpretations based on clinical space utilisation data may ultimately be contingent on the depth of context understood. For example, Sam talked through feelings on the pros and cons of continuous electronic observation:

> *I guess, if you've got somebody who occupies a space and they're in and out of that space throughout the day, whether it's a clinic room, or an office room or whatever, then it would look as though you're not at 100 per cent occupancy, or whatever in daily use, regular use. But I think on the whole… I think it gives you an overall baseline. Yeah.*

As Sam notes, judgements on 'optimal utilisation' may come down to understanding the function of the individual roles and patterns of the inhabitants of each space. Comparing this extended exploration of using context to interpret data with current practice in understanding patterns of clinical space utilisation however, some data would still be better than no data. Casey reminds us, 'if you don't know what you don't know about the utility of your space, how can you best manage it?' Therefore, the first step in judging optimal utilisation was starting to learn more about how spaces were used.

4.3.2.8.2 Ongoing maintenance of context

Once context was understood at one point in time however, Quinn wondered how any system would be maintained over time. Quinn queried: '… so how do you update the system to flag a given room is now a consult room, and the education room is being transformed back to an office … like who updates (the system) to allow that (to) happen?' Judgements made on utilisation data require context. Systems that support the reviewing, recording and reporting of utilisation data therefore need to be flexible. These systems need to be easily adaptable to the high pace of change inherent to the provision of healthcare. If the process of managing the data in these systems is cumbersome or burdensome, the context may not be maintained. Without accurate context, the information extracted from the data, and therefore the judgements made on that information, could ultimately prove fruitless.

4.3.2.8.3 Context improving decision-making capacity

Understanding context supports improved decision-making on optimising clinical space utilisation. Without context, interpreting the data becomes ineffective and at worst, useless. Despite the challenges of inputting and maintaining contextual data in a healthcare environment, respondents generally felt the process was worth pursuing. Therefore, the collection of utilisation data alone would be insufficient to make sound judgements on optimising clinical space utilisation. The data needs to be placed in the context of its model of care, design and functional intent of the space, the type of activity being undertaken, and in some cases the needs of individuals. Quinn was envisioning long-term implications of putting a clinical space management system in place:

… over time, if you're not updating that system, key elements will go missing; you're going to lose the context of the service … and *if you set up a system that runs and then it's never edited, the data over time will become contaminated with errors*.

The ongoing governance and management of contextual data, therefore, was considered critical to the success of any future implementation strategies. Good governance emerged as a significant overarching element supporting sound judgement on realising the opportunities inherent in optimising clinical space utilisation.

4.3.2.9 Theme 7: Rigorous governance required

The previous subsection lays the foundation for this final and perhaps most far-reaching theme emergent from the interview data. Maintaining rigorous governance practices was considered key to the successful implementation of any suite of technologies designed to optimise the utilisation of clinical spaces. Aspects that must be controlled if success is to be achieved include:

- Clear and consistent communication about the purposes of data collection
- Collecting only the data advised and using it only for the stated purposes
- Responsibly managing the collected data with the same rigour as patient data, including access control, breach protection, quality management, etc.
- Capacity to demonstrate efficiency gains from any improvement initiatives.

Interviewees felt that governments were obliged to demonstrate the efficient use of public funds. This demonstration includes the efficient use of high-value healthcare spaces. Also, this obligation extends to the efficient use of resources to collect the clinical space utilisation data.

4.3.2.9.1 Ongoing transparent, two-way communication required

Ensuring transparent communication was considered critical by several interviewees. Jessie maintained a single primary sentiment throughout the interview. This sentiment was that essentially anything was acceptable if staff were liaised with and kept informed of what data was being collected and why. Jessie said: '... as long as staff are informed and told the reason for it, I don't think it's an issue.', and 'Informing staff and letting them know for transparency and what purpose these are being put in place, yes.' This sentiment was evident from all respondents to varying degrees.

Jessie also wanted assurances that effective safeguards were in place to follow up on any governance promises. Jamie echoed Jessie's sentiments that rigorous control of the data stream was important, suggesting most methods and density of data were acceptable: 'as long as there's no confidentiality, breaches or whatever'. This position was reinforced by Kai, who suggested many things to improve clinical space utilisation would be considered acceptable 'as long as things like privacy are protected.'. With these caveats in mind, Jessie felt confident that success was achievable, and necessary to do: ‘in terms of what we build, we should be making sure that we’re utilising what we’ve got first. To decide what we build’. This sentiment was echoed by Kai: ‘If there’s good governance around privacy and good explanations as to the purpose … I think staff will be fine with it’.

Collectively, interviewees suggested that the optimisation of clinical space utilisation was an important goal to pursue and were generally supportive, with caveats including those above to mitigate the concerns raised through the remainder of this section. The stated reason for this support was due to the importance of clinical space to the provision of healthcare, and to them personally. Jessie felt that it was important to demonstrate ‘effective and efficient use of resources and space in our hospital.’ This was followed closely with ‘I think we owe that to the public, and to ourselves to ensure we utilise our spaces effectively’. One key reason for the efficient use of resources was the high cost of providing public healthcare, which was fully funded by tax dollars.

The high cost of providing healthcare in Australia was widely understood by the workforce operating the healthcare sector. Beyond operational costs, Quinn provided the following commentary on the implications of reducing capital costs with and improved understanding of existing clinical space utilisation:

> *… it also can save the health service hundreds of thousands, if not millions of dollars in redevelopment money because if you’ve got the correct space assigned for your service model … you need to know that you’re spending in the right areas.*

4.3.2.9.2 Capital costs and ongoing maintenance costs

In addition to the high capital cost of building new healthcare facilities, operating costs were also a key consideration. The following sentiment was offered by Akira as the only response associated with the performance of the built environment in the interview: ‘on a square metre, the cost of maintenance, air-conditioning, electricity, cleaning, it would be very interesting to explore how you optimise all resources supporting your work’. Reflecting on the value of utilisation data to the HHS, and the implications of implementing clinical space optimisation strategies, Kai said:

I think this data would be immensely useful, but it would mean a change of culture. It would be taking that away from the doctors or their teams and putting it down onto use of rooms, which I think this HHS sees the doctors as a more expensive resource, whereas in fact the room is probably the more expensive resource.

The broadly positive sentiment above was common throughout most interviewees' responses. Interviewees seemed to all agree that the optimisation of clinical space was an important endeavour to undertake and get right. On a sliding scale of what appeared to be subtle distinctions between acceptability and appropriateness of data collection, interviewees appeared to agree. Collectively, interviewees were supportive of collecting utilisation data, preferably by electronic means. Their responses indicated they accepted the mild discomfort of being observed to gather low-to-medium density data for the purposes of clinical space utilisation.

This approval came with caveats, however. Staff wanted assurances that rigorous governance processes including ongoing, transparent communication and robust data management were put in place to manage the many sensitivities associated with human-activity monitoring inside clinical spaces. These assurances included the collection of specific data for the exclusive use of optimising clinical space utilisation. Interviewees felt strongly that any system monitoring human utilisation of clinical spaces required rigorous governance. Rigorous governance not only applies to the system that collects, organises, re-presents and predicts data to support optimisation decision-making, but to the responsible governance of high-value public resources: clinical spaces.

4.3.2.9.3 Healthcare systems and sensitive information

Fortunately, modern health systems have established extensive protection mechanisms and existing rigorous governance structures to manage sensitive data. If this level of rigour was applied to establishing and maintaining clinical space utilisation systems and their supporting data, the vision of optimising clinical space utilisation may be achievable. In addition to existing policies and procedures, the creation of bespoke tools governing the collection, use and management of clinical space utilisation data should satisfy these demands. The latter sentiment held true if they were enforced through appropriate governance practices.

4.3.3 Interview analysis summary

Probing interviewees' feelings about data gathered to understand patterns of activity in clinical spaces has elicited a wide variety of deeply personal emotions. These emotions range from concerns about the quality of data obtained, to patient and staff concerns about privacy, consent and a range of trust issues. Also, staff questioned the capability of judgements to be made based on the raw data without sufficiently accurate context to make the judgements meaningful. All these responses were set against the backdrop of a rigid healthcare system that limits cross-disciplinary communication. The lack of transparency and a common platform for managing clinical space across the HHS breeds a culture of mistrust and suspicion. With all this in context it becomes difficult for executives to make data-driven decisions on the allocation of limited capital improvement funding.

Paraphrasing, the most common sentiment for low-to-midlevel data gathering through electronic means was: 'I'm ok with it, as long as…'. In general, interviewees felt that despite the numerous challenges associated with the design and implementation of a robust, rigorously governed clinical space utilisation system, this was a goal worth pursuing. Supporting this claim, Jamie advised: 'I think to have the information available for me in this role would be invaluable'. Summarising his concerns in comparison to the value of clinical space utilisation data gathering, Sam said: 'I think most of this is around the context, but for me if in terms of the transparency and the rationale for what we're doing then for me there isn't an issue personally.' While suggesting additional data may be needed to identify sentiments from a wider audience, Sam provided one of the two critical pillars that address staff concerns. Casey provided the following consideration that echoes the sentiment from Jessie provided above: 'I think it's just about transparency with the team, to make sure they're fully aware of what's happening, why it's happening and I think you'd probably get pretty good buy-in on that basis'. The need for utilisation data was underscored by Kai: 'I think it's a must. I think it's a gap at the moment, to be honest with you'.

Interviewees provided an abundance of data on their feelings towards the collection of clinical space utilisation data gathered through two distinct methods: human and electronic data gathering. These staff also provided their sentiments on increasingly dense data being gathered for space utilisation purposes. Based on the above analysis, the research questions that drove the need for interviews can now be answered.

4.3.4 Answering interview research questions

The core research questions underpinning the interviews were originally provided at the beginning of this section:

1) How do staff feel about clinical occupancy data being collected by two different types of data gathering: human observation and electronic observation?
1) How do staff feel about increasing levels of data density being collected in clinical spaces to optimise clinical space utilisation?

Broadly speaking, staff were very positive about low-level collection of clinical space utilisation data by electronic means. This positivity largely extended to the collection of the same data by human means, but most felt the multiple costs of proceeding with this method were not feasible.

The latter broadly negative opinion had numerous underlying perspectives. These perspectives included: expected low-quality data, negative impacts of humans continuously observed by other humans in the workplace, and ultimately the very high associated costs supported these generally negative feelings. Therefore, most interviewees felt that the while collection of utilisation data was worthwhile, increasingly dense data collection was reflected by a decrease in positivity. Also, the collection of this data by human observation was not feasible from a practical, cost and data-quality perspective.

Similarly, staff also felt positively about the potential of electronic devices collecting low-density clinical space utilisation data. Like sentiments about increasing data density collected through human observation, staff reported increasingly negative sentiments as data density increased. This suggests that regardless of the data collection method used, the higher the density of data, the less appropriate staff felt these technologies were if deployed in clinical spaces. Also, the relative comfort of staff declined under what seems to be interpreted as oppressive data collection. The only caveat to the previous statement was an increase in sentiment for the collection of identity data over the collection of tracking data. This mild 'uptick' in sentiment was despite a clear and repeated explanation, including visual aids, identifying that all categories contain all previous kinds of data. Additional research would be required to explore the subtleties associated with these feelings, as staff were only repeatedly asked 'how would you feel if …'. The survey discussed in the following section was intended to extract these subtleties as part of confirming to what degree the sentiments of the interviewees reflected most of the broader HHS staff opinions on the subject.

4.3.5 Interview summary

The interviews illuminated the sentiments of a small number of staff perceptions (nine) on various data gathered from both electronic and human methods. Human observation was generally considered inferior to electronic data gathering. Also, support was considered high for low-density data gathering and trends lower as data density increased with an unexpected positive sentiment at the identity category. Finally, the overarching theme of the interview data was clear. Ongoing low-density data gathering of data for the purposes of optimising clinical space utilisation was both acceptable and appropriate, with several caveats. It remained unclear whether the opinions of this subset of staff who were either involved in the phase 3 IoT study or managing clinics, reflected the opinions of the broader HHS staff. Since interviewing every staff member was not feasible, a staff-wide survey was deployed to compare the opinions of the many to those of the few.

4.4 Survey results

Though quantitative data was not gathered in the interviews, some clear trends had emerged. Staff felt more positive about electronic data gathering than human data gathering. Broadly speaking, sentiment tended from positive to negative as data density increased. During the interviews, staff were asked about their feelings about these subjects without clarifying the nature of these feelings. Also, the number of staff participating in one-on-one interviews was restricted by necessity.

The all-staff survey was primarily designed to answer questions emergent from the interviews. First, was the spectrum of opinions on electronic data gathering from the interviews the same across all staff? Second, was there a common 'tipping point' where diminishing returns on increasingly dense data collection outweighed perceived benefits from the optimisation of clinical space utilisation? Lastly, what was the association, if any, between staff demographics and opinions on increasing density of space utilisation data collected by electronic devices? The results of the all-staff survey are presented in the following section.

4.4.1.1 Survey responses versus final dataset

The Qualtrics (XM) software provided data from 519 staff out of a total staff of approximately 6400 staff which represented an 8.1% response rate. Of these responses the following summary is provided (**Error! Reference source not found.**):

1) 15x respondents did not agree to take the survey
2) 129x respondents agreed to take the survey, but one or more core survey questions were blank
3) 3x responses were incomplete due to technical errors in the survey system
4) 14x respondents provided responses to all core survey questions but one or more demographic responses were blank.

With anomalies excluded from the database, the original 519 potential responses were reduced to 360 complete responses. These anomalies resolve into a response rate of 5.6 per cent. Further discussion on the representation of this response rate follows in the demographics section below.

4.4.1.2 Demographics overview

After the survey data analysis outlined in Chapter 3, an examination of the impact of demographics on survey responses was undertaken. The purpose of collecting demographic data was to understand any associations between demographics and survey responses. This section presents demographic results for all responses provided.

An overview of the demographic responses provided, suggests the modest survey response rate (see 4.4.1.1) was considered reasonable due to the demographic data broadly reflecting nominal ratios within the target HHS (**Error! Reference source not found.**). For example, the ratio of staff roles reflects a reasonable ratio in a modern hospital (**Error! Reference source not found.**a) with nursing representing nearly 40 per cent of the workforce, and an approximate ratio of 3:1 clinical versus nonclinical staff (73.8 per cent clinical). The age distribution of respondents broadly reflects workforce expectations (**Error! Reference source not found.**b) with 55 per cent of respondents aged between 36 and 55, with 26 per cent and 19 per cent being younger and older than the majority respectively. A response rate of 78 per cent tertiary-educated workers (**Error! Reference source not found.**c) was also considered reasonably reflective of an organisation providing tertiary healthcare services. Also, a nominal 19:1 ratio of females to males in the nursing profession [142], combined with the nursing profession being close to 40 per cent of the workforce at the target HHS, the 69 per cent female gender identity response rate also seems to reasonably reflective whole-of-staff expectations (**Error! Reference source not found.**d). Therefore, based on the demographic responses provided, the responses received from this all-staff survey reasonably reflect whole-of-staff demographics.

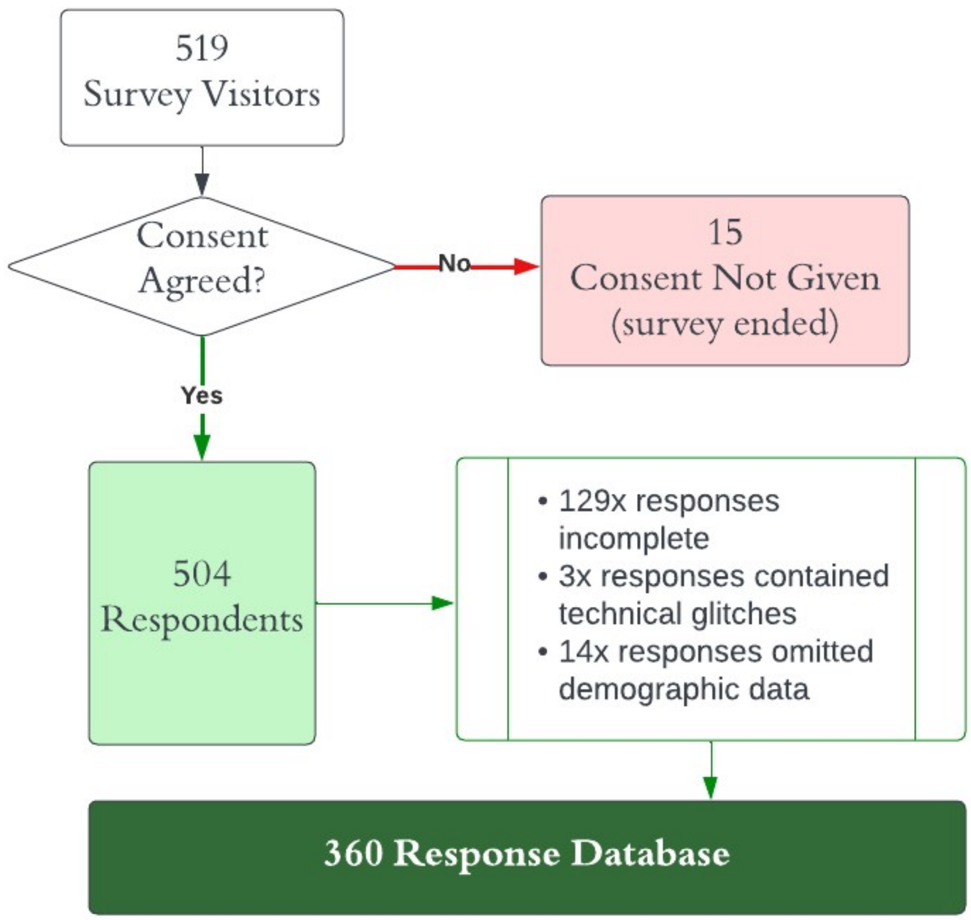


Figure 35 – Diagram of results leading to final survey data set

4.4.1.3 Demographic associations

By combining data from core research questions associated with acceptability and appropriateness with the various demographic data from **Error! Reference source not found.**, the relationship between the two was illuminated. Examples cross-referencing each demographic with a sample core research question have been presented in **Error! Reference source not found.** for demonstration purposes. For all demographic data cross-referenced with each core survey question, refer to Appendix 9. Demographics received reasonably matched expectations for a healthcare system. The predominant role was nursing, the predominant age groups were 36-55, and the predominant gender was female. Responses did not differ substantially according to demographic subgroups such as role, age or gender. With this finding confirmed, a further exploration of the core survey data is presented below.

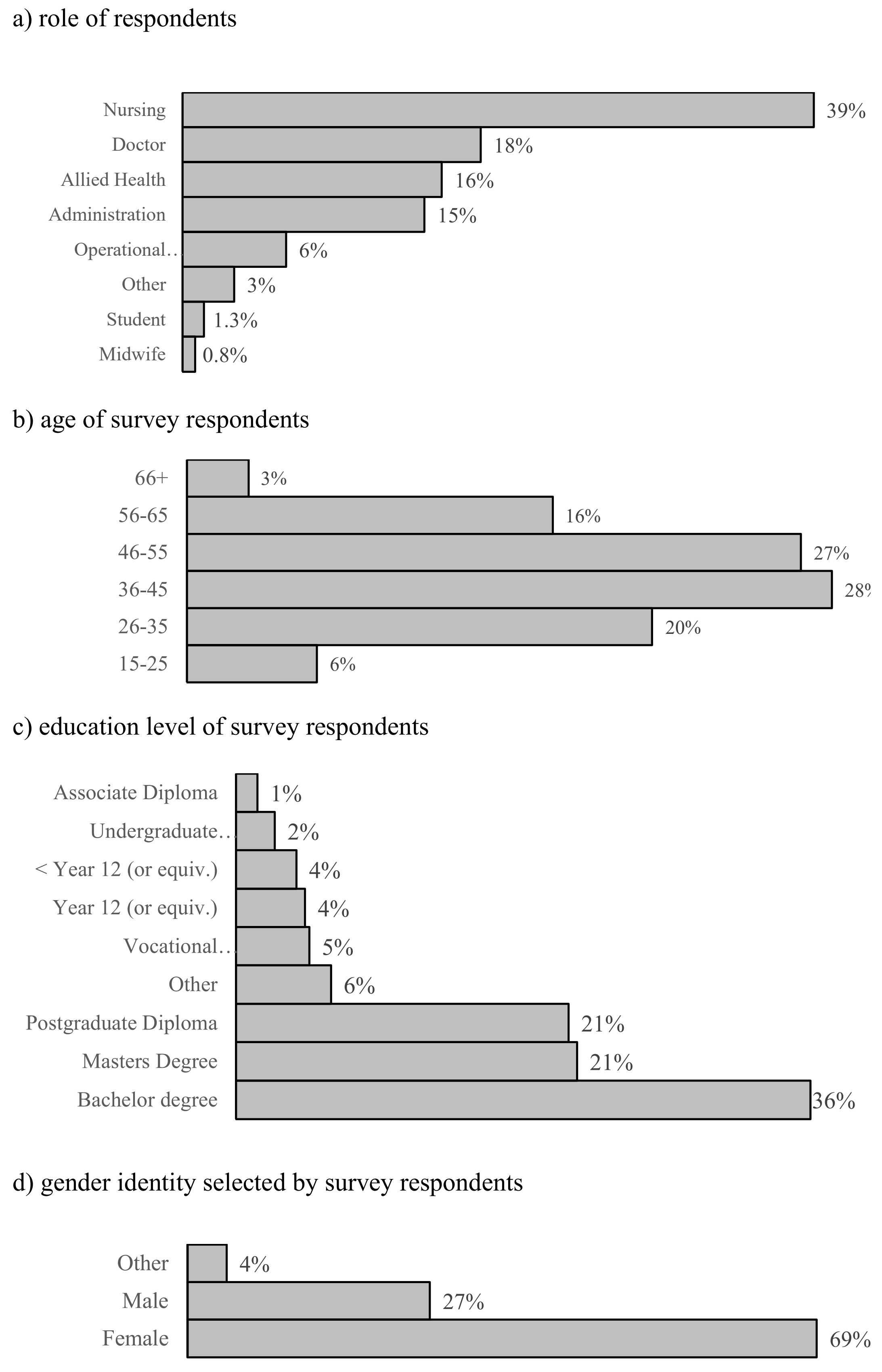
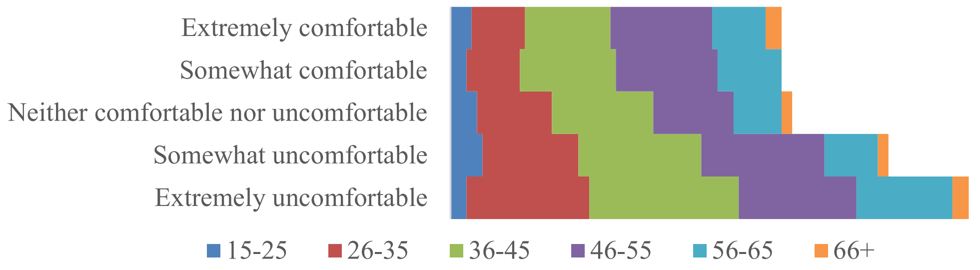
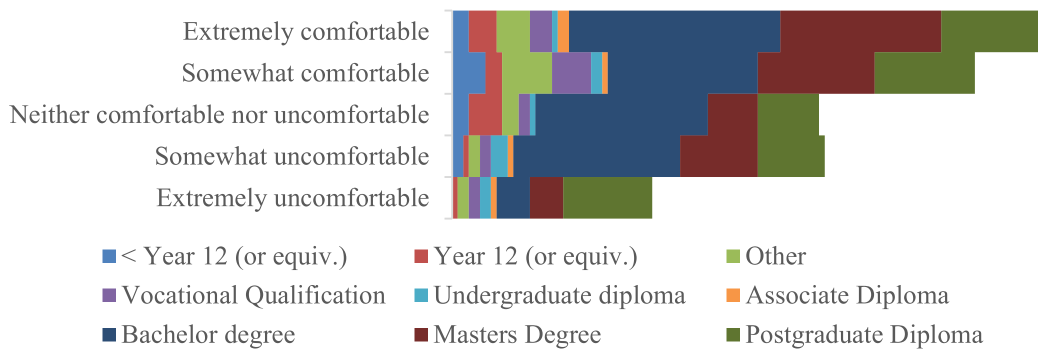


Figure 36 – Representative % of each demographic sub-category from the all-staff survey with respect to respondent's role at the HHS (a), age (b), education level (c) and gender identity (d)

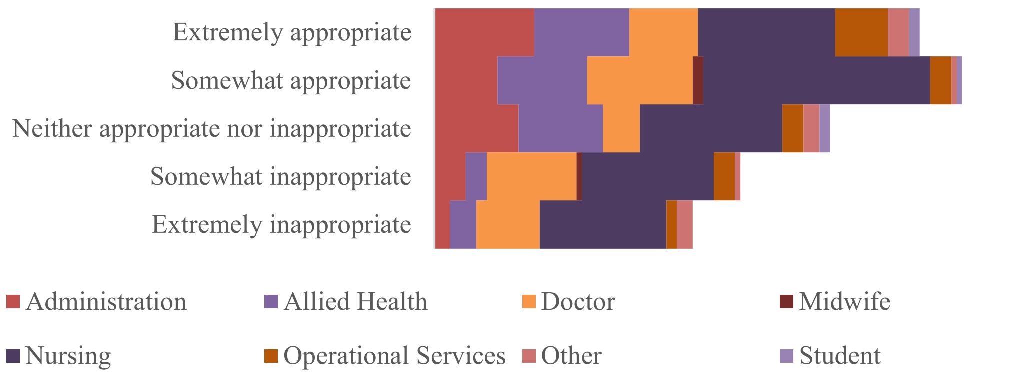
a) acceptability (comfort) of respondents with electronic devices collecting identity data with age bracket demographics inset



b) acceptability of respondent with electronic devices collecting occupancy data with education level demographics inset



c) appropriateness of respondent with electronic devices collecting tracking data with role demographics inset



c) appropriateness of respondent with electronic devices collecting location data with gender identity demographics inset

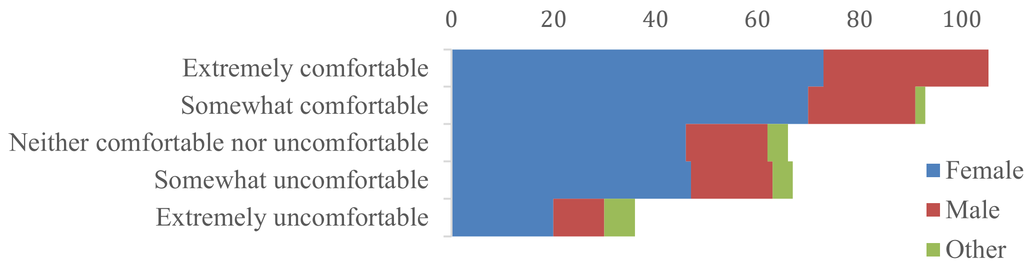


Figure 37 – Demographic data inset into core survey question responses demonstrating limited association between demographics and specific response categories.

4.4.1.4 Core survey question responses

With demographic effects clarified, core research question results can be explored. This subsection presents staff responses to the two primary themes of the survey: *appropriateness* and *acceptability*. These themes were emergent, along with effectiveness, from the staff one-on-one interview. The purpose of the survey was to capture staff feelings on the former from a broader sample set and compare survey results with the interview results.

Staff interviews provided qualitative data on staff feelings with respect to both human and electronic data gathering. As noted in subsection 4.3.2.5.6 the expected linear progression from positive to negative sentiment as the density of data gathered increased generally emerged as expected (Appendix 7). Instead of a linear progression from positive low-density sentiment to negative high-density sentiment, this progression emerged only from *occupancy* through *tracking* categories. The linear progression from positive to negative sentiment was interrupted by an unexpected trend reversed at *identity* back towards positive sentiment. Exploring this trend reversal through the survey results, a possible explanation has emerged.

A visualised presentation of the whole survey response dataset has been provided in Figure 38 and

Figure 39, and more detailed graphs on the whole dataset is provided through Appendix 8. In the figure below, data density progresses from low density on the left to high density on the right. Staff sentiment has been presented for both *appropriateness* (a) and *acceptability* (b) from negative (bottom) to positive (top). For both graphs, the median has been represented as a solid horizontal line, while quartiles have been presented as dashed lines. These graphs illustrate changing sentiment through the response data.

4.4.1.4.1 Survey theme: appropriateness

The first theme explored through the all-staff survey was about how appropriate it was for electronic devices to collect increasingly dense data on clinical space utilisation within operational healthcare environments. One primary distinction between the nature of the interview questions and the survey questions was that the latter did not ask for opinions on human observation, only electronic observation. Summarised in Figure 38, *appropriateness* responses generally progress linearly from positive to negative as data density increases (Table 13). This full-theme summary was a representation of the full dataset expanded in Appendix 9. This linear progression aligns with the original forecast prior to undertaking staff interviews.

Table 13: Survey response data for the theme of appropriateness

Appropriateness Response Category	Occupancy	Count	Location	Tracking	Identity
Extremely appropriate	48%	34%	26%	25%	26%
Somewhat appropriate	33%	37%	35%	27%	35%
Neither appropriate nor inappropriate	13%	16%	13%	20%	13%
Somewhat inappropriate	4%	10%	19%	15%	19%
Extremely inappropriate	3%	4%	7%	13%	7%

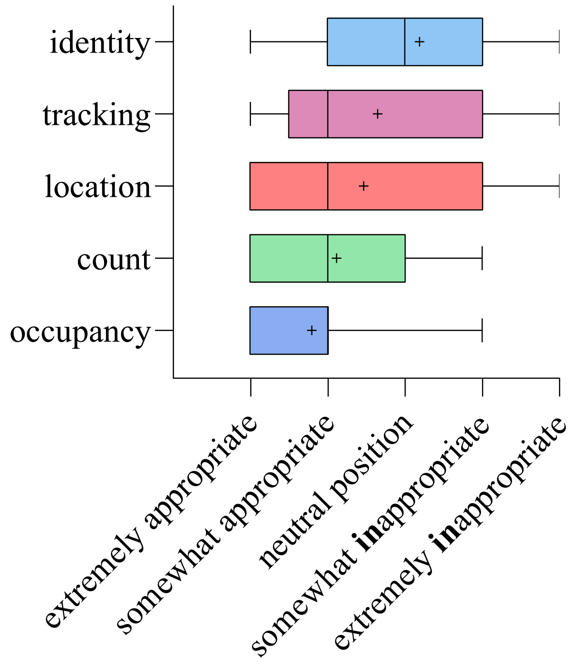


*Figure 38 –Staff sentiment from extremely approproate to extrememly inappropriate on the **Appropriateness** of increasingly dense electronic data gathering from low to high density (y-axis), from bottom to top respectively*

The data in this theme suggests that occupancy sensors, such as the PIR sensors (Figure 10) were widely considered appropriate in operational healthcare environments. Also, that sensor devices were still considered appropriate overall for use in live hospital environments, even when collecting identity data. Based on the interview results presented in Section 4.3, this broad support for sensor devices was accompanied by similar caveats. As data density increased, the mean sentiment remained 'somewhat appropriate' across four out of five categories: *occupancy*, *count*, *location and tracking*.

4.4.1.4.2 Survey theme: acceptability

The second survey theme was associated with acceptability, or how comfortable healthcare staff were with electronic devices collecting increasingly dense data in their workplace (**Error! Reference source not found.**). Combined acceptability survey data has been graphically presented through

Figure 39 below, and individually visualised in Appendix 9. The data suggests staff are highly comfortable working under sensors gathering low-density data, and progressively less comfortable as data density increases.

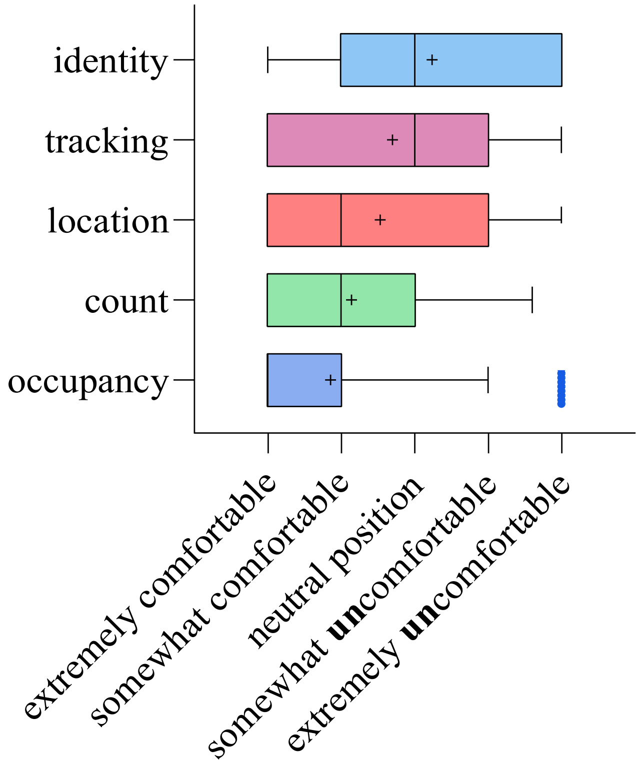


*Figure 39 – Staff sentiment from extremely comfortable to extremely uncomfortable (x-axis) on the **Acceptability** of increasingly dense electronic data gathering from low to high density (y-axis), from bottom to top respectively*

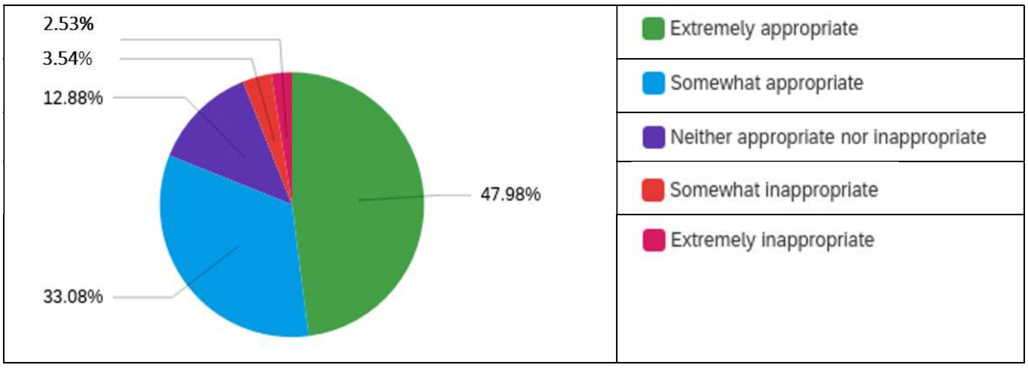
4.4.2 Staff survey – summary

Through this survey, staff recorded their feelings about the appropriateness of using sensor devices to collect increasingly dense clinical space utilisation data. Also, staff recorded how acceptable it would be if these technologies were used in their workplace. Staff felt it was appropriate to use these technologies to gather low-density occupancy data with 81 per cent somewhat or extremely appropriate while only 7 per cent felt it was somewhat or extremely inappropriate (Appendix 9). Staff also felt positive about working under sensor devices collecting this same type of data with 77 per cent somewhat or extremely comfortable versus 10 per cent somewhat or extremely uncomfortable (Table 13 and **Error! Reference source not found.**). The combined results for low-density data, and high-density data gathering have been visualised in Figure 40 and Figure 41 respectively.

As the density of data increased, these two themes diverged slightly. This diversion continued until the highest level of density was considered, which contained all other categories of data: identity. Staff still considered this type of data gathered through sensor devices appropriate for use in clinical environments (61 per cent positive, 25 per cent negative). However, respondents were personally much less comfortable working under the observation of this level of data gathering intensity (34 per cent positive, 48 per cent negative).

The themes of appropriateness and acceptability (comfort) emerged from the one-on-one staff interviews. Though no quantitative data was gathered during the interviews, sentiment on the use of electronic devices in healthcare spaces to study clinical space utilisation was mixed. While the general trend of sentiment was from positive to negative as density increased, the path seemed nonlinear and appeared to track upwards at the last category (identity). This diversion was hypothesised to be unique to the necessarily small sample size of one-on-one staff interviews, and this is generally reflected in the data. The appropriateness of data gathering was essentially the same, following a linear path from positive to negative. The acceptability of

APPROPRIATENESS OF IOT DEVICES GATHERING OCCUPANCY DATA



ACCEPTABILITY OF IOT DEVICES GATHERING OCCUPANCY DATA

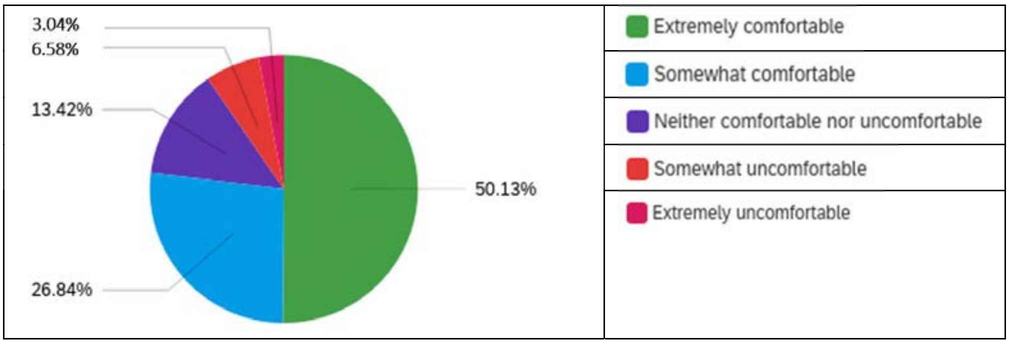
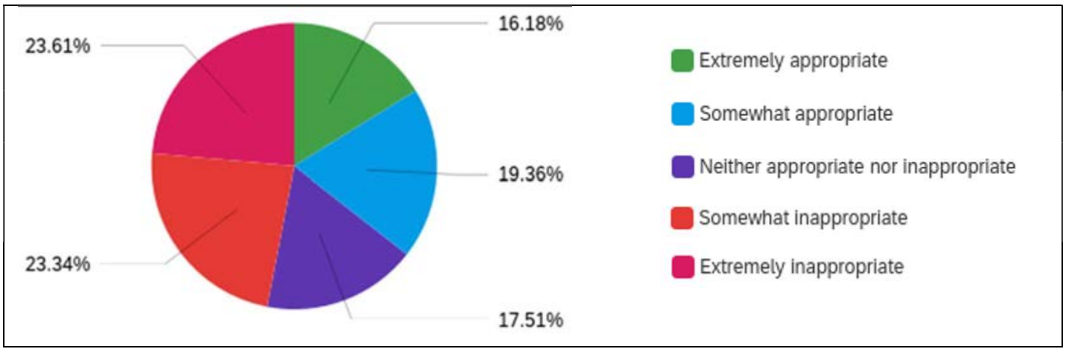


Figure 40 - Survey results for ***low-density*** *data gathering for both Acceptability and Appropriateness (comfort)*

working under electronic sensor observation did follow the linear path from positive to negative originally hypothesised prior to undertaking the initial interviews.

APPROPRIATENESS OF IOT DEVICES GATHERING **IDENTITY** DATA



ACCEPTABILITY OF IOT DEVICES GATHERING **IDENTITY** DATA

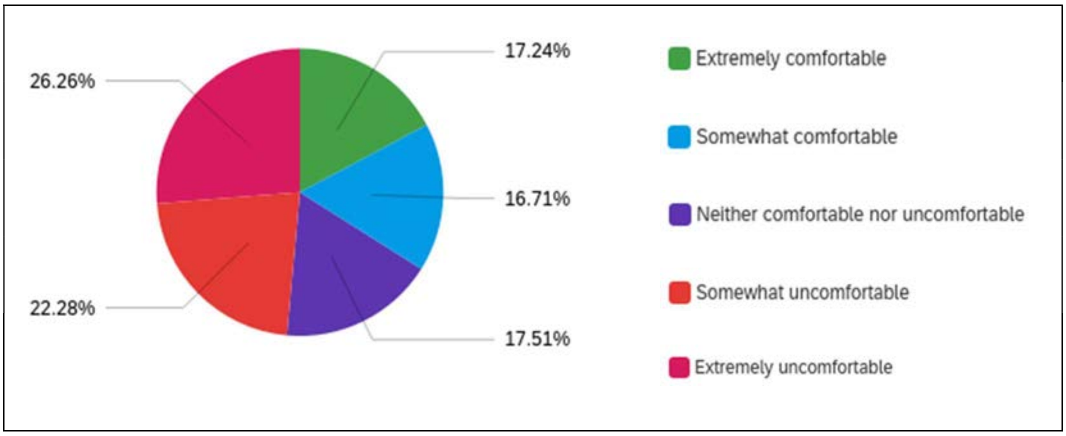


*Figure 41- Survey results for **high-density** data gathering for both Acceptability and Appropriateness (comfort)*

CHAPTER 5

DISCUSSION AND CONCLUSION

5.1 Introduction

Previous chapters outlined the research problems addressed by this research project. These chapters provided context for the research, and detailed activities undertaken to address the problem, guided by six research questions. Results from each activity were then summarised with identification of the relative successes or failures of the research project to answer the core research questions. This chapter presents an overall summary of the research project, places the research in the context of other current literature, and discusses potential implications from the findings.

5.2 Summary of the thesis

Activities described in detail in Chapter 3 were undertaken to answer the core research questions of this project, with results presented in Chapter 4. These questions have been represented below for reference, and naturally form two consecutive stages of activity:

<u>Phases 1 to 3 – IoT installation</u>: exploration, installation, data collection and processing

- Can IoT devices identify patterns of utilisation in operational clinical spaces?
- Can humans gain insight into historical patterns of clinical space utilisation by interacting with IoT data?
- Is it possible to predict future utilisation patterns from historical data?

<u>Interviews and Survey – staff feedback</u>: staff one-on-one interviews and all-staff survey

- Were IoT devices appropriate to study space utilisation in clinical environments?
- How comfortable were staff with being observed by IoT devices gathering human activity data in their workplace?
- As the density of human activity data gathered by electronic devices increased, was there a common limit to staff comfort levels?

For ease of discussion, the above format has been used for the remainder of this publication. Also, the above two phases of work form the structure of this subsection. After this subsection, the body of work presented is placed into context with other contemporary research.

5.2.1 Phases 1-3 – IoT installation

Exploring the capacity of IoT devices to capture data on human activity patterns within high-privacy clinical spaces was the generative question that sparked this research project. After assessing the potential of numerous commercially available options, few emerged. Those that did emerge, were demonstrated to be insufficiently accurate to collect data beyond the first rung of the data density ladder: 'occupancy' (Figure 22). Most options in the commercial area involve optical data gathering to some capacity. Optical cameras were wholly ruled out due to many factors including the perception of privacy on the part of consumers, regardless of the assurances of sensor vendors. What remained was Photovoltaic Infrared (PIR) sensors. These sensors were in common domestic use, the technology was mature, the data they provided was incapable of personal identification, and they were demonstrated to be sufficiently accurate.

Once an appropriate IoT sensor was identified based on PIR sensors, these sensors were trialled in an active nonclinical healthcare space managed through a room reservation system. Data on the actual use of the target space was compared with the room reservation system. This comparison demonstrated several differences between 'intended use' and 'actual use'. Results from this initial trial were published in the Special Issue on Artificial Intelligence in Health Informatics [1]. This article is published in journal: *Health Information Science and Systems* and contains additional data visualisations (Appendix 2).

Sensors used in the nonclinical healthcare space noted above were then applied across an operational multidisciplinary clinic space in a regional tertiary teaching hospital. The PIR sensors collected data on patterns of clinical occupancy for 25 months before they were de-commissioned. Through the previous installation and more than 2.7 million data points gathered in the operational clinic, the first research question had been answered. The capacity of IoT devices appropriate to collect human activity data, from a research ethics perspective, within high-privacy spaces was confirmed. The dataset by itself however was insufficient to accomplish the goal of optimising clinical space utilisation. The data needed to be transformed into information (Figure 6).

To extract meaningful information from the large dataset created by the IoT devices, more work was required. IoT data was presented in a dynamic, human-centric dashboard format including a floor plan of the space. The dashboard allowed human exploration of clinic occupancy data and facilitated human-based identification of low-occupancy periods within the clinic. This data, when combined with human intuition using the data dashboard, answered the second question in this phase: humans *can* gain insight into historical patterns of clinical space utilisation by interacting with IoT data. Without human interaction however, the data collected by these devices was challenging to put into action.

To increase the actionability of the information extracted from the IoT-based clinical occupancy data, the tools of machine learning (ML) were applied to the data. These tools were applied to explore their capacity to predict future opportunities to optimise clinical space utilisation. Through third-party data science support, future vacancies and other patterns of occupancy were predicted through the training of a standard KNN algorithm. An accuracy of 82 per cent was demonstrated as possible. This result was achieved by third-year computer science graduates with a basic understanding of ML in two weeks with minimal guidance. Their accomplishment suggests that the accuracy rate could be improved by applying the labour of experienced data scientists. Though higher accuracies would be preferable, this result was sufficient to answer the research question, that it was possible to predict future utilisation patterns from historical data. Accuracy could be improved through future work.

In this subsection, the three research questions driving phase I were answered. IoT devices *can* collect human activity data within high-privacy clinical areas. Humans *can* extract meaningful information from this data. Finally, it was possible to predict future patterns of human activity using this data. Once the capability of these technologies was demonstrated, the question remains: should they be used? To address this concern, staff were asked to provide feedback on their opinions and perceptions of using this technology in operational healthcare settings.

5.2.2 Interviews and Survey – staff feedback

Staff opinions were sought through a series of one-on-on interviews. Following the interviews, an all-staff survey was undertaken. In this subsection, a discussion is provided combining results from both interviews and survey research in answering the associated research questions.

The first area of inquiry in this phase was whether staff felt it was appropriate to study space utilisation in clinical environments using IoT devices. Staff were asked about their opinions associated with two different kinds of data collection in the interviews: human data collection and electronic data collection. Though there were some positives associated with human data collection, such as the ability to provide context to the data, opinions were more favourable to electronic data gathering. Therefore, the interview responses answered the first research question in this phase: healthcare staff considered IoT devices appropriate to study space utilisation in clinical environments. As healthcare environments were the personal workplaces of healthcare staff, it was also considered critical to understand how staff felt about being monitored by these devices.

Subtleties contained in interviewee responses suggested further nuances contained within 'how do you feel' responses were required. These responses were a mixture of emotions ranging between feelings on the appropriateness of IoT device installation to personal responses to working under their observation. Broadly speaking, working under the observation of IoT devices was generally positive with several caveats. These caveats were tied not only to personal concerns, but to a range of staff and patient concerns. Prevalent among these concerns were issues of trust, privacy, context and perhaps most importantly, the need for highly transparent and rigorous governance processes underpinning these generally positive feelings. The research question could therefore be answered: staff were generally comfortable being observed by IoT devices gathering human activity data in their workplace, however this support requires assurance that concerns about trust, privacy and context were rigorously managed through a robust governance process. Most responses were asked when interviewees were considering low-density data gathering, such as 'occupancy' data (Figure 22). As the level of data density increased, the level of support for working under the observation of IoT devices changed.

5.2.2.1 Alignment between interview and survey

The results from the all-staff survey generally matched the interview responses. The all-staff survey sought to separate 'how do you feel' questions into two distinct but important categories. The first was a question of how appropriate staff felt it was for different levels of data be collected by IoT devices for the purposes of optimising clinical space utilisation in a clinical setting. Second was how comfortable staff were working under the observation of IoT devices collecting increasingly dense data on clinical space utilisation. Both categories of responses reflected general sentiments picked up from the interviews, that as data density increased, sentiment decreased along a generally linear path. The data from the two themes, appropriateness and comfort, diverged at the *identity* level of data density, which was the highest density category discussed in this research project.

Interview data suggested an overall 'uptick' in sentiment, which appeared when considering the collection of 'identity' data. This deviation within interviewee responses did not match the hypothesised linear progression from positive to negative sentiment as data density increased. The deviation was matched by survey responses on the appropriateness of collecting high-density data. Considering their own comfort level working under high-density data gathering, staff opinions more closely matched the linear progression from positive to negative sentiment. This suggests that though staff sentiment increased for the collection of identity data, they didn't necessarily feel as positive about working under constant observation of such high-density data collection. Therefore, the final research question can now be addressed: as the level of human activity data gathered by electronic devices increased, there was no universally held opinion on the limit to staff comfort levels.

The previous phase of work demonstrated the capacity of IoT devices to collect data on human activity levels within high-privacy clinical areas. Also, phase I activities confirmed it was possible to identify optimisation opportunities within this data using both human and electronic data processing. Once this capacity was confirmed however (was it possible?), questions about the feasibility of these systems remained. These questions were associated with the sentiment of those who inhabit these spaces daily (should it be done?). Through interviews and an all-staff survey, this research project identified that staff felt comfortable with low-density electronic data collection for the purposes of optimising clinical space utilisation. This comfort was however tied to the consideration of key caveats described earlier. As data density increased, sentiment for both appropriateness and acceptability (comfort) trended negative. The exception to this trend was a slight deviation towards the positive when considering the appropriateness of collecting identity dat. However, this deviation was not found when staff considered their personal comfort levels working under such high-density data gathering conditions.

5.2.3 Conclusion

This chapter subsection has summarised the activities and findings driven by the generative research questions underpinning this research project. IoT devices were demonstrated capable of identifying opportunities to optimise clinical space utilisation. Also, at low levels of data-density, staff considered the use of this technology both appropriate and acceptable for the stated purpose of optimising clinical space utilisation, with caveats. As the questions driving this research project have now been answered through the rigorous exploration, experimentation and analysis summarised in this section, this research project was considered fully resolved. Next the outcomes from this inquiry have been placed in the context of existing research literature.

5.3 Key findings set within the context of the other related research

This section sets the findings of this research project within the context of existing literature. As a multidisciplinary inquiry, no single canon of literature can be expected to provide a suitable context for this research. Consequently, research from multiple individual and combined disciplines was necessary. After a summary of data gathering methodologies, the collective focus of these research elements has been explored in comparison to the focus of this research project. Finally, research from other disciplines has been presented to provide further context to aspects of the findings from this project that have not been explored by previous researchers focused on optimising healthcare service delivery.

5.3.1 Data collection methodologies

There have been many attempts at collecting data on the efficient operation of people undertaking activities within outpatient clinics. The following summary of issues encountered by previous researchers provides a backdrop to the alternative method of data collection demonstrated possible through the findings of this research. The methods of data collection provided in this thesis provide a viable alternative that addresses most, if not all, these issues.

5.3.1.1 Manual data gathering

Many previous researchers have addressed the issue of improving the efficiency of healthcare service delivery in outpatient facilities. These previous research efforts predominantly relied on manual data gathering in some form, which appeared to have also been their common challenge. Manual data gathering was human-resource intensive, repetitive, expensive, relies on human judgement and was therefore prone to human error. Direct human observation of other humans also gives rise to perceived behavioural changes. This was described by interviewees as an expected response, if not a direct example, of the so-called ‘Hawthorne effect’.

Due to the high cost of human labour conducting these surveys, they were typically short-lived with nearly all previous studies lasting under one month. These ‘snapshot’ surveys cannot accurately reflect the dynamic nature of an adaptive modern healthcare system. As consumer demands were unlikely to remain constant, the method of conducting these surveys needed to change. Despite the need to modernise, recent advice from the National Health Service in the United Kingdom still presents patient flow guidelines based on historical data [143]. Also, recent work acknowledges the ongoing challenges of collecting clinical ‘performance data’: ‘Performance measurement is ultimately useful as an approach for obtaining an accurate and meaningful picture of patient flow and helping determine where improvements can be made. Unfortunately, many hospitals have considerable difficulty making such measurements due to inadequate computer information systems or due to not having the financial resources to create and operate the necessary information system.'[144]. The results presented in this thesis suggest one potential option to obtain data on aspects of clinical flow with limited up-front and ongoing costs.

5.3.1.2 Outpatient process improvement through emerging technology

Research continues in the use of RTLS and other technologies, exploring optimisation opportunities in clinical spaces. Identifying the location of occupants within healthcare spaces through Bluetooth is becoming more common [145], though precision remains a challenge. Research incorporating user-worn 'tags' remains a common way to explore patient flow, as in one recent paper using UWB tags and building-mounted readers entitled 'Understanding Patient Flow using IoT in a Pop Up Eye Clinic' [146]. As the latter paper's title demonstrates, the distinction between RTLS and IoT may not be widely appreciated. Despite advances in the RTLS field, challenges associated with the more human aspects of implementing this type of research into practice remain as noted in Chapter 2. Utilising remote sensors within the built environment as demonstrated by the PI in this thesis removes many stochastic variables introduced when involving humans into the data collection process.

5.3.2 A shift in focus: from time to space

In the literature associated with optimising outpatient healthcare service delivery, there had been many research projects exploring aspects of time [45, 147-150]. These include exploring ways of optimising patient flow, clinician 'uptime' and other aspects of how activities take, and in what order. Patient flow activities in this definition include research associated with the movement and timing of patients before arriving at the clinic, or during their stay at the target outpatient clinic. Focusing on the time clinicians spend on various activities was another common research method. Clinicians had been asked to self-report timing, record activities in a logbook, carry or swipe cards or carry/use carefully calibrated technology correctly. In both kinds of study, the focus was on optimising aspects of time with spatial resources playing a consequential bit part.

There have been other studies on efficiency of spatial layout, such as their architectural design, but these studies focused on the organisation of space to improve travel time and clinic functionality [62, 147]. Despite limited representation in the literature, a small body of researchers are exploring optimisation of physical layouts within outpatient clinics, such as the use of network simulation [151] and genetic algorithms [148]. Introducing remote IoT sensors into studies seeking to optimise the physical design of clinics may help bridge the gap between simulation and practice. By necessity these studies were focused on how spaces were used through time, but research focused on the utilisation of space itself remains relatively rare. Again, challenges with data collection may have informed this work. The results of this research project have demonstrated the capacity of IoT devices to collect privacy-preserving data on human activity within clinical spaces. Hopefully, now that this capability has been demonstrated feasible, appropriate and acceptable, research focused squarely on the utilisation of space can expand.

5.3.3 IoT devices and presence detection

There is a growing body of literature on the use of existing and bespoke sensors and IoT devices to detect aspects of human activity within the built environment. Some researchers use thermal emissivity like the PIR and/or thermopile sensors used in this research [152]. Others are focused on visually representing the location and utilisation of equipment and spaces [113]. Most focus on standard building sensors to detect occupancy at the scale of whole buildings [82, 85, 86], floors [3], and individual rooms [87] depending on the level of infrastructure in place. The latter was an advanced, LEED-accredited building with established sensors, so would be challenging to retrofit to the target healthcare facility without sufficiently compartmentalised mechanical systems.

Determining presence using ultrasound, radar and infrared energy were the most promising privacy-preserving technologies in the space. This research project used sensors based on human infrared (IR) emissivity, but with more development any of these three sensor types, or a combination of them, could be utilised. For example, recent research using ultrasound exceeds the potential of IR systems to remotely identify hidden room occupants, such as under a table, while monitoring their vital signs [153]. The latter's privacy-preserving approach to human activity detection is particularly promising for future clinical applications.

As tangential research on digital privacy has shown, humans demonstrated a willingness to give away their privacy in return for relatively small returns [154, 155]. Without sufficient research in the area of privacy-preserving data gathering on the utilisation of space, cameras and computer vision [156] may continue dominating this nascent field of research. If these cheap and powerful, yet invasive means of collecting space utilisation data continue unchecked, the consequences could be great. Once society accepts this path, it may become overly tempting to start combining this data with other data sources, applying ML to it and shifting individual behaviour to align with corporate or personal agendas. Electronic monitoring of human activity in the workplace of any kind must walk a fine line between the need for data and the potentially negative human impacts of gathering this data. Corporate entities must work hard to gain and maintain the trust of their employees if space monitoring for the purposes of optimising utilisation is to realise its potentially high positive contribution to society. The data collected, and the subsequent data artefacts created, must be tightly controlled through rigorous and transparent governance processes. Fortunately, the healthcare sector is well placed to understand the sanctity of personal information, and as such is an ideal place for trusted space utilisation research to blossom.

5.3.4 Data artefacts and ML

Large datasets, such as those generated by IoT devices, can be difficult to comprehend for researchers unfamiliar with the tools of data science, and impenetrable for nontechnical frontline users. The several data artefacts used in this research have allowed this large dataset to be 'explorable' by both nontechnical human frontline workers, as well as the algorithms of ML. Human intuition applied to millions of data points through data artefacts can lead to a previously impossible level of engagement directly with the data. Direct engagement with visualised data can set up an 'iterative process of generation and evaluation of ideas in digital media, as well as planning, execution, and refinement of the associated actions' [157]. These artefacts combine the depth and breadth of data to be combined with the intuition, context and judgement of human operators leading to personal insights not possible through descriptive analytics. As interesting as this exploratory process has been, human analysis of large datasets was further complemented when combined with the predictive capacity of ML. Applying ML to large datasets, combined with data artefacts such as data dashboards, provides nontechnical users with powerful tools for creative insight and problem solving [158]. Through iteration with these artefacts, humans can extend their capacity. These artefacts can provide support in forming opinions, providing utilisation feedback, formulating optimisation plans and gauging the effectiveness of any improvement strategies after implementation.

Unfortunately, all the above potential demonstrated by this research would be moot if the humans generating the activity observed by the IoT devices rejected them. This rejection could take the form of IoT devices being considered inappropriate for use in clinical environments. These devices may also generate a sense of oppression and feelings of distress working under the unwavering electronic observation constantly collecting data on human activity for the government. Therefore, understanding the human perspective on these devices in both the workplace of clinical workers, and in the clinical environments they operate within, was critical to demonstrating the effectiveness of these systems.

5.3.5 Human responses to space monitoring

Research exploring human perspectives on workplace monitoring is reasonably common. In summary, as the degree of electronic monitoring in the workplace increases, so does the negative impact on human wellbeing. In one early study from 1992, workers being personally monitored for the purposes of performance evaluation reported 'working conditions as more stressful, and reported higher levels of job boredom, psychological tension, anxiety, depression, anger, health complaints and fatigue.' [159]. This finding was reinforced by recent research into digital workplace surveillance which underscores the need for rigorous policy and governance enshrining transparent data collection and limiting the use of this data beyond the stated means of optimising clinical space utilisation. Should panoptic workplace surveillance be introduced to collect personally identifiable information, used to monitor personal performance, dystopian outcomes may emerge. The papers summarised in this subsection provide context to the findings of this research project within contemporary literature. Next an exploration of future work emerging from this research project is provided followed by the implication of these findings on current practice.

5.4 Future research work

This section explores potential avenues of exploration to extend this research project. Potential extension options are abundant, given the nascent nature of the architectural informatics research field, to which the PI humbly suggests this research belongs. Though it may be trivial to expand implementation beyond healthcare, maintaining focus on optimising elements of the healthcare system in the short-medium term offers the greatest societal benefit. Opportunities defined below are not limited to research but include policy and commercialisation to potentially expand any emergent suite of technologies across the host state, and beyond.

5.4.1 Translate research

The favourable outcomes of this research are ripe for implementation research to transition the observed and predicted opportunities to optimise clinical space utilisation into an operational reality. The first suggested research activity, including commensurate HREC approvals, would be to expand the IoT-based observational network to consult rooms across two adjoining outpatient clinics. The intention of this expansion is to see whether access to this data would improve the utilisation of clinical spaces. An initial baseline of six months would establish business as usual prior to allowing any data access. During the initial observation period, policy on the use of electronic monitoring in healthcare spaces would be developed, and procedures with associated tools for reserving and managing clinical spaces would be established. These tools support the application of temporary contracts for space management between groups.

The research question to be explored would be as follows:

1) Does open access to clinical occupancy data alone lead to improved clinical space utilisation?
2) Can a proof-of-concept shared system for clinical space reservation/release support interdivisional space sharing?

The above works are planned to be resolved within 12 months of implementation. During the second half of this experiment, the proof-of-concept IoT device established during this current research project can be advanced into alpha and beta testing in preparation for market-ready solution release. Finally, if the translational and developmental aims above can be achieved, additional funding could be sought to expand these works across an operational hospital. After expansion across at least one campus, staff can be re-surveyed to confirm ongoing support for space monitoring.

5.4.2 Efficient clinical spaces

Future work using the thermopile sensor could capture vector-based datasets exploring paths of travel within a study area taken by staff performing different roles such as doctor, nurse, admin officer etc., to discern activities undertaken in the space. By identifying 'activity zones' within the space and recording human presence within these zones, it may be possible to explore efficiency and training opportunities. This proposed research may extend the capacity of time-motion studies commonly found in the literature and provide the capacity to demonstrate efficiencies through direct measurement from IoT devices.

5.4.3 Policy development for use of IoT devices in healthcare

Policy development may be critical to supporting future implementation of this kind of translational IoT-based research within the public healthcare system. Due to the emerging and evolving nature of this technology, healthcare leaders still have the opportunity to create policies supportive of the introduction of these technologies while ensuring consumer privacy and safety. Thoroughly considered policies would support multidisciplinary translational work of researchers, industry leaders and healthcare providers while safeguarding positive outcomes for healthcare consumers.

The potential benefits of IoT devices and ML to provide personalised medicine and improved healthcare journeys for consumers were high, but so were the potential negative effects. These potential dangers included data breaches, misleading data, erroneous predictions and potential physical and psychological harm. Creating supportive policy defining expectations and obligations for potential researchers and developers can support translational research that safeguards consumer protections, while enabling improved healthcare consumer outcomes.

5.5 Implications of findings

The implications of this research project are wide ranging. These implications emerge from the research outcomes. The final section of this document explores the implications of the research outcomes for practice, policy and education.

5.5.1 Implications for practice

This research has demonstrated the capability of IoT devices to support the optimisation of clinical space utilisation. Frontline managers now have the capacity to optimise the use of clinical spaces in their care and demonstrate this efficiency to not only their executives, but also their peers. Clinical planners can predict future vacancy rates across multidisciplinary clinics, enabling the development of optimisation strategies for discussion and approval. Once strategies have been conceived and implemented, the suite of technologies demonstrated in this research can provide feedback on the effectiveness of implemented strategies. This demonstrated capacity to sustainably identify historic patterns of clinical occupancy and predict future clinical vacancies was a world first, as far as can be determined. A solution to the challenges of collecting privacy-preserving human activity data within clinical spaces for the purpose of optimising their utilisation has now been demonstrated. Optimising clinical space utilisation increases the healthcare services deliverable through existing healthcare spaces. Increasing healthcare service delivery leads to improved access to healthcare services for consumers, in turn leading to earlier diagnosis or treatment opportunities which can delay or reduce reliance on intensive and costly downstream services. The cost of providing healthcare services was also reduced by expanding the physical footprint of the healthcare system only when it can be demonstrated that existing facilities are being used efficiently.

5.5.1.1 Opportunities for policy development

The potential positive implications for not only the supporting healthcare system are substantial. Beyond the host healthcare system however, these results can be directly translated to other healthcare services internationally. These positive implications can also be extended to any large estate holder, such as the higher education sector, at relatively low cost.

Despite the large potentially positive implication for practice, a brief note on the potentially negative implications is required. The digital age has brought about incredible opportunities for positive change into society but has also been eroding our collective sense of privacy. In implementing any of the technologies demonstrated through this work, researchers must remain focused on preserving the privacy of the occupants of target spaces. In the absence of a high priority on personal privacy, any positive outcomes would be ultimately undermined. Without rigorously maintaining human privacy while monitoring human activities, progressing the results of this research project could lead to oppressive behaviour, and a dystopian future for society. Transparent implementation of well-conceived, privacy-preserving policies, managed through rigorous governance, can realise the positive potential of this work while avoiding dystopian consequences.

5.5.1.2 Challenges for policy development

Careful consideration of policies maintaining personal privacy while electronically monitoring high-value spaces was considered critical to the successful implementation of the results of this research project at scale. Overly dense data collection, or the collection of personally identifiable data, could quickly shift the nascent field of ‘space utilisation’ into a dystopian nightmare. The creation of carefully considered, consultative policies, supported by rigorous governance, is considered key to realising the positive potential of this work while avoiding any negatives. Unfortunately for society, research has shown that humans are prone to giving up their privacy in exchange for minor conveniences [155, 160]. Therefore, policy must concentrate on the point of data collection in developing policies that allow electronic monitoring but maintain personal privacy. Staff feedback gathered through this research strongly suggests that a balance is possible. Policy makers can enshrine privacy protection within the data collection process. By maintaining a focus on privacy from the outset, subsequent policies and procedures maximise the positive utility of data collection, while minimising negative downstream impacts.

5.5.2 Implications for education

With the growing adoption of digital technologies in the delivery of healthcare services, clinical educators should focus on health informatics. Education in the fundamentals of data collection, management and analysis can support a general understanding of the tools that healthcare providers can apply through their careers. A general awareness of the tools of data science can provide an understanding of the underlying technical and potential ethical implications of how this data could be gathered or subsequently used. This grounding would prepare students with a broad understanding of the technology and tools that may be encountered through their careers in the health profession. Ultimately, health informatics can broaden potential employment opportunities and identify further education pathways that may otherwise go unnoticed. An understanding of the basic tenants of ML applied to health informatics may support the contextualisation of AI decision-support tool recommendations that may become commonplace in future healthcare settings.

Computer science educators should integrate the experiences and enthusiasm of tertiary computer sciences education through internships within the public healthcare system. The combination of established experience and practice with youthful perspectives and the latest technologies combine to create a dynamic and rewarding experience for both parties, who together can solve problems neither group could accomplish independently. Exposure to the power of informatics to improve service provision was also an appropriate component in the curriculum of health care providers, at both undergraduate and postgraduate levels.

In the nascent field of IoT engineering, this research has many implications. Technically, students should consider the long-term maintenance of their IoT devices. Even devices with long battery lives become unwieldy when spread across large institutions with thousands of instantiations of bespoke IoT devices. Each battery that requires replacement requires natural resources and energy to create, and through its lifetime, these devices may require substantial effort to maintain. IoT engineering educators are also encouraged to ensure students receive sufficient grounding in the ethics of IoT development. This could include the implications of personal medical data breaches, the potential for hacking medical devices for nefarious purposes, and the ethics of collecting and potentially cross-referencing personally identifiable data. In the case of this research, the IoT devices selected were incapable of collecting personally identifiable information, even if fully compromised. This ethical grounding would be an increasing benefit to society as IoT devices become ubiquitous as technology advances. For the development of future IoT devices, a high priority on human-centric concerns was recommended, to be considered equally alongside technical aspects of device design. Quoting from one of the PI's publications pertinent to this subsection:

> *For example, architectural education could prepare future architects to use sensor technology and edge computing to engage with their creations as they evolve through time. Architects could expand their practice from strictly 'birthing' the built environment to an advisory role providing support through the full building lifecycle. This change is analogous to obstetrics clinicians' focus on 'birthing', compared to general practitioners' broader participation across the full lifespan of their patients. [137]*

5.5.3 Mapping the expanding and fracturing field of architecture

The challenges facing architectural education are many. As the scope and responsibility of the architectural profession continues to expand and diversify, educators also need to prepare future architects for the emerging impacts of 'smart' buildings. Rather than creating additional pressure on the profession, the use of IoT devices in the built environment has the potential to be a unifying force in an otherwise fracturing field [161]. Architects are ideally positioned to shape the emergence of smart building technology with a focus on the ethical introduction of this technology to society. Moreover, architects have a professional obligation to ensure their creations avoid enabling the dystopian future discussed previously in this chapter, to the best of their ability. Architects grounded in the fundamentals of IoT-enabled smart buildings are ideally positioned to maintain an ongoing connection to their creations, guiding the evolving use of the building through time. Without engagement by the architectural profession with the inevitable rise of IoT devices in the built environment, smart buildings may ultimately lead to further fracturing. This research has demonstrated IoT devices capable of providing insight into how the built environment was used through its lifecycle. As smart buildings become ubiquitous, and artificial intelligence becomes increasingly powerful, architectural educators currently have a limited opportunity to engage with this emerging technology before it becomes yet another pressure point for the industry. It is not too late for architectural education to engage with this technology and prepare future architects to master the nascent field of Architectural Informatics.

5.5.4 Idealised Scenario

Prior to the finalisation of this thesis, it may provide value to project idealised scenarios potentially emergent from this research. If cost were no option, non-contact ubiquitous sensors collecting ambient, non-personally-identifiable human presence detection would be deployed across all spaces every healthcare system. Every clinical space within every system could be compared for their respective utilisation in an open and transparent manner. Clinical service managers would be provided robust tools to optimise the use of their spaces, allowing them the capacity to demonstrate their effective management of this critical resource. Utilisation data would be combined with building information models [78], and extend facility management systems [113], to manifest the 'smart hospital' as a digital twin [114] of operational healthcare facilities. Semi-autonomous digital agents trained on the rich, well organised data would interact conversationally with key stakeholders on the optimal use of these scarce spatial resources. Distribution of new physical and financial resources to managers of clinical spaces would first require a demonstration of existing resources being used efficiently.

The combined effect of realising the idealised scenarios above would be powerful. The technological barriers towards implementation of such a system are challenging but viable. Without rigorously embedding transparent ethical practices to the core of the system, this ideal scenario may become dystopic. Therefore, careful consideration must be given to the robust development of strict policies and procedures governing the ethical collection and management of this data. If nothing else, this thesis is a call to action for the establishment of an ethical basis for spatial management systems as the technology is advancing regardless.

5.5.5 Closing remarks

Healthcare staff surveyed through this research identified broad support for low-density, non-personally-identifiable electronic monitoring of clinical spaces. However, this support was underpinned by an expectation of rigorous governance managing transparency, integrity and privacy preservation guided by informed and well considered government policies. As the government custodians of the medical information on its citizenry, the healthcare system was an ideal starting point for this research. If these concerns can be addressed by building and maintaining appropriate levels of trust, the potential gains from optimising clinical space utilisation for society can be realised. Through optimised clinical space utilisation, more healthcare services could be delivered through the same clinical spaces, delivering healthcare services sooner to those that need it. Increasing early access to healthcare services also reduces demand on more intensive and expensive downstream treatments which can cause bottlenecks at healthcare service delivery points and impact the timely delivery of healthcare services.

Finally, with optimised clinical space utilisation, the need to continuously expand the physical environment of the healthcare system was reduced. This reduction could potentially save the Australian taxpayer billions of dollars by avoiding construction of new healthcare spaces. Trillions more could be saved by eliminating the cleaning, servicing, repairing and otherwise operational demands required by these additional spaces. In summary, this research project has demonstrated that IoT devices are effective, appropriate and acceptable (with caveats) in supporting the optimisation of clinical space utilisation in live healthcare environments.

REFERENCES

[1] T. McNabb, T. Myers, K. Wicking, L. Lei, and W. Xiang, 'Optimizing spatial healthcare assets with Internet of Things,' *Health information science and systems,* vol. 6, no. 1, p. 11, 2018.

[2] S. Guarisco, E. Oddone, and D. Simel, 'Time analysis of a general medicine service,' *J. Gen. Intern. Med.,* journal article vol. 9, no. 5, pp. 272-277, May 01 1994, doi: 10.1007/bf02599655.

[3] S. Wang, J. Burnett, and H. Chong, 'Experimental Validation of CO_2-Based Occupancy Detection for Demand-Controlled Ventilation,' *Indoor and Built Environment,* vol. 8, no. 6, pp. 377-391, 1999, doi: 10.1177/1420326X9900800605.

[4] J. A. Fisher and T. Monahan, 'Tracking the social dimensions of RFID systems in hospitals,' *International journal of medical informatics,* vol. 77, no. 3, pp. 176-183, 2008.

[5] M. W. Isken, V. Sugumaran, T. J. Ward, D. Minds, and W. Ferris, 'Collection and Preparation of Sensor Network Data to Support Modeling and Analysis of Outpatient Clinics,' (in English), *Health Care Management Science,* vol. 8, no. 2, pp. 87-99, May 2005 2005.

[6] K. Anderson, 'Environment and healthcare: Creating momentum towards a greener healthcare system,' (in English), *Australian Nursing and Midwifery Journal,* Journal Article vol. 27, no. 11, pp. 14-17, 2023.

[7] M. J. Miller, D. M. Ferrin, T. Flynn, M. Ashby, K. P. White Jr, and M. G. Mauer, 'Using RFID technologies to capture simulation data in a hospital emergency department,' in *Proceedings of the 38th conference on Winter simulation*, 2006: Winter Simulation Conference, pp. 1365-1370.

[8] T. Teixeira, G. Dublon, and A. Savvides, 'A Survey of Human-Sensing: Methods for Detecting Presence, Count, Location, Track, and Identity,' *ACM Computing Surveys,* vol. 5, pp. 1-35, 2010.

[9] S. R. Islam, D. Kwak, M. H. Kabir, M. Hossain, and K.-S. Kwak, 'The internet of things for health care: a comprehensive survey,' *IEEE Access,* vol. 3, pp. 678-708, 2015.

[10] B. Guo, D. Zhang, and Z. Wang, 'Living with internet of things: The emergence of embedded intelligence,' in *Internet of Things (iThings/CPSCom), 2011 International Conference on and 4th International Conference on Cyber, Physical and Social Computing*, 2011: IEEE, pp. 297-304.

[11] J. Yang, M. Santamouris, and S. E. Lee, 'Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings,' *Energy & Buildings,* vol. 121, pp. 344-349, 2016, doi: 10.1016/j.enbuild.2015.12.019.

[12] A. Liberati *et al.*, 'The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration,' *Ann. Intern. Med.,* vol. 151, no. 4, pp. W-65-W-94, 2009.

[13] A. A. Zhilenkov, D. D. Gilyazov, I. I. Matveev, and Y. V. Krishtal, 'Power line communication in IoT-systems,' in *2017 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus)*, 1-3 Feb. 2017 2017, pp. 242-245, doi: 10.1109/EIConRus.2017.7910538.

[14] M. Pandurov, I. Lazarevic, R. Pavlovic, and N. Smiljkovic, 'Unified device access in home automation environment,' Piscataway, 2014 2014: The Institute of Electrical and Electronics Engineers, Inc. (IEEE), p. 971. [Online]. Available: . [Online]. Available:
[15] M. Kambombo, 'Optimized patient flow process-A case of outpatient and surgical departments in Sub-Saharan Africa healthcare systems,' PhD, College of science and Technology), University of Rwanda, 2022.
[16] P. T. Moore and M. Sharma, 'Enhanced patient management in a hospital setting,' *IT CoNvergence PRActice (INPRA),* vol. 1, no. 3, pp. 1-21, 2013.
[17] M. S. Osman *et al.*, 'BLE-based real-time location system integration with hospital information system to reduce patient waiting time,' in *2021 International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*, 2021: IEEE, pp. 1-6.
[18] S. Safdar, S. A. Khan, A. Shaukat, and M. U. Akram, 'Genetic algorithm based automatic out-patient experience management system (GAPEM) using RFIDs and sensors,' *IEEE Access,* vol. 9, pp. 8961-8976, 2020.
[19] D. Tomasic, 'Health sciences literature review made easy: The matrix method,' ed: Oxford University Press, 2011.
[20] W. L. Hurley, C. R. Denegar, and J. Hertel, *Research methods: a framework for evidence-based clinical practice*. Wolters Kluwer/Lippincott Williams & Wilkins Health, 2011.
[21] M. Lopetegui, P.-Y. Yen, A. Lai, J. Jeffries, P. Embi, and P. Payne, 'Time motion studies in healthcare: What are we talking about?,' *Journal of Biomedical Informatics,* vol. 49, pp. 292-299, 2014/06/01/ 2014.
[22] M. Bryant and R. O. Essomba, 'Measuring time utilization in rural health centres,' *Health Policy and Planning,* vol. 10, no. 4, pp. 415-422, 1995.
[23] J. H. Bratt, J. Foreit, P.-L. Chen, C. West, B. Janowitz, and T. De Vargas, 'A comparison of four approaches for measuring clinician time use,' *Health Policy and Planning,* vol. 14, no. 4, pp. 374-381, 1999, doi: 10.1093/heapol/14.4.374.
[24] M. J. Cote, 'Patient flow and resource utilization in an outpatient clinic,' *Socio-economic planning sciences,* vol. 33, no. 3, pp. 231-245, 1999, doi: 10.1016/S0038-0121(99)00007-5.
[25] B. Overmoyer *et al.*, 'Using real time locating systems (RTLS) to redesign room allocation in an ambulatory cancer care setting,' ed: American Society of Clinical Oncology, 2014.
[26] J. E. Stahl, M. A. Drew, and A. B. Kimball, 'Real-time location systems, normative messaging and modifying clinician behavior: a pilot study,' (in English), *Health Systems,* vol. 3, no. 3, pp. 165-172, 2014-10-09 2014.
[27] J. E. Stahl, J. K. Holt, and N. J. Gagliano, 'Understanding Performance and Behavior of Tightly Coupled Outpatient Systems Using RFID: Initial Experience,' *Journal of Medical Systems,* journal article vol. 35, no. 3, pp. 291-297, 2009, doi: 10.1007/s10916-009-9365-7.
[28] Google. Google Scholar [Online] Available: https://scholar.google.com/schhp?hl=en&as_sdt=0,5
[29] M. Eshghali, D. Kannan, N. Salmanzadeh-Meydani, and A. M. Esmaieeli Sikaroudi, 'Machine learning based integrated scheduling and rescheduling for elective and emergency patients in the operating theatre,' *Annals of Operations Research,* 2023/01/19 2023, doi: 10.1007/s10479-023-05168-x.

[30] A. G. Kalton, M. R. Singh, D. A. August, C. M. Parin, and E. J. Othman, 'Using simulation to improve the operational efficiency of a multi-disciplinary clinic,' *Journal of the Society for Health Systems,* vol. 5, no. 3, p. 43, 1997.

[31] D. Blumenthal *et al.* (1999, 1999/04//) The duration of ambulatory visits to physicians. (Original Research). *Journal of Family Practice* [Brief article]. 264+.

[32] P. Santibáñez, V. S. Chow, J. French, M. L. Puterman, and S. Tyldesley, 'Reducing patient wait times and improving resource utilization at British Columbia Cancer Agency's ambulatory care unit through simulation,' (in English), *Health Care Management Science,* vol. 12, no. 4, pp. 392-407, Dec 2009 2009.

[33] F. Marchand-maillet, C. Debes, F. Garnier, N. Dufeu, D. Sciard, and M. Beaussier, 'Accuracy of Patient's Turnover Time Prediction Using RFID Technology in an Academic Ambulatory Surgery Center,' (in English), *Journal of Medical Systems,* vol. 39, no. 2, pp. 1-5, Feb 2015 2015.

[34] J. M. Griffin *et al.*, 'Attitudes and Behavior of Health Care Workers Before, During, and After Implementation of Real-Time Location System Technology,' *Mayo Clinic proceedings. Innovations, quality & outcomes,* vol. 4, no. 1, pp. 90-98, 2020, doi: 10.1016/j.mayocpiqo.2019.10.007.

[35] H. Guo, Z. Huang, J. Y. P. Yeo, Y. Wang, and A. Chow, 'Psychosocial determinants of healthcare personnel's willingness to carry real-time locating system tags during daily inpatient care in hospital managing COVID-19 patients: insights from a mixed-methods analysis,' *JAMIA open,* vol. 4, no. 3, pp. ooaa072-ooaa072, 2021, doi: 10.1093/jamiaopen/ooaa072.

[36] A. Juels, 'RFID security and privacy: A research survey,' in *IEEE Journal on Selected Areas in Communications* vol. 24, ed, 2006, pp. 381-394.

[37] X. Li, C. Guo, C. Mattie, T. Berg, and J. Wilck, 'Optimizing a Healthcare Clinic using Real-Time Location System and Simulation,' (in English), *IIE Annual Conference. Proceedings,* pp. 1409-1417, 2013 2013.

[38] W. Yao, C. H. Chu, and Z. Li. The adoption and implementation of RFID technologies in healthcare: A literature review.

[39] W. Yao, C.-h. Chu, and Z. Li, 'The Adoption and Implementation of RFID Technologies in Healthcare: A Literature Review,' (in English), *Journal of Medical Systems,* vol. 36, no. 6, pp. 3507-25, 2014-07-26 2012.

[40] A.-M. Vilamovska, 'Improving the quality and cost of healthcare delivery: The potential of radio frequency identification (RFID) technology,' 3407318 Ph.D., The Pardee RAND Graduate School, Ann Arbor, 2010.

[41] X. Ma, K. Yang, P. Reeves, and S. Yu, 'RFID-Based Healthcare Workflow Management in Sterile Processing Departments,' (in English), *IIE Annual Conference. Proceedings,* pp. 1-10, 2012.

[42] D. Min and Y. Yih, 'Fuzzy Logic-Based Approach to Detecting a Passive RFID Tag in an Outpatient Clinic,' *Journal of Medical Systems,* journal article vol. 35, no. 3, pp. 423-432, 2009, doi: 10.1007/s10916-009-9377-3.

[43] X. Ma, 'RFID-based business process and workflow management in healthcare: Design and implementation,' 3527850 Ph.D., Wayne State University, Ann Arbor, 2012.

[44] J. C. Chen and T. J. Collins, 'Creation of a RFID Based Real Time Tracking (R-RTT) System for Small Healthcare Clinics,' *Journal of Medical Systems,* journal article vol. 36, no. 6, pp. 3851-3860, 2012, doi: 10.1007/s10916-012-9858-7.

[45] A. Vankipuram, S. Traub, and V. L. Patel, 'A method for the analysis and visualization of clinical workflow in dynamic environments,' *Journal of Biomedical Informatics,* vol. 79, pp. 20-31, 2018/03/01/ 2018.
[46] S. J. P. Shim, A. P. Kumar, and R. P. Jiao, 'Using a Radiofrequency Identification System for Improving the Patient Discharge Process: A Simulation Study,' (in English), *The Journal of Medical Practice Management : MPM,* vol. 31, no. 6, pp. 383-387, May/Jun 2016 2016.
[47] S. Abudalfa and K. Bouchard, 'Two-stage RFID approach for localizing objects in smart homes based on gradient boosted decision trees with under- and over-sampling,' *Journal of Reliable Intelligent Environments,* 2023/01/12 2023, doi: 10.1007/s40860-022-00199-w.
[48] E. S. Huang *et al.*, 'Health care resource utilization associated with a diabetes center and a general medicine clinic,' (in eng), *Journal of general internal medicine,* vol. 19, no. 1, pp. 28-35, Jan 2004.
[49] Z. Tariq, D. Cheema, M. Kamran, and I. Naqvi, 'Non-GPS Positioning Systems: A Survey,' *ACM Computing Surveys (CSUR),* vol. 50, no. 4, pp. 1-34, 2017, doi: 10.1145/3098207.
[50] T. S. Prentow, A. J. Ruiz-Ruiz, H. Blunck, A. Stisen, and M. B. Kjærgaard, 'Spatio-temporal facility utilization analysis from exhaustive WiFi monitoring,' *Pervasive and Mobile Computing,* vol. 16, pp. 305-316, 2015/01/01/ 2015.
[51] J.-H. Youn, H. Ali, H. Sharif, J. Deogun, J. Uher, and S. H. Hinrichs, 'WLAN-based real-time asset tracking system in healthcare environments,' in *Third IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob 2007)*, 2007: IEEE, pp. 71-71.
[52] S. Shyam, S. Juliet, and K. Ezra, 'Tracking and Monitoring of Medical Equipments using UWB for Smart Healthcare,' in *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*, 29-31 March 2022 2022, pp. 631-637, doi: 10.1109/ICCMC53470.2022.9753719.
[53] G. Han, G. J. Klinker, D. Ostler, and A. Schneider, 'Testing a proximity-based location tracking system with Bluetooth Low Energy tags for future use in the OR,' in *2015 17th International Conference on E-health Networking, Application & Services (HealthCom)*, 2015: IEEE, pp. 17-21.
[54] A. Alyami, R. CAMPION, and A. ATKINS, 'Tracking and Monitoring Patients and Assets in Saudi Arabia'Healthcare Environment,' 2016.
[55] J. Wei and S. Cao, 'Application of Edge Intelligent Computing in Satellite Internet of Things,' in *2019 IEEE International Conference on Smart Internet of Things (SmartIoT)*, 9-11 Aug. 2019 2019, pp. 85-91, doi: 10.1109/SmartIoT.2019.00022.
[56] J. F. Bard, Z. Shu, D. J. Morrice, D. Wang, R. Poursani, and L. Leykum, 'Improving patient flow at a family health clinic,' (in English), *Health Care Management Science,* vol. 19, no. 2, pp. 170-191, 2016.
[57] S. T. Ponis, A. Delis, S. P. Gayialis, P. Kasimatis, and J. Tan, 'Applying Discrete Event Simulation (DES) in healthcare: the case for outpatient facility capacity planning,' (in English), *International Journal of Healthcare Information Systems and Informatics,* Report vol. 8, no. July-September, p. 58+, 2013 2013.
[58] A. Erekat, A. Al-Shaebi, A. Alhaider, M. Khasawneh, and A. Khasawneh, 'Optimizing Outpatient Access Center Staffing Using Discrete Event

Simulation: A Case Study,' (in English), *IIE Annual Conference. Proceedings,* pp. 1918-1924, 2017 2017.
[59] M. Rezaeiahari, L. Adwan, and M. T. Khasawneh, 'Patient Scheduling at a Breast Center Using Discrete Event Simulation,' (in English), *IIE Annual Conference. Proceedings,* pp. 2075-2080, 2017.
[60] J. F. Bard, Z. Shu, D. J. Morrice, D. Wang, R. Poursani, and L. Leykum, 'Improving patient flow at a family health clinic,' in *Health Care Management Science* vol. 19, ed, 2014, pp. 170-191.
[61] V. Vahdat, J. Griffin, and J. E. Stahl, 'Decreasing patient length of stay via new flexible exam room allocation policies in ambulatory care clinics,' *Health care management science,* vol. 21, no. 4, pp. 492-516, 2018.
[62] A. Gosavi, E. A. Cudney, S. L. Murray, and C. M. Masek, 'Analysis of Clinic Layouts and Patient-Centered Procedural Innovations Using Discrete-Event Simulation,' *Engineering Management Journal,* vol. 28, no. 3, pp. 134-144, 2016-09-22 2016, doi: 10.1080/10429247.2016.1195664.
[63] V. Vahdatzad and J. Griffin, 'Outpatient clinic layout design accounting for flexible policies eh,' 2016 2016: IEEE Press, pp. 3668-3669, doi: 10.1109/WSC.2016.7822391.
[64] A. R. S. Amaral, 'The corridor allocation problem,' *Computers & Operations Research,* vol. 39, no. 12, p. 3325, 2012, doi: 10.1016/j.cor.2012.04.016.
[65] S. Helber, D. Böhme, F. Oucherif, S. Lagershausen, and S. Kasper, 'A hierarchical facility layout planning approach for large and complex hospitals,' *Flexible Services and Manufacturing Journal,* vol. 28, no. 1, pp. 5-29, 2016, doi: 10.1007/s10696-015-9214-6.
[66] T. R. Rohleder, P. Lewkonia, D. P. Bischak, P. Duffy, and R. Hendijani, 'Using simulation modeling to improve patient flow at an outpatient orthopedic clinic,' *Health Care Management Science,* vol. 14, no. 2, pp. 135-145, 2011, doi: 10.1007/s10729-010-9145-4.
[67] F. J. Roethlisberger and W. J. Dickson, *Management and the Worker*. Psychology Press, 2003.
[68] J. B. Jun, S. H. Jacobson, and J. R. Swisher, 'Application of discrete-event simulation in health care clinics: A survey,' *Journal of the Operational Research Society,* Journal vol. 50, no. 2, pp. pp 109–123, 09 February 1999 1999, doi: 10.1057/palgrave.jors.2600669.
[69] T. Cayirli, E. Veral, and I. Global, 'Outpatient scheduling in health care: a review of literature*,' *Production and Operations Management,* vol. 12, no. 4, pp. 519-549, 2003, doi: 10.1111/j.1937-5956.2003.tb00218.x.
[70] S. Chand, H. Moskowitz, J. B. Norris, S. Shade, and D. R. Willis, 'Improving patient flow at an outpatient clinic: study of sources of variability and improvement factors,' *Health care management science,* vol. 12, no. 3, pp. 325-340, 2009, doi: 10.1007/s10729-008-9094-3.
[71] H. H. Haraldsson, 'Improving Efficiency in Allocating Pediatric Ambulatory Care Clinics,' Master of Science, University of Washington, 2014.
[72] A. Ahmed, C.-A. Chou, and K. S. Shehadeh, 'Joint Effect of Appointment Scheduling Rules and Resource Selection on Outpatient Clinics Performance,' (in English), *IIE Annual Conference. Proceedings,* pp. 3729-3736, 2014 2014.
[73] K. J. Klassen and R. Yoogalingam, 'Strategies for Appointment Policy Design with Patient Unpunctuality,' *Decision Sciences,* vol. 45, no. 5, pp. 881-911, 2014, doi: 10.1111/deci.12091.

[74] X. Guo, D. Tiller, G. Henze, and C. Waters, 'The performance of occupancy-based lighting control systems: A review,' *Lighting Research & Technology,* vol. 42, no. 4, pp. 415-431, 2010, doi: doi:10.1177/1477153510376225.
[75] D. Bourgeois, 'Detailed occupancy prediction, occupancy-sensing control and advanced behavioural modelling within whole-building energy simulation,' *Simulation,* p. 148, 2005.
[76] D. Bourgeois, C. Reinhart, and I. Macdonald, 'Adding advanced behavioural models in whole building energy simulation: A study on the total energy impact of manual and automated lighting control,' *Energy and Buildings,* vol. 38, no. 7, pp. 814-823, 2006, doi: 10.1016/j.enbuild.2006.03.002.
[77] P. Hoes, J. L. M. Hensen, M. G. L. C. Loomans, B. de Vries, and D. Bourgeois, 'User behavior in whole building simulation,' *Energy and Buildings,* vol. 41, no. 3, pp. 295-302, 2009, doi: 10.1016/j.enbuild.2008.09.008.
[78] H. Wang, A. Gluhak, and H. Tafazolli, 'Integration of BIM and live sensing information to monitor building energy performance,' in *CIB W78 International Conference, Beijing*, 2013.
[79] K. Akkaya, I. Guvenc, R. Aygun, N. Pala, and A. Kadri, 'IoT-based occupancy monitoring techniques for energy-efficient smart buildings,' 2015 2015: IEEE, pp. 58-63, doi: 10.1109/WCNCW.2015.7122529.
[80] A. Daissaoui, A. Boulmakoul, L. Karim, and A. Lbath, 'IoT and Big Data Analytics for Smart Buildings: A Survey,' (in English), *Procedia computer science,* vol. 170, pp. 161-168, 2020, doi: 10.1016/j.procs.2020.03.021.
[81] D. Trivedi and V. Badarla, 'Occupancy detection systems for indoor environments: A survey of approaches and methods,' vol. 29, ed. London, England: SAGE Publications, 2020, pp. 1053-1069.
[82] A. Dey *et al.*, 'Namatad: Inferring occupancy from building sensors using machine learning,' 2016 2016: IEEE, pp. 478-483, doi: 10.1109/WF-IoT.2016.7845462.
[83] J. Qi and G.-P. Liu, 'A Robust High-Accuracy Ultrasound Indoor Positioning System Based on a Wireless Sensor Network,' *Sensors,* vol. 17, no. 11, p. 2554, 2017, doi: 10.3390/s17112554.
[84] E. Baccelli *et al.*, 'Privacy-preserving crowd incident detection: a holistic experimental approach,' presented at the Proceedings of the 1st ACM SIGSPATIAL International Workshop on the Use of GIS in Emergency Management, Bellevue, Washington, 2015.
[85] D. Calì, P. Matthes, K. Huchtemann, R. Streblow, and D. Müller, 'CO_2 based occupancy detection algorithm: Experimental analysis and validation for office and residential buildings,' *Building and Environment,* vol. 86, pp. 39-49, 2015, doi: 10.1016/j.buildenv.2014.12.011.
[86] S. Wang and X. Jin, 'CO_2-Based Occupancy Detection for On-Line Outdoor Air Flow Control,' *Indoor and Built Environment,* vol. 7, no. 3, pp. 165-181, 1998, doi: 10.1177/1420326x9800700305.
[87] A. Azimil Gani, H. Rahman, K. Jung-Kyung, and H. Han, 'Uncertainties in neural network model based on carbon dioxide concentration for occupancy estimation,' (in English), *Journal of Mechanical Science and Technology,* vol. 31, no. 5, pp. 2573-2580, May 2017 2017.
[88] N. Abedi, A. Bhaskar, and E. Chung, 'Tracking spatio-temporal movement of human in terms of space utilization using Media-Access-Control address data,'

Applied geography (Sevenoaks), vol. 51, pp. 72-81, 07/2014 2019, doi: 10.1016/j.apgeog.2014.04.001.
[89] N. Hernández *et al.*, 'WiFiNet: WiFi-based indoor localisation using CNNs,' *Expert Systems with Applications,* vol. 177, p. 114906, 2021.
[90] W. Wang, J. Chen, T. Hong, and N. Zhu, 'Occupancy prediction through Markov based feedback recurrent neural network (M-FRNN) algorithm with WiFi probe technology,' *Building and Environment,* vol. 138, pp. 160-170, 2018.
[91] X. Zheng *et al.*, 'A Novel Device-Free Positioning Method Based on Wi-Fi CSI with NLOS Detection and Bayes Classification,' *Remote Sensing,* vol. 15, no. 10, p. 2676, 2023.
[92] W. Wang, J. Chen, and T. Hong, 'Modeling occupancy distribution in large spaces with multi-feature classification algorithm,' *Building and Environment,* vol. 137, pp. 108-117, 2018.
[93] A. Lorenc, J. Szarata, and M. Czuba, 'Real-Time Location System (RTLS) Based on the Bluetooth Technology for Internal Logistics,' *Sustainability,* vol. 15, no. 6, p. 4976, 2023.
[94] L. Li, 'Simulating Federated Learning for Smartphone based Indoor Localisation,' University of Twente, 2021.
[95] P. Zappi, E. Farella, and L. Benini, 'Tracking Motion Direction and Distance With Pyroelectric IR Sensors,' *IEEE Sensors Journal,* vol. 10, no. 9, pp. 1486-1494, 2010, doi: 10.1109/JSEN.2009.2039792.
[96] V. L. Erickson, M. Á. Carreira-Perpiñán, A. E. Cerpa, and A. Miguel, 'Occupancy Modeling and Prediction for Building Energy Management,' *ACM Transactions on Sensor Networks,* vol. 10, no. 3, pp. 1-28, 2014, doi: 10.1145/2594771.
[97] J. Yun, D. Kim, D. M. Kim, T. Song, and J. Woo, 'GAN-based sensor data augmentation: Application for counting moving people and detecting directions using PIR sensors,' *Engineering Applications of Artificial Intelligence,* vol. 117, p. 105508, 2023.
[98] A. Tyndall, R. Cardell-Oliver, and A. Keating, 'Occupancy Estimation Using a Low-Pixel Count Thermal Imager,' *IEEE Sensors Journal,* 2016.
[99] C. Basu and A. Rowe, 'Tracking Motion and Proxemics using Thermal-sensor Array,' *arXiv preprint arXiv:1511.08166,* 2015.
[100] J. L. Honorato, I. Spiniak, and M. Torres-Torriti, 'Human Detection Using Thermopiles,' in *2008 IEEE Latin American Robotic Symposium*, 29-30 Oct. 2008 2008, pp. 151-157, doi: 10.1109/LARS.2008.21.
[101] M. Kuki, H. Nakajima, N. Tsuchiya, and Y. Hata, 'Human movement trajectory recording for home alone by thermopile array sensor,' in *2012 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 14-17 Oct. 2012 2012, pp. 2042-2047, doi: 10.1109/ICSMC.2012.6378039.
[102] A. A. Trofimova, A. Masciadri, F. Veronese, and F. Salice, 'Indoor Human Detection Based on Thermal Array Sensor Data and Adaptive Background Estimation,' *Journal of Computer and Communications,* vol. 5, pp. 16-28, 2017, doi: 10.4236/jcc.2017.54002.
[103] J. Karlsson, 'Multi-Bernoulli Tracking Approach for Occupancy Monitoring of Smart Buildings Using Low-Resolution Infrared Sensor Array,' (in English), *Remote Sensing,* vol. 13, no. 16, p. 3127, 2021-08-28 2021.
[104] H. M. Ng, 'Poster abstract: human localization and activity detection using thermopile sensors,' presented at the Proceedings of the 12th international

conference on Information processing in sensor networks, Philadelphia, Pennsylvania, USA, 2013.
[105] M. Berger and A. Armitage, 'Room occupancy measurement using low-resolution infrared cameras,' 2010.
[106] A. Beltran, V. L. Erickson, and A. E. Cerpa. ThermoSense: Occupancy Thermal Based Sensing for HVAC Control.
[107] V. Chidurala and X. Li, 'Occupancy Estimation Using Thermal Imaging Sensors and Machine Learning Algorithms,' (in English), *IEEE sensors journal,* vol. 21, no. 6, pp. 8627-8638, 2021, doi: 10.1109/JSEN.2021.3049311.
[108] U. Saralegui, M. A. Antón, and J. Ordieres-Mere, 'Taking advantage of an existing indoor climate monitorization for measuring occupancy,' *WSEAS Transactions on Environment and Development,* 2017.
[109] S. Kumar, J. Singh, and O. Singh, 'Ensemble-based extreme learning machine model for occupancy detection with ambient attributes,' *International journal of system assurance engineering and management,* vol. 11, no. suppl 2, pp. 173-183, 01/2020 2020.
[110] H. Elkhoukhi, Y. NaitMalek, A. Berouine, M. Bakhouya, D. Elouadghiri, and M. Essaaidi, 'Towards a Real-time Occupancy Detection Approach for Smart Buildings,' (in English), *Procedia computer science,* vol. 134, pp. 114-120, 2018, doi: 10.1016/j.procs.2018.07.151.
[111] M. Wiberg, 'Making the Case for “Architectural Informatics”: A New Research Horizon for Ambient Computing?,' in *Pervasive and Ubiquitous Technology Innovations for Ambient Intelligence Environments*: IGI Global, 2013, pp. 128-135.
[112] M. Wiberg, 'From interactables to architectonic interaction,' *interactions,* vol. 24, no. 2, pp. 62-65, 2017.
[113] T. Å. Evjen, S. R. Hosseini Raviz, S. A. Petersen, and J. Krogstie, 'Smart Facility Management: Future Healthcare Organization through Indoor Positioning Systems in the Light of Enterprise BIM,' *Smart Cities,* vol. 3, no. 3, pp. 793-805, 2020.
[114] A. K. Tyagi, 'Sensors and Digital Twin Application in Healthcare Facilities Management,' *Artificial Intelligence-Enabled Blockchain Technology and Digital Twin for Smart Hospitals,* pp. 369-390, 2024.
[115] J. Peacock and P. Peacock, *Oxford handbook of medical statistics*. Oxford university press, 2011.
[116] R. H. Von-Alan, S. T. March, J. Park, and S. Ram, 'Design science in information systems research,' *MIS quarterly,* vol. 28, no. 1, pp. 75-105, 2004.
[117] V. Erickson, S. Achleitner, and A. Cerpa, 'POEM: power-efficient occupancy-based energy management system,' *Proceedings of the 12th,* 2013, doi: 10.1145/2461381.2461407.
[118] N. Kirchner, A. Alempijevic, A. Virgona, X. Dai, P. Ploger, and R. K. Venkat, 'A robust people detection, tracking, and counting system,' in *Australian Conference on Robotics and Automation 2014*, 2014: Australasian Robotics and Automation Association.
[119] Australasian-Health-Infrastructure-Alliance. 'Australasian Health Facility Guidelines (AusHFG).' Australasian Health Infrastructure Alliance (AHIA). (accessed 24-12-2018, 2018).
[120] A. Furnham and V. Swami, 'An investigation of attitudes toward surveillance at work and its correlates,' *Psychology,* vol. 6, no. 13, p. 1668, 2015.

[121] K. Ball, 'Workplace surveillance: An overview,' *Labor History,* vol. 51, no. 1, pp. 87-106, 2010.
[122] J. C. Liando, A. Gamage, A. W. Tengourtius, and M. Li, 'Known and Unknown Facts of LoRa: Experiences from a Large-scale Measurement Study,' *ACM Trans. Sen. Netw.,* vol. 15, no. 2, p. Article 16, 2019, doi: 10.1145/3293534.
[123] C. Shearer, 'The CRISP-DM model: the new blueprint for data mining,' *Journal of data warehousing,* vol. 5, no. 4, pp. 13-22, 2000.
[124] C. Schröer, F. Kruse, and J. M. Gómez, 'A systematic literature review on applying CRISP-DM process model,' *Procedia Computer Science,* vol. 181, pp. 526-534, 2021.
[125] I. Holloway and L. Todres, 'The status of method: flexibility, consistency and coherence,' *Qualitative research,* vol. 3, no. 3, pp. 345-357, 2003.
[126] V. Braun and V. Clarke, 'Using thematic analysis in psychology,' *Qualitative Research in Psychology,* vol. 3, no. 2, pp. 77-101, 2006/01/01 2006, doi: 10.1191/1478088706qp063oa.
[127] V. Clarke and V. Braun, 'Teaching thematic analysis: Overcoming challenges and developing strategies for effective learning,' *The psychologist,* vol. 26, no. 2, 2013.
[128] V. Braun and V. Clarke, 'What can "thematic analysis" offer health and wellbeing researchers?,' vol. 9, ed: Taylor & Francis, 2014, p. 26152.
[129] G. W. Ryan and H. R. Bernard, 'Techniques to identify themes,' *Field methods,* vol. 15, no. 1, pp. 85-109, 2003.
[130] V. Clarke and V. Braun, 'Thematic analysis: a practical guide,' *Thematic Analysis,* pp. 1-100, 2021.
[131] T. Ligita, I. Nurjannah, K. Wicking, N. Harvey, and K. Francis, 'From textual to visual: the use of concept mapping as an analytical tool in a grounded theory study,' *Qualitative Research,* vol. 22, no. 1, pp. 126-142, 2022.
[132] D. A. Dillman, *Mail and Internet surveys: The tailored design method--2007 Update with new Internet, visual, and mixed-mode guide*. John Wiley & Sons, 2011.
[133] A. Fink, *How to conduct surveys : a step-by-step guide*, 6 edition. ed. Los Angeles: SAGE, 2017.
[134] D. F. Polit and C. T. Beck, *Essentials of nursing research : methods, appraisal, and utilization*, 6th ed. ed. Philadelphia: Lippincott Williams & Wilkins, 2006.
[135] R. H. Riffenburgh and D. L. Gillen, *Statistics in medicine*. Academic press, 2020.
[136] T. McNabb, D. Kristin Wicking, A. P. Trina Myers, and D. Lei Lei, 'Optimizing Clinical Spatial Resources with IoT,' in *Proceedings of the Australasian Computer Science Week Multiconference*, 2020, pp. 1-6.
[137] T. McNabb, D. Kristin Wicking, and P. Trina Myers, 'Occupation versus Utilisation of Clinical Spaces Using Internet of Things Devices: Are Consult Rooms Well Utilised?" ' *ICMHI '23: Proceedings of the 7th International Conference on Medical and Health Informatics,* 2023.
[138] S. R. Sahoo and H. R. Lone, 'Occupancy counting in dense and sparse settings with a low-cost thermal camera,' in *2023 15th International Conference on COMmunication Systems & NETworkS (COMSNETS)*, 3-8 Jan. 2023 2023, pp. 537-544, doi: 10.1109/COMSNETS56262.2023.10041292.

[139] S. Thorne, 'On the use and abuse of verbatim quotations in qualitative research reports,' ed: Wiley Online Library, 2020.
[140] J. E. Miller, 'Preparing and presenting effective research posters,' *Health Serv. Res.,* vol. 42, no. 1p1, pp. 311-328, 2007.
[141] G. Orwell, *1984: nineteen eighty-four*. BoD–Books on Demand, 2023.
[142] P. Sullivan, 'Nurses decry profession's 1:19 male-to-female ratio,' *Can. Med. Assoc. J.,* vol. 164, no. 12, pp. 1738-1738-b, 2001.
[143] I. Radnaeva, A. Muthusami, and S. Ward, 'NHS advice and guidance – improving outpatient flow and patient care in general surgery,' *The surgeon (Edinburgh),* 2023, doi: 10.1016/j.surge.2023.02.004.
[144] R. Hall, D. Belson, P. Murali, and M. Dessouky, 'Modeling Patient Flows Through the Health care System,' (International Series in Operations Research & Management Science. Boston, MA: Springer US, 2013, pp. 3-42.
[145] K. Hadian, G. Fernie, and A. Roshan Fekr, 'Development and Evaluation of BLE-Based Room-Level Localization to Improve Hand Hygiene Performance Estimation,' *Journal of Healthcare Engineering,* vol. 2023, 2023.
[146] P. Waldie, M. Attef, C. Trudel, A. D. Chan, and B. Wallace, 'Implementation and Use of Real-Time Location Systems in Hospital Environments–Rapid Scoping Review of Human Factors Considerations,' in *Proceedings of the International Symposium on Human Factors and Ergonomics in Health Care*, 2023, vol. 12, no. 1: SAGE Publications Sage CA: Los Angeles, CA, pp. 164-168.
[147] I. Arnolds and S. Nickel, 'Layout planning problems in health care,' *Applications of location analysis,* pp. 109-152, 2015.
[148] J. R. Munavalli, S. V. Rao, A. Srinivasan, and F. Van Merode, 'Dynamic Layout Design Optimization to Improve Patient Flow in Outpatient Clinics Using Genetic Algorithms,' *Algorithms,* vol. 15, no. 3, p. 85, 2022, doi: 10.3390/a15030085.
[149] M. d. El-Sharo, B. Zheng, S. W. Yoon, and M. T. Khasawneh, 'An overbooking scheduling model for outpatient appointments in a multi-provider clinic,' *Operations Research for Health Care,* Article vol. 6, pp. 1-10, 9/1/September 2015 2015, doi: 10.1016/j.orhc.2015.05.004.
[150] J. Mensah, D. Asamoah, and A. A. Tawiah, 'Optimizing Patient Flow and Resource Utilization in Out Patient Clinic: A Comparative Study of Nkawie Government Hospital and Aniwaa Health Center,' *The Journal of Applied Business and Economics,* vol. 16, no. 3, p. 181, 2014.
[151] K. Sailer, 'Routine action networks: An architectural study of spatial layouts and performativity in outpatient clinics,' *Social networks,* 2022, doi: 10.1016/j.socnet.2021.12.004.
[152] T. Zhang, B. Yang, and N. Gu, 'Application of A Priori Map in Dynamic Background Removal for Indoor Human Perception Using a Thermopile Array,' *IEEE Sensors Journal,* vol. 22, no. 2, pp. 1154-1162, 2022, doi: 10.1109/JSEN.2021.3130199.
[153] C. Song, A. D. Droitcour, S. M. M. Islam, A. Whitworth, V. M. Lubecke, and O. Boric-Lubecke, 'Unobtrusive occupancy and vital signs sensing for human building interactive systems,' *Sci. Rep.,* vol. 13, no. 1, p. 954, 2023/01/18 2023, doi: 10.1038/s41598-023-27425-6.
[154] P. A. Norberg, D. R. Horne, and D. A. Horne, 'The privacy paradox: Personal information disclosure intentions versus behaviors,' *Journal of consumer affairs,* vol. 41, no. 1, pp. 100-126, 2007.

[155] S. Barth and M. D. T. de Jong, 'The privacy paradox – Investigating discrepancies between expressed privacy concerns and actual online behavior – A systematic literature review,' *Telematics and Informatics,* vol. 34, no. 7, pp. 1038-1058, 2017/11/01/ 2017.
[156] C. S. Hagen, L. Bighash, A. B. Hollingshead, S. J. Shaikh, and K. S. Alexander, 'Why are you watching? Video surveillance in organizations,' *Corporate communications,* vol. 23, no. 2, pp. 274-291, 2018, doi: 10.1108/CCIJ-04-2017-0043.
[157] J. L. Cybulski, S. Keller, L. Nguyen, and D. Saundage, 'Creative problem solving in digital space using visual analytics,' *Comput. Human Behav.,* vol. 42, pp. 20-35, 2015, doi: 10.1016/j.chb.2013.10.061.
[158] A. Abbasi, S. Sarker, and R. H. Chiang, 'Big data research in information systems: Toward an inclusive research agenda,' *Journal of the association for information systems,* vol. 17, no. 2, p. 3, 2016.
[159] M. J. Smith, P. Carayon, K. J. Sanders, S.-Y. Lim, and D. LeGrande, 'Employee stress and health complaints in jobs with and without electronic performance monitoring,' *Appl. Ergon.,* vol. 23, no. 1, pp. 17-27, 1992.
[160] L. Chen, Y. Huang, S. Ouyang, and W. Xiong, "The data privacy paradox and digital demand," National Bureau of Economic Research, 2021.
[161] S. Golden, 'Mapping the expanding and fracturing field of architecture,' in *Architectural Research Addressing Societal Challenges*: Taylor & Francis, 2017, pp. 705-712.

APPENDIX 1: IOT INSTALLATION INFORMATION SHEET

Townsville Hospital
and Health Service

Fact sheet

Space Utilisation Study:
A JCU Research Pilot Project

Introduction

The THHS Medical Outpatient Clinic is taking part in a research project in conjunction with James Cook University to understand how clinical spatial resources are used in the THHS.

Currently, room utilisation is measured through a physical audit which is not only resource-intensive, it provides a 'snapshot' understanding of room utilisation which may or may not reflect 'business as usual' operations.

Subsequently, this research project aims to demonstrate an improved method for understanding average patterns of utilisation over an initial six month period.

Purpose

The aim of this study is to better understand patterns of occupancy within THHS outpatient clinical spaces to establish an occupancy baseline and be able to demonstrate the effectiveness of service improvement initiatives over time.

Outcome

Data collected during this project will provide an evidence base to support informed decision-making both at the front-line and strategic levels, and ideally provide hard data on the effectiveness of future improvement strategies.

Should it prove useful, this technology is envisioned to be a tool to support the Clinical Nurse Unit manager in the management of the outpatient clinics.

Methodology

Information collected by these sensors is the presence of thermal movement, designed to identify the presence or absence of human occupation.

Sensors used are standard in both residential and commercial environments, commonly used in security systems or motion sensor lighting:

No personally identifiable information on either the occupant(s) or the activity undertaken in target rooms will be collected, processed, or stored.

How does the technology work?

The sensor units collect time-stamped motion sensor data, and broadcast this data to a central repository for collation and analysis.

Scope

Participating rooms are limited to clinic rooms where healthcare services are administered including consult and interview/education rooms, but excluding treatment rooms.

All other spaces, such as staff stations, reception, waiting areas, corridors, etc are not participating in this study.

HREC#: HREC17QTHS54

VERSION 1.0 (2017-80-29)

Queensland Government

APPENDIX 2: *OPTIMISING SPATIAL HEALTHCARE ASSETS WITH IOT*

Appendix Contents:

2.1) Rights Printable License
2.2) Publication

Author Contribution Table:

Author	**Contribution**
Tim McNabb	Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Visualisation, Funding Acquisition, Project Administration
Prof. Trina Myers	Supervision, Writing – Review & Editing, Resources
Dr. Kristin Wicking	Supervision, Writing – Review & Editing, Resources
Dr. Lei Lei	Supervision, Writing – Review & Editing
Prof. Wei Xiang:	Supervision

This administrative form has been removed

McNabb *et al. Health Inf Sci Syst (2018) 6:11*
https://doi.org/10.1007/s13755-018-0052-2

Health Information Science and Systems

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

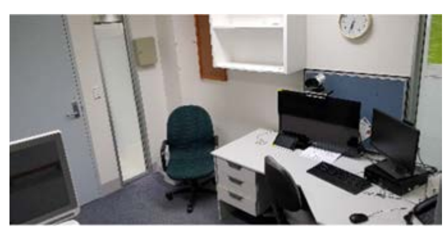
The clinical spaces targeted in this project's phase two are broken into three primary categories: (1) consult rooms; (2) education rooms; and (3) treatment rooms, which are the three highest-value spaces to patients, clinicians and management (Table 1). Notably, there are other space types that support 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	

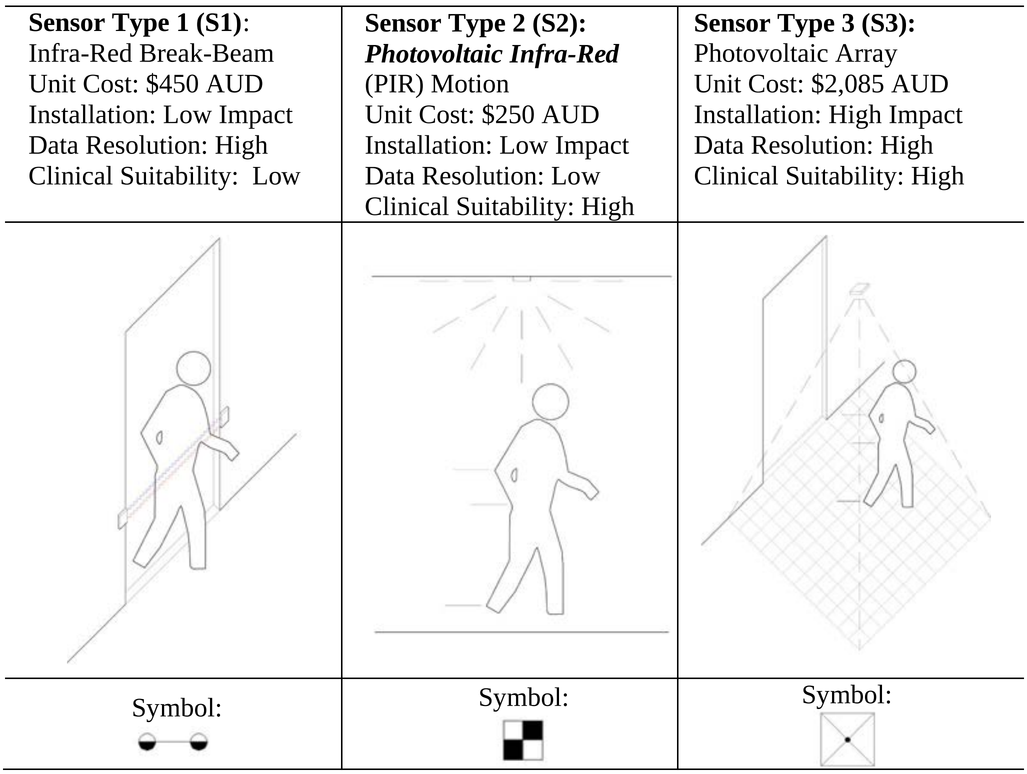


Fig. 1 Sensor types chosen to study outpatient space utilization across a multi-disciplinary clinic within a live public healthcare environment

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 ¾ through the room. The outcome of phase one is intended to inform the placement of sensors in the full phase two deployment (Fig. 2).

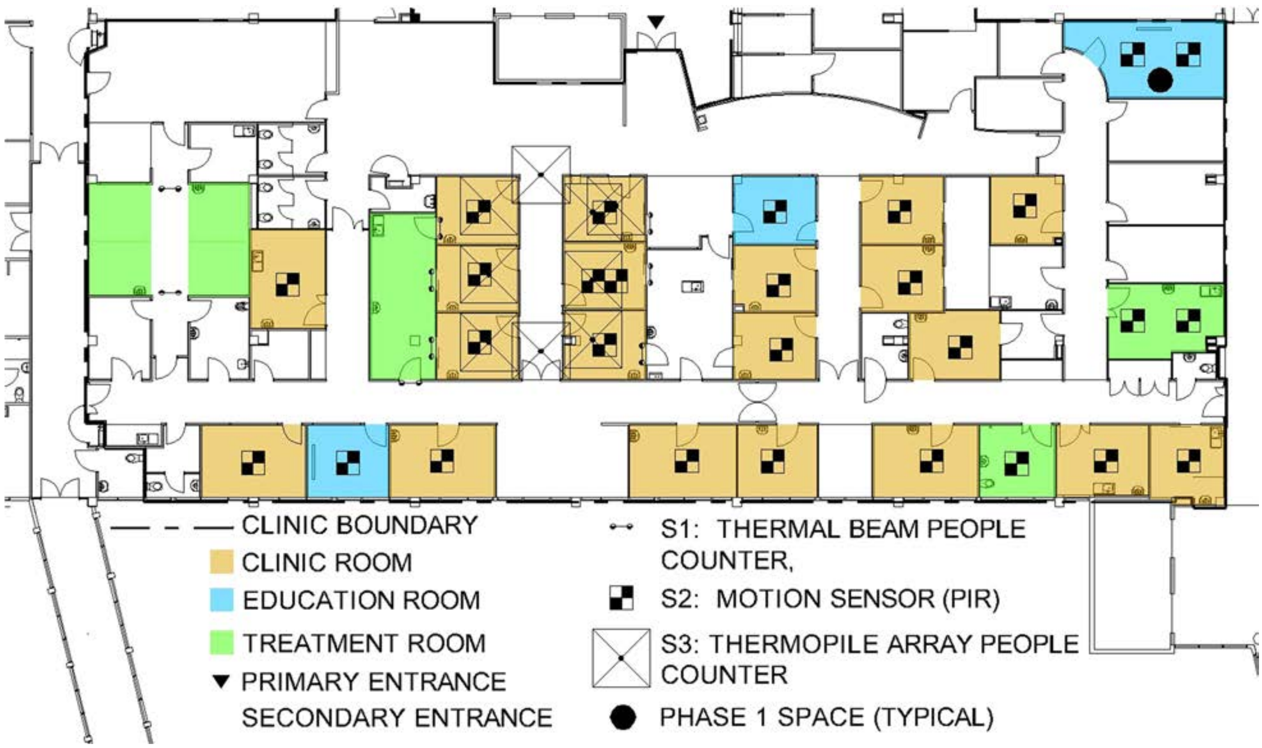


Fig. 2 Floor plan on proposed clinical area illustrating the placement of the three sensors types in the three types of clinical rooms (type 1 = beige, consult room; type 2 = blue, non-clinical room; type 3 = green, treatment room)

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 ¾ 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

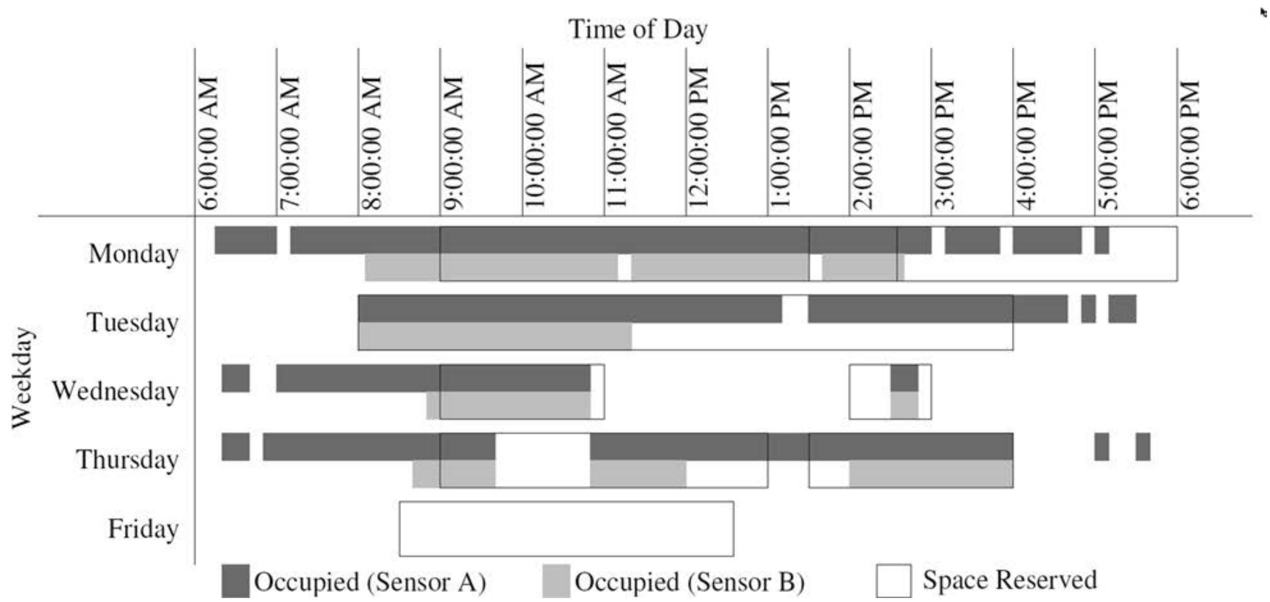


Fig. 3 "Room as occupied" versus "room as reserved" for non-clinical, reservable space

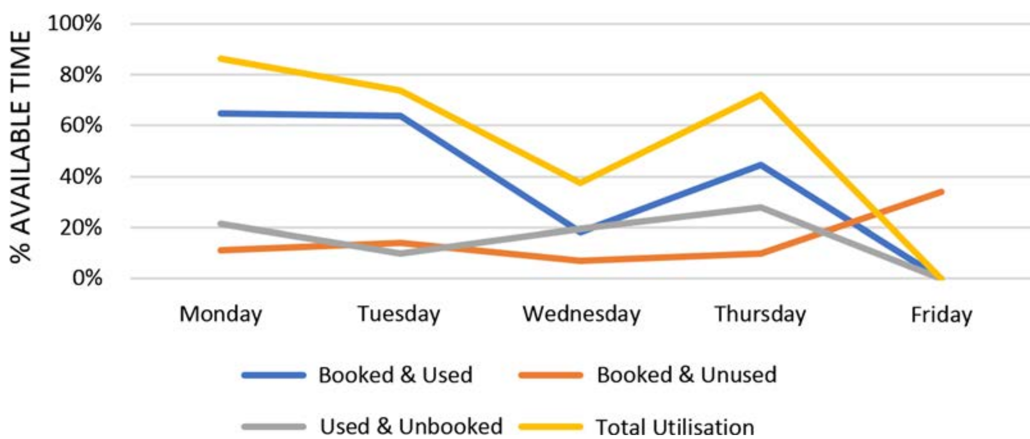


Fig. 4 Correlation of usage from 6 a.m. to 6 p.m

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 cancelation of reservations for un-occupied 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.

APPENDIX 3: *OPTIMISING CLINICAL SPATIAL RESOURCES WITH IOT*

Appendix Contents:

3.1) Author Rights & Responsibilities (open access)

3.2) Publication

Author Contribution Table:

Author	Contribution
Tim McNabb	Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Visualisation, Funding Acquisition, Project Administration
Prof. Trina Myers	Supervision, Writing – Review & Editing, Resources
Dr. Kristin Wicking	Supervision, Writing – Review & Editing, Resources
Dr. Lei Lei	Supervision, Writing – Review & Editing

This administrative form
has been removed

Optimizing Clinical Spatial Resources with IoT

Tim McNabb
College of Healthcare Sciences
James Cook University,
Townsville, Queensland, Australia,
Tim.McNabb@my.jcu.edu.au

Dr. Kristin Wicking
College of Healthcare Sciences
James Cook University,
Townsville, Queensland, Australia,
Kristin.Wicking@jcu.edu.au

A/Prof. Trina Myers
College of Science and Engineering
James Cook University,
Townsville, Queensland, Australia,
Trina.Meyers@jcu.edu.au

Dr. Lei Lei
College of Science and Engineering
James Cook University, Townsville, Queensland, Australia, Lei.Lei@jcu.edu.au

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

ACM ISBN 978-1-4503-7697-6/20/02.
https://doi.org/10.1145/3373017.3373047

ACM Reference format:

Tim McNabb, Dr. Kristin Wicking, A/Prof. Trina Myers and Dr. Lei Lei. 2020. Optimizing Clinical Spatial Resources with IoT. In *Proceedings of Australasian Computer Science Week (ACSW 2020), February 04-06, 2020, Melbourne, VIC, Australia.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3373017.3373047

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 (CO_2) 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, finding 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 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], CO_2 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 CO_2 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 CO_2 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.

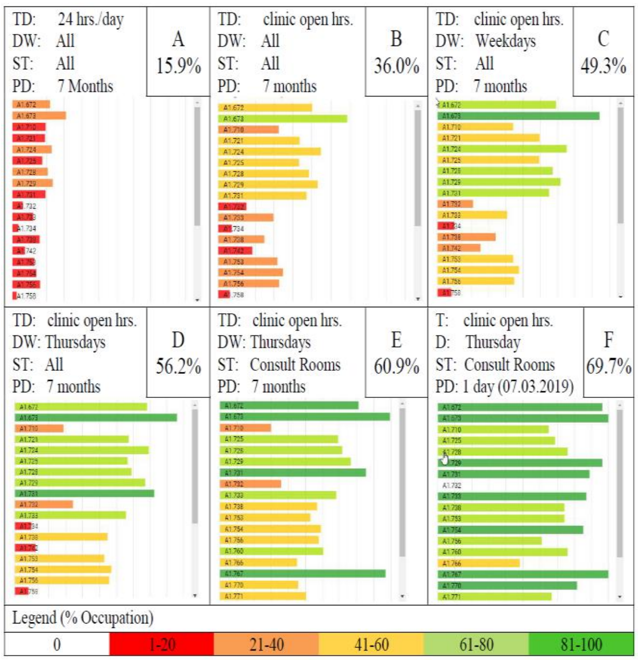
Clinician-patient encounter spaces host confidential activities and interactions protected by Australian privacy laws, so all research activities were bound by strict regulations as identified in the approved Health Research Ethics Committee approval obtained prior to sensor installation. To study operational 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 patents 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.

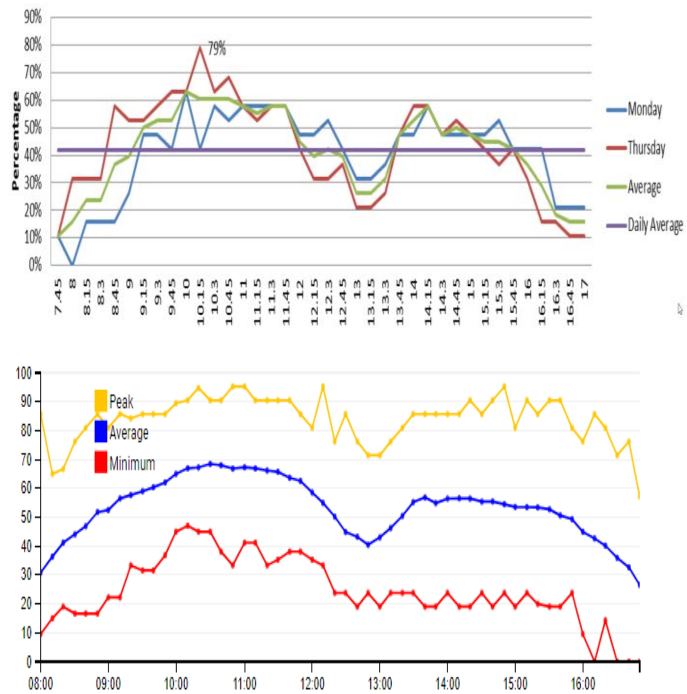


Figure 2 - Comparison of manual data gathering for Monday, Thursday and Friday in the week of March 14th 2016 (top graph excerpt from [2]) vs. the IoT-gathered data averaged over 7 months from March 01st 2019 to October 01st 2019 limited to Mondays, Thursdays, and Fridays (bottom graph excerpt from https://www.occupeye.com/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

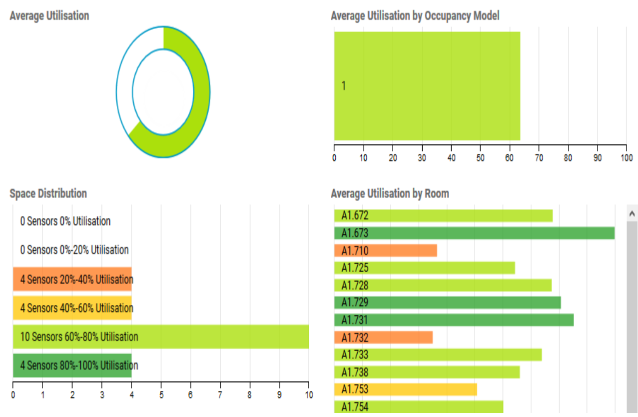


Figure 3 - Excerpt from proprietary dynamic cloud-based data dashboard showing occupation data all spaces in the target clinic for a nominal period from [33]

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.

ACKNOWLEDGMENTS

This research has been funded by the Townsville Hospital and Health Services: Study, Education, Research Trust Account (SERTA) Grant;
Support for this research was provided in part by Occupeye (an Assure Software company) who provided a reduced cost for research purposes on sensor purchase price and cloud-based dashboard hosting.

REFERENCES

[1] A. Malik, M. Lenzen, S. McAlister, and F. McGain, "The carbon footprint of Australian health care," The Lancet Planetary Health, vol. 2, pp. e27-e35, 2018.
[2] Australian_Institute_of_Health_and_Welfare, "Health expenditure Australia 2015–16," A. I. o. H. a. Welfare, Ed., ed. Canberra: AIHW, 2017.
[3] J.A. Fisher and T. Monahan, "Tracking the social dimensions of RFID systems in hospitals," International journal of medical informatics, vol. 77, pp. 176-183, 2008.
[4] C. Beyrouthy, E. Burke, D. Landa-Silva, B. Mccollum, P. Mcmullan, and A. Parkes, "Towards improving the utilization of university teaching space," Journal of the Operational Research Society, vol. 60, pp. 130-143, 2009.
[5] A. Ahmed, C.-A. Chou, and K. S. Shehadeh, "Joint Effect of Appointment Scheduling Rules and Resource Selection on Outpatient Clinics Performance," IIE Annual Conference. Proceedings, pp. 3729-3736, 2014 2014.
[6] T. T. Nguyen, A. I. Sivakumar, and S. C. Graves, "Scheduling rules to achieve lead-time targets in outpatient appointment systems," Health Care Manag Sci, Aug 08 2016.
[7] M. Rezaeiahari, L. Adwan, and M. T. Khasawneh, "Patient Scheduling at a Breast Center Using Discrete Event Simulation," IIE Annual Conference. Proceedings, pp. 2075-2080, 2017.
[8] S. Helber, D. Böhme, F. Oucherif, S. Lagershausen, and S. Kasper, "A hierarchical facility layout planning approach for large and complex hospitals," Flexible Services and Manufacturing Journal, vol. 28, pp. 5-29, 2016.

[9] J. Reijula, E. Reijula, and K. Reijula, "Insight into healthcare design: lessons learned in two university hospitals," Journal of Facilities Management, vol. 14, pp. 266-282, 2016.
[10] R.V. Bradley, T. L. Esper, J. In, K. B. Lee, B. C. Bichescu, and T. A. Byrd, "The Joint Use of RFID and EDI: Implications for Hospital Performance," Production and Operations Management, vol. 27, pp. 2071-2090, 2018.
[11] J. F. Bard, Z. Shu, D. J. Morrice, D. Wang, R. Poursani, and L. Leykum, "Improving patient flow at a family health clinic," Health Care Management Science, vol. 19, pp. 170-191, 2016.
[12] V. Vahdat, J. Griffin, and J. E. Stahl, "Decreasing patient length of stay via new flexible exam room allocation policies in ambulatory care clinics," Health care management science, vol. 21, pp. 492-516, 2018.
[13] K.A. Johannessen and N. Alexandersen, "Improving accessibility for outpatients in specialist clinics: reducing long waiting times and waiting lists with a simple analytic approach," BMC Health Services Research, vol. 18, 2018.
[14] J. Ai, C. Oglevee, and O. Pianykh, "Determining Waiting Room Occupancy at an Outpatient Clinic Using Simulated Observations and Probability-Duration Curves," Journal of the American College of Radiology, vol. 13, pp. 620-627.e2, 06/2016 2016.
[15] V. Soni, "Predicting Length of Stay of Emergency Department Patients Using Tree-Based Machine Learning Models," Wayne State University, 2019.
[16] A. Riise, C. Mannino, and L. Lamorgese, "Recursive logic-based Benders' decomposition for multi-mode outpatient scheduling," European Journal of Operational Research, vol. 255, pp. 719-728, 12/16/ 2016.
[17] A. Nelson, D. Herron, G. Rees, and P. Nachev, "Predicting scheduled hospital attendance with artificial intelligence," npj Digital Medicine, vol. 2, p. 26, 2019/04/12 2019.
[18] W. Wang, J. Chen, T. Hong, and N. Zhu, "Occupancy prediction through Markov based feedback recurrent neural network (M-FRNN) algorithm with WiFi probe technology," Building and Environment, vol. 138, pp. 160-170, 2018.
[19] M. Amayri, A. Arora, S. Ploix, S. Bandhyopadyay, Q. D. Ngo, and V. R. Badarla, "Estimating occupancy in heterogeneous sensor environment," Energy and Buildings, vol. 129, pp. 46-58, 2016.
[20] D. Calì, P. Matthes, K. Huchtemann, R. Streblow, and D. Müller, "CO2 based occupancy detection algorithm: Experimental analysis and validation for office and residential buildings," Building and Environment, vol. 86, pp. 39-49, 2015.
[21] J. Huang, M. Demir, T. Lian, and K. Fujimura, "An Online Multi-lidar Dynamic Occupancy Mapping Method," in2019 IEEE Intelligent Vehicles Symposium (IV), 2019, pp. 517-522.
[22] M. Abedi and F. Jazizadeh, "Deep-learning for Occupancy Detection Using Doppler Radar and Infrared Thermal Array Sensors," in ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction, 2019, pp. 1098-1105.
[23] Q. Huang, Z. Ge, and C. Lu, "Occupancy Estimation in Smart Buildings using Audio-Processing Techniques," arXiv:1602.08507, 2016.
[24] L. Korduner and M. Sundquist, "Determining an optimal approach for human occupancy recognition in a study room using non-intrusive sensors and machine learning," 2019.
[25] G. Mannea-Paxton, "Clinic Room Utilisation Report - Sept," in Review, ed. Townsville Hospital and Health Services (THHS): THHS, 2016.
[26] F. Dehais, H. M. Hodgetts, M. Causse, J. Behrend, G. Durantin, and S. Tremblay, "Momentary lapse of control: A cognitive continuum approach to understanding and mitigating perseveration in human error," Neuroscience & Biobehavioral Reviews, 2019.
[27] R. J. Mieloszyk, J. I. Rosenbaum, C. S. Hall, D. S. Hippe, M. L. Gunn, and P. Bhargava, "Environmental Factors Predictive of No-Show Visits in Radiology: Observations of Three Million Outpatient Imaging Visits Over 16 Years," Journal of the American College of Radiology, vol. 16, pp. 554-559, 2019.
[28] C.-h. Cheng and Y.-h. Kuo, "RFID analytics for hospital ward management," Flexible Services and Manufacturing Journal, vol. 28, pp. 593-616, 2016-11-30 2016.
[29] J.C. Chen and T. J. Collins, "Creation of a RFID Based Real Time Tracking (R-RTT) System for Small Healthcare Clinics," Journal of Medical Systems, vol. 36, pp. 3851-3860, 2012.
[30] M. J. Miller, D. M. Ferrin, T. Flynn, M. Ashby, K. P. White Jr, and M. G. Mauer, "Using RFID technologies to capture simulation data in a hospital emergency department," in Proceedings of the 38th conference on Winter simulation, 2006, pp. 1365-1370.
[31] T. McNabb, T. Myers, K. Wicking, L. Lei, and W. Xiang, "Optimizing spatial healthcare assets with Internet of Things," Health information science and systems, vol. 6, p. 11, 2018.
[32] G. Mannea-Paxton, "Clinic Room Utilisation Report - March," THHS, Townsville Hospital and Health Services (THHS)March 2016 2016.
[33] Occupeye_(An_Assure_Software_company). (2019, 2019-10-10). Data Dashboard - Townsville Hospital and Health Service. Available: https://occ.cadcap.co.uk/OccupEye/Account/Login?ReturnUrl=%2FOccupEye%2F
[34] T. Teixeira, G. Dublon, and A. Savvides, "A Survey of Human-Sensing: Methods for Detecting Presence, Count, Location, Track, and Identity," ACM Computing Surveys, vol. 5, pp. 1-35, 2010.
[35] N. Smith, C. Mitton, S. Bryan, A. Davidson, B. Urquhart, J. L. Gibson, et al., "Decision maker perceptions of resource allocation processes in Canadian health care organizations: a national survey," BMC Health Serv Res, vol. 13, p. 247, Jul 02 2013.
[36] M. Garbey, G. Joerger, A. Huang, R. Salmon, J. Kim, V. Sherman, et al., "An intelligent hospital operating room to improve patient health care," Journal of Computational Surgery, vol. 2, p. 3, 2015.

APPENDIX 4: *OCCUPATION VERSUS UTILISATION OF CLINICAL SPACES USING IOT DEVICES: ARE CONSULT ROOMS WELL UTILISED?*

Appendix Contents:

Author Contribution Table:

Author	**Contribution**
Tim McNabb	Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Visualisation, Funding Acquisition, Project Administration
Prof. Trina Myers	Supervision, Writing – Review & Editing, Resources
Dr. Kristin Wicking	Supervision, Writing – Review & Editing, Resources

This administrative form has been removed

Occupation versus Utilisation of Clinical Spaces Using Internet of Things Devices: Are Consult Rooms Well Utilised?

Tim Mcnabb
James Cook University
Tim.McNabb@my.jcu.edu.au

Dr. Kristin Wicking
James Cook University
Kristin.Wicking@jcu.edu.au

Prof. Trina Myers
Queensland University of Technology
trina.myers@deakin.edu.au

ABSTRACT

The cost of building, renovating, and maintaining the physical healthcare environment is up to 6% of the total cost of providing healthcare. Despite being the fastest growing category of healthcare expenditure, few tools exist to understand the use of spatial clinical resources. Previous research in live healthcare environments demonstrated that Internet of Things (IoT) devices are effective in understanding patterns of occupancy in clinical spaces. Healthcare managers answering the question "are consult rooms well utilized?" require data beyond 'occupied' or 'vacant'. Using the novel approach to clinical space management presented in this paper, understanding 'how' consult rooms are used is now possible. Proof-of-concept results are presented demonstrating the target consult room was predominantly either 'well utilized' (55%), 'vacant' (29%), or 'intermittently used' (14%) for the target period. Implications of undertaking technology research in live healthcare settings are discussed for academia and professional practice across multiple sectors.

CCS CONCEPTS

• **Online analytical processing**; • **Expert systems**; • **Sensor networks**; • **Ubiquitous and mobile computing systems and tools**;

KEYWORDS

IoT, Internet of Things, space management, architectural informatics, health informatics, digital health, healthcare management, edge computing, sensor networks

ACM Reference Format:
Tim Mcnabb, Dr. Kristin Wicking, and Prof. Trina Myers. 2023. Occupation versus Utilisation of Clinical Spaces Using Internet of Things Devices: Are Consult Rooms Well Utilised?. In *2023 the 7th International Conference on Medical and Health Informatics (ICMHI) (ICMHI 2023), May 12–14, 2023, Kyoto, Japan.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3608298.3608355

1 INTRODUCTION

The cost of building, renovating, and maintaining the physical healthcare environment in Australia was on average 5.6% of the total cost of providing healthcare for the 2010-2011 to 2020-2021 period [2]. Despite being one of the fastest growing categories of healthcare expenditure, few tools exist to understand the use of spatial clinical resources. Internet of Things (IoT) devices can support clinical space management and demonstrating how clinical space utilisation is planned but does not necessarily reflect actual use [3]. In live healthcare environments, IoT devices have been shown to be effective in understanding patterns of occupancy in clinical spaces, and superior to manual, human-based data gathering [4]. Occupancy patterns based on presence-detection can identify *when* clinical spaces are used but cannot provide insight into *how* they are used. Proof-of-concept results presented in this paper demonstrate a multidisciplinary approach to optimising clinical space utilisation using IoT devices to study patterns of activity inside high-privacy outpatient clinic spaces. Activity within each clinical space can be used to determine utilisation beyond 'occupied or vacant'. Healthcare provider decision-makers now have tools to make informed, data-driven decisions to optimise spatial clinical resources which will reduce the cost of providing healthcare and improve healthcare access and outcomes for consumers of healthcare services.

2 BACKGROUND

Research into improving access to healthcare services is not new with many researchers using a combination of visual observation [5] historical records [6] and simulation [7] to seek efficiency gains. Typically, the literature considers clinical space indirectly as a function of either patients' time [6] or healthcare providers' time [8]. Clinical spaces are often not considered a consumable resource in the body of literature [9], with notable exceptions [10]. Numerous presence detection and/or tracking sensor technologies exist [11] and several have been trialed in healthcare settings. Radio Frequency Identification (RFID) has been extensively implemented [12] to track objects and occupants of healthcare spaces. Despite potential privacy concerns [13], healthcare staff may be increasingly willing to participate in real-time tracking [14] to support improved health outcomes.

Like RFID deployments, other less common technologies such as IR Tags [15], and WiFi [16] equally rely on occupants (including both staff and consumers), to reliably carry or wear precisely calibrated technology. Tracking consumers as well as staff requires significant human resources to manage [10], typically relying on already over-burdened nursing staff to manage [17]. The combination of the high ongoing costs with the high cost of implementation has limited the widespread clinical adoption of this technology. Compounding any cost concerns, many technologies rely on patients and/or providers carrying a specific combination of technologies (i.e. cell phone, turned on, with WiFi or Bluetooth enabled), or impose 'correct' use conditions on the users [15] which are challenging

ICMHI 2023, May 12–14, 2023, Kyoto, Japan

ACM ISBN 979-8-4007-0071-2/23/05…$15.00
https://doi.org/10.1145/3608298.3608355

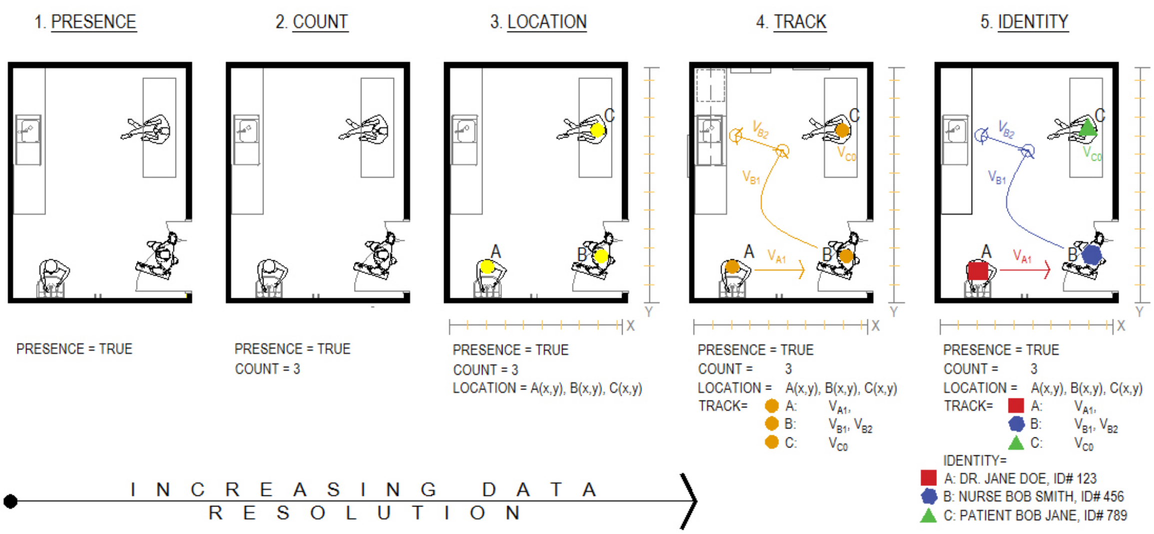


Figure 1: Adaptation of Teixeira et. al.'s 'five human spatio-temporal properties' ([1] Figure 2)

to enforce in clinical settings. Many potential privacy-preserving, low-maintenance, presence-detection technologies are emerging [18] including ultra-wide-band (UWB) radar [19], ultrasound [20], and thermopile arrays [21-23]; however, most are not (yet) broadly commercially available. Of these three emerging technologies, the thermopile array has attracted the broadest combination of research and commercial adoption, though the latter has been primarily utilized in commercial appliances (microwaves, air-conditioners, etc).

Previous research demonstrated that IoT devices relying on photovoltaic infra-red (PIR) are appropriate to detect 'presence' [3] in live clinical spaces; this data is limited to the first category of Teixara et al's [1] Taxonomy "inferences of spatio-temporal properties" (Fig.1). The proof-of-concept combination of sensor and edge-processor technologies discussed in this paper has been demonstrated capable of both detecting human presence and counting humans inside high-privacy clinical spaces and are considered appropriate for this context. This *count* data provides an order-of-magnitude better understanding of how clinical spaces are utilised beyond merely being 'occupied'. A lack of widely available, low-cost, low-management, privacy-preserving tools to appropriately study activities inside consult rooms has contributed to clinical space utilisation being underrepresented in the literature.

3 METHODOLOGY

This research seeks to demonstrate the proof-of-concept capacity of IoT sensors to support an assessment of *how* clinical spaces are being used beyond identifying *if* they are being used [4]. PIR sensors have previously demonstrated capacity to differentiate 'occupied' from 'vacant' status by collecting time-stamped occupancy data. The sensor type chosen to provide *count* data (Fig. 1) is a thermopile array (TA) sensor, branded as the 'grideye' sensor by Panasonic. A thermopile is a collection of thermocouples (temperature sensors) whose electric charge varies in direct proportion to the level of infra-red energy received by the sensor. Each thermopile's current is measured, averaged, and converted to a temperature by the sensor as a serial output. In the sensor used, thermopiles are arranged in an 8x8 grid with each receiving infra-red energy restricted to a 60° square-based-pyramid sensing area. The limited sensing angle required a horizontal mounting position resulting in a ceiling-mounted position.

The sensor was purchased pre-mounted on an 'off the shelf' printed circuit board (PCB) including additional elements to control power and data flow. This PCB was installed into a discrete, ad-hoc enclosure and mounted to the underside of the ceiling of a single consult room of approximately standard proportions [24]. A palm-sized computer was concealed in the ceiling space (Fig. 2), powered using 240v power to a 5v transformer, and connected to the PCB with discrete wires. The computer accessed thermopile array data through a proprietary multi-level Application Programming Interface (API). Data was processed and logged locally until it was transmitted to a cloud-based middle-ware provider via a Wi-Fi router linked to the cellular network, for storage, visualisation, and downstream processing. Data was recorded in 10-minute intervals,

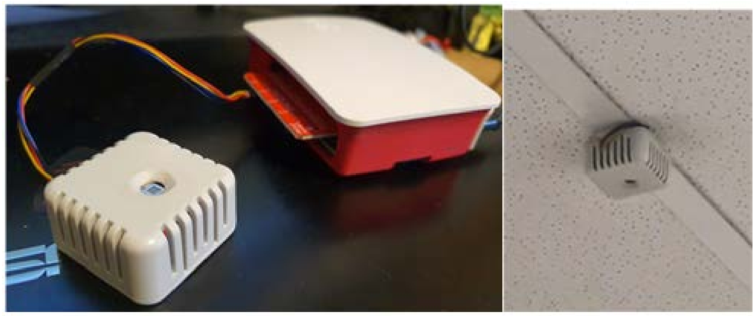


Figure 2: Thermopile array sensor in the middle of a discrete enclosure (left) connected to Raspberry Pi3 computer (middle) mounted to the underside of ceiling grid (right) while computer is concealed in the ceiling space

Table 1: Sample 'utilisation category' framework to interpret sensor data with respect to 'optimal

Count (#)	Hourly Activity Description	Utilisation Category
# = 0	Space is vacant with no activity	No Usage (Vacant)
0 < # < 1	Space is used, but intermittently	Poor Usage
# = 1	Space is used continuously by one person	Sub-Optimal Usage
# > 1	Space is used continuously by more than one person	Optimal Usage

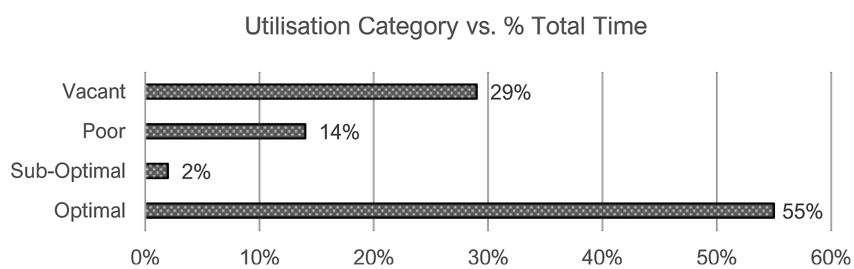


Figure 3: Utilisation categories of target clinical space for one week of clinical operating hours

24 hours per day, 7 days per week over a 1-week period, and post-processed to reduce the data set to hourly averages for operational clinic hours (8:30am to 4:30pm).

4 RESULTS

Interpretation of raw count data to understand how well a space is utilized depends largely on the model of care delivered through these spaces, the intended function of the space and its organisation. For the context of this paper, an example utilisation category framework is provided in Table 1. This framework guided the data categorization presented in Fig. 3 - Utilisation categories of target clinical space for one week of clinical operating hours in Fig. 3

If only PIR data was recorded as per previous research [4], the results would show a 71% occupation rate. The count data identifies an additional 16% of the observed time that is either poorly or sup-optimally utilised for the observed period beyond simply being 'occupied'. Collectively, the three categories of Vacant, Poor and Sub-Optimal represent 45% of the total potential usable clinic time, which can be collectively termed 'under utilised' time for reporting and optimisation purposes Fig. 4. It is worth noting that in the example category framework in Table 1 the context does not allow a category for 'over utilisation', which may be required in other contexts.

For an 8-hour clinic day and a 5-day operational week, a 45% 'under utilisation' rate represents 18 hours that could be re-allocated, including 11.6 operational clinic hours the room was unoccupied. Any proposed optimisation strategies must consider the context of the data. This room forms part of a wider multidisciplinary clinic, operating through diverse models of care specific to each service delivered across a two-week rotation. Also, this data reflects utilisation of a brief timescale; optimisation strategies would benefit from considering data across a much longer time period, similar to the 2-year time scale of previous IoT-based clinical space uitlisation research [4].

5 DISCUSSION

The thermopile array sensors demonstrated their capacity to provide *count* data, thereby providing additional information on the

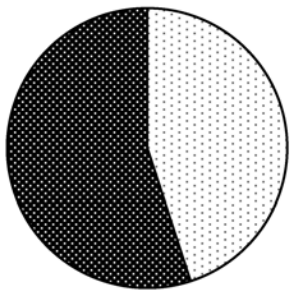


Figure 4: Utilisation Ratio

activities inside closed-door clinical spaces beyond their occupation status. This increase in data resolution has provided a commensurate increase in capacity to optimise how these high-value clinical resources are utilized. When determining utilisation category criteria, such as the ones outlined in the methodology section above, the function and context of each space is critical. For this research, any occupation of the clinical rooms by two or more individuals was considered *optimally utilised.* Many potential combinations are possible to fulfil this criterion, such as:

- One provider of healthcare services (minimum), and one consumer of healthcare services (minimum), or
- Two or more consumers of healthcare services, or
- Two or more providers of healthcare services.

The low rate of *sub-optimal utilisation* demonstrates the target clinical space was predominantly *not* used as a single-person administrative space during the study period. According to the stated categorisation framework (Table 1), any single-person activity in clinical space is considered a poor use of clinical space, as this work *could* be performed in non-clinical areas (including tele-health). Other spaces may require an additional category: 'over-utilised', depending on the function of the target space. Ensuring clinical spaces are used exclusively for clinical service delivery supports the optimal utilisation of limited spatial healthcare resources.

The TA sensors used in this research have the capacity to collect increasing quantities of data up to and including the tracking category (Fig. 1), however only count data was collected for this research. The ambient, non-personally-identifiable nature of the data collected by these sensors was in accordance with the Human Research Ethics Committee approval supporting this research. Increasing the data resolution may also increase negative sentiment about being watched by these sensors in the workplace. More research is required to understand the feelings and perspectives of healthcare staff about being continuously observed by technological means in the name of efficient use of clinical spatial resources.

Sensor data can be visualized and overlaid on a graphical floor plan including furniture, fixtures, and equipment (Fig. 5). Each element in the floor plan (e.g., consultant desk, patient bed, visitor chair, sink, etc) reflects pre-defined 'activity stations' within the room. It may be possible to infer the likely *role* of each individual in the room (i.e. healthcare provider, patient, or support person) from their spatial inhabitation of the clinical space over time. While this would not be a perfectly accurate reflection of the role of every occupant, it may still be a significant correlation. Identifying the *role* of individual participants in the activity space of clinical rooms may add a sub-category '*role'* to the established spatio-temporal property categories (Fig. 1) between *tracking* and *identify*, which may prove useful to future researchers.

Other aspects of this research have proven challenging. Autonomous sensors used in this research required no maintenance but did require a continuous in-ceiling 5v power supply which could be costly to implement at scale. Limitations in power consumption are expected to be overcome in future with increasing sensor efficiency and improved battery performance. Also, infra-red based presence detection can be triggered by non-human heat signatures (e.g., a computer); however, Shetty et. Al, and Qu et al. have both demonstrated 'grideye' filters to remove non-human data such as stationary heat sources [28], and background temperatures [29]. For this paper, *a priori* knowledge of heat signatures from the space's desk-top computer were manually excluded from the dataset used to determine *count* data.

Solely using thermopile to determine *count* data caused some challenges. Residual human heat on chairs and patient beds tended to dissipate over approximately one to three minutes; averaging *count* data over hourly time periods minimised the impact of these additional heat signatures. Additional work is required to identify the typical pattern of reducing heat signatures over time and adjust *count* data accordingly.

Also, post-processing is required to remove both background radiation [33, 34] and to separate physically close human heat signatures [31], while omitting non-human thermal signatures without a priori intervention. Another drawback of thermopiles is that the face of the sensor cannot be protected from chemical damage (cleaning), environmental damage (dust or liquids) or physical tampering (removal/obstruction). Protecting the sensor with glass or plastic will distort the infra-red waves that locate individuals, which may limit their future application as a sole sensor providing data on space utilisation.

Finally, reflecting the multi-disciplinary nature of this research, the implications of this research stretch beyond clinical informatics to architectural informatics. For example, Architectural education could prepare future architects to use sensor technology and edge computing to engage with their creations as they evolve through time. Architects could expand their practice from strictly 'birthing' the built environment to an advisory role providing support through the full building lifecycle. This change is analogous to Obstetrics Clinicians' focus on 'birthing', compared to General Practitioners' broader participation across the full lifespan of their patients.

6 CONCLUSION

The combination of sensors and edge computing trialed through this research has demonstrated the capacity for a significant (16%) improvement over previous research. This improvement is the key difference between knowing *if* clinical spaces are used, to having insight into *how* clinical spaces are used. Occupancy data alone may be more suitable for single-use spaces such as vehicular parking

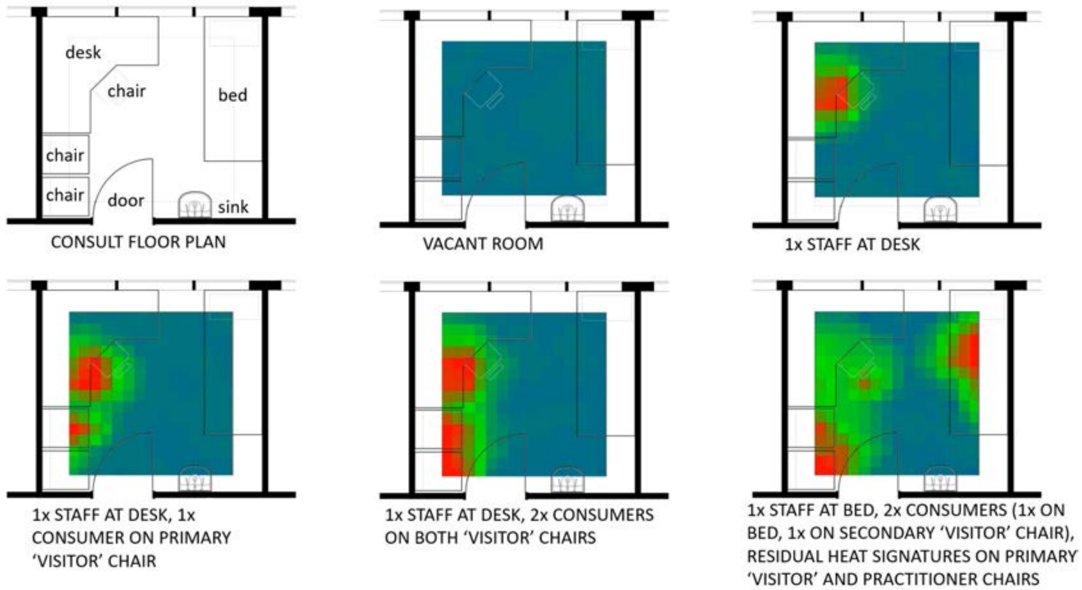


Figure 5: Data from 8x8 thermopile array interpolated to 16x16 pixels, color coded to relative temperature, and overlayed onto a Consult Room floor plan for visualisation

bays or washroom cubicles. Spatial allocation decisions can now be based on real-world data and provide iterative feedback to monitor the success of implemented optimisation strategies.

If the use of spatial clinical resources can be optimized, more consumers can access clinical services, and do so more rapidly. Earlier provision of healthcare services through existing outpatient clinical spaces can reduce pressure on more intensive downstream services, which are typically higher risk, higher cost, and higher demand (i.e., ambulance, emergency services, in-patient stays, etc.). Furthermore, the pressure to buy, build, renovate (and subsequently maintain) new healthcare spaces would be reduced, which decreases the financial and ecological burden of healthcare costs. Funds saved can be re-invested into core services providing healthcare for consumers, and the overall cost of providing healthcare can be reduced.

ACKNOWLEDGMENTS

Grant funding has been received by the Queensland Government, Australia through a THHS SERTA Fellowship Grant (2022_RFG5).

REFERENCES

[1] T. Teixeira, G. Dublon, and A. Savvides, “A Survey of Human-Sensing: Methods for Detecting Presence, Count, Location, Track, and Identity,” *ACM Computing Surveys,* vol. 5, pp. 1-35, 2010.

[2] Australian_Institute_of_Health_and_Welfare, "Health expenditure Australia 2020-21," AIHW, ed., Australian Government, 2021, p. 107.

[3] T. McNabb, T. Myers, K. Wicking, L. Lei, and W. Xiang, “Optimizing spatial healthcare assets with Internet of Things,” *Health information science and systems,* vol. 6, no. 1, pp. 11, 2018.

[4] T. McNabb, D. Kristin Wicking, A. P. Trina Myers, and D. Lei Lei, "Optimizing Clinical Spatial Resources with IoT." pp. 1-6.

[5] S. Chand, H. Moskowitz, J. B. Norris, S. Shade, and D. R. Willis, “Improving patient flow at an outpatient clinic: study of sources of variability and improvement factors,” *Health care management science,* vol. 12, no. 3, pp. 325-340, 2009.

[6] T. B. T. Nguyen, A. I. Sivakumar, and S. C. Graves, “A network flow approach for tactical resource planning in outpatient clinics,” *Health Care Management Science,* vol. 18, no. 2, pp. 124-136, 2015.

[7] H. H. Haraldsson, “Improving Efficiency in Allocating Pediatric Ambulatory Care Clinics,” University of Washington, 2014.

[8] M. Hutchison, C. C. Dacso, D. Sabin, and A. Shaw, “Opportunities for Optimizing Resource Utilization in Ambulatory Academic Practices,” *The Journal of Ambulatory Care Management,* vol. 20, no. 2, pp. 61-69, 1997.

[9] B. Liang, A. Turkcan, M. E. Ceyhan, and K. Stuart, “Improvement of chemotherapy patient flow and scheduling in an outpatient oncology clinic,” *International Journal of Production Research,* vol. 53, no. 24, pp. 7177-7190, 2015/12/17, 2014.

[10] J. C. Chen, and T. J. Collins, “Creation of a RFID Based Real Time Tracking (R-RTT) System for Small Healthcare Clinics,” *Journal of Medical Systems,* vol. 36, no. 6, pp. 3851-3860, 2012.

[11] Y. Chu, D. Mitra, Z. O’neill, and K. Cetin, “Influential variables impacting the reliability of building occupancy sensor systems: A systematic review and expert survey,” *Science and Technology for the Built Environment,* vol. 28, no. 2, pp. 200-220, 2022/02/07, 2022.

[12] W. Yao, C. H. Chu, and Z. Li, "The adoption and implementation of RFID technologies in healthcare: A literature review," *Journal of Medical Systems*, 2012, pp. 3507-3525.

[13] IEEE Journal on Selected Areas in Communications, Title 24, RFID security and privacy: A research survey, 2006, pp. 381-394.

[14] H. Guo, Z. Huang, J. Y. P. Yeo, Y. Wang, and A. Chow, “Psychosocial determinants of healthcare personnel’s willingness to carry real-time locating system tags during daily inpatient care in hospital managing COVID-19 patients: insights from a mixed-methods analysis,” *JAMIA open,* vol. 4, no. 3, pp. ooaa072-ooaa072, 2021.

[15] M. J. Miller, D. M. Ferrin, T. Flynn, M. Ashby, K. P. White Jr, and M. G. Mauer, "Using RFID technologies to capture simulation data in a hospital emergency department." pp. 1365-1370.

[16] T. S. Prentow, A. J. Ruiz-Ruiz, H. Blunck, A. Stisen, and M. B. Kjærgaard, “Spatio-temporal facility utilization analysis from exhaustive WiFi monitoring,” *Pervasive and Mobile Computing,* vol. 16, pp. 305-316, 2015/01/01/, 2015.

[17] J. A. Fisher, and T. Monahan, “Tracking the social dimensions of RFID systems in hospitals,” *International journal of medical informatics,* vol. 77, no. 3, pp. 176-183, 2008.

[18] S. T. Kouyoumdjieva, P. Danielis, and G. Karlsson, “Survey of Non-Image Based Approaches for Counting People,” *IEEE Communications Surveys & Tutorials*, pp. 1-1, 2019.

[19] B. B. Bhagat, and A. A. B. Raj, "Detection of Human Presence Using UWB Radar." pp. 1-6.

[20] T. van Groeningen, H. Driessen, J. Söhl, and R. Vôute, “An Ultrasonic Sensor For Human Presence Detection to Assist Rescue Work in Large Buildings,” *ISPRS annals of the photogrammetry, remote sensing and spatial information sciences,* vol. IV-4/W7, pp. 135-140, 2018.

[21] D. Qu, B. Yang, and N. Gu, "Indoor multiple human targets localization and tracking using thermopile sensor," *Infrared physics & technology,* vol. 97, pp. 349-359, 2019.
[22] A. D. Shetty, Disha, S. B, and S. K, "Detection and tracking of a human using the infrared thermopile array sensor - "Grid-EYE"." pp. 1490-1495.
[23] M. Kuki, H. Nakajima, N. Tsuchiya, and Y. Hata, "Human movement trajectory recording for home alone by thermopile array sensor." pp. 2042-2047.
[24] Australasian-Health-Infrastructure-Alliance. "Australasian Health Facility Guidelines (AusHFG)," 24-12-2018, 2018.

APPENDIX 5: *PREDICTING OPTIMISATION OPPORTUNITIES FOR CLINICAL SPACE UTILISATION* (UNPUBLISHED)

Appendix Contents:

1) Unpublished paper on anonymised template

Author Contribution Table:

Author	Contribution
Tim McNabb	Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Visualisation, Funding Acquisition, Project Administration
Prof. Trina Myers	Conceptualization Supervision, Writing – Review & Editing, Resources
Dr. Kristin Wicking	Conceptualization Supervision, Writing – Review & Editing, Resources
A. P. Rudolf Schnetler	Formal Analysis, Validation, Writing – Original Draft
Nicholas Barty	Formal Analysis, Software, Data Curation
Peter Pannam	Formal Analysis, Software, Data Curation
Alicia Libera	Visualisation, Software
Jordan Togo	Visualisation, Software
Ben Crowley	Writing – Original Draft

Predicting Optimisation Opportunities for Clinical Space Utilisation

Author 1 - TBC[1], Author 2 - TBC[2], Author 3 - TBC[3], Author 4 - TBC[4], Author 5 - TBC[5],

Abstract:

Can machine learning be used to predict optimisation opportunities for clinical space utilisation? This research seeks to demonstrate the capacity of machine learning on 2.78 million clinical occupancy data points to support future optimisation of clinical space utilisation. Increasing clinical space utilisation leads to reduced infrastructure expansion and/or reconfiguration. Previous research demonstrated the capacity of Internet of Things (IoT) technology to identify low historic occupancy periods; future utilisation prediction remained a challenge. Machine learning algorithms are applied to 24 months of historical occupancy data previously gathered by privacy-preserving IoT devices in a live public-healthcare environment. Predicted data was visualised via. graphical interface, and user-manipulated through time and location filters. Preliminary results demonstrate the capacity for machine learning to identify future optimisation opportunities for clinical space utilisation, achieving accuracies of 82% using a 'K Nearest Neighbours' algorithm. The resultant data-

---

[1] Author 1 (🖂)
Affiliation, Location
e-mail: a@b.com

[2] Author 2(🖂)
Affiliation, Location
email: a@b.com

[3] Author 3(🖂)
Affiliation, Location
email: a@b.com

[4] Author 4
Affiliation, Location
email: a@b.com

[5] Author 5
Affiliation, Location
email: a@b.com

dashboard combined human experience/intuition with model predictions supporting dynamic exploration of future clinical occupation patterns. Previous research demonstrated the capacity of IoT devices to support identification of historic occupancy gaps. This research demonstrates improved capacity for resource planning to improve consumer experience, reduce reliance on more intensive/expensive downstream services, and lower healthcare costs.

1 Introduction

Healthcare systems operate many interconnected services simultaneously. These services each consume resources through interconnected chains of supply and demand. Delays in one service can cascade delay-effects through other services, reducing timely access to healthcare services for consumers. Managing the consumption and utilisation of clinical resources is critical to the sustainable operation of outpatient clinics. The physical healthcare environment contains and enables the delivery of nearly all healthcare services. Despite this criticality, research focused on optimising utilisation of spatial clinical resources is under-represented in the literature.

Optimising clinical activity scheduling using the tools of machine learning has becoming increasingly common across the healthcare system. Recently, these tools have been applied to scheduling outpatient appointments (Tu-San et al., 2022), and predicting non-attendance rates (Giunta et al., 2023). Unfortunately, the intended use of clinical space has been demonstrated to inadequately reflect their actual utilisation (McNabb et al., 2018). Collecting historical data on clinical occupancy patterns are useful to explore opportunities lost, but identifying future clinical space vacancies would produce more actionable outcomes. Presented in this paper are results from the application of machine learning tools to historical clinic occupation data to predict future vacancies using a dynamic, human-centric data dashboard.

Optimising the use of clinical spaces allows increased occasions of care through limited spatial resources. Increasing healthcare services delivered through existing clinical spaces cam reduce wait times, diagnoses can be made earlier preventing further deterioration, and quality of life improvements can be realised for consumers. Improving access to healthcare services can reduce the duration and intensity of personal disability for consumers. For healthcare service providers, improved access means earlier treatment, reducing pressure on ambulance callouts, emergency services, inpatient services, etc.; all of which are more expensive episodes of care. Finally, optimising clinical space utilisation would reduce the demand to increase the number of available clinical spaces. Efficient use of existing clinical space increases available funds to spend on core healthcare service delivery, reduces acceleration of the systems’ carbon footprint and avoids unnecessary ongoing maintenance costs.

2 Methods

Previous research by McNabb et al. (2020) established a continuous occupancy dataset using ceiling-mounted IoT devices. These internet-connected devices were installed across a multi-disciplinary outpatient clinic in a tertiary teaching hospital in Australia for a period of 25 months. Data was stored in cloud-based repositories for downstream processing. The data was accessible through an application programming interface (API) provided by the sensor vendor.

The following high-level overview provides context for the subsequent detailed methodology. First, cloud-based occupancy data was downloaded through a *Docker* service to a local database. Through an iterative process, various 'default' machine learning models were trialled, followed by pre-processing using the tools of data science to identify appropriate algorithms for further training. Promising default models were trained and evaluated using additional scripts. Finally, occupancy predictions were calculated, and a bespoke user interface was created to visualise queries from human operators using a dynamic data dashboard. In future final versions, this loop will repeat regularly to keep predictions current. A high-level process flowchart of this process can be seen in Figure 1.

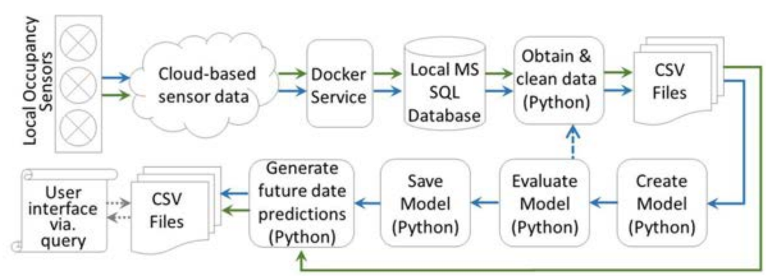


Figure 1 – High-level process flowchart from locally deployed IoT sensors to user interface in both generative (blue) and deployment (green) configurations

The methodology used by the research team closely follows the CRISP-DM methodology (Shearer, 2000) for data science project management. In an iterative process, numerous default machine learning models were applied using the *Python* programming language's *scikit-learn* toolkit to the full dataset to guide further pre-processing decisions. This open source, industry-standard toolkit was chosen due to the broad array of basic algorithms and pre-processing capacity available, in addition to extensive documentation and community support.

Using the proprietary API, data is 'pulled' through corporate firewalls for storage enabling commencement of data cleaning (pre-processing). Sensor data streamed into the cloud service contained, (1) the sensor ID, (2) room number, (3) datetime

(EPOCH), (4) meridian and (5) occupied status. In the final stage of the first round of pre-processing, a timeseries database was created/updated containing location and occupancy status (5), at a specific time (3) with additional metadata (1-2 and 4). The resultant 'clean' data was saved locally for the next stage of pre-processing. Initial results from default models suggested a *random forest* classifier provided the most promising results, though accuracy was relatively low. To improve accuracy of the initial model, additional standard pre-processing activities were undertaken through *scikit-learn*, guided by the typology of data in the cleaned dataset.

Additional pre-processing steps included min-max normalisation of time data, translation of date text into integers, and one-hot encoding to split categorical values into both categorical and binary features (Li, 2019). After pre-processing, default *scikit-learn* machine learning algorithms were re-applied to the dataset. Subsequent evaluation identified that a *k-nearest-neighbours* classifier (KNN) demonstrated the best balance between accuracy and speed. The latter was a dominant requirement due to limitations on available processing power, with accuracy considered suitable for proof-of-concept predictions. Improved computing hardware would have improved results supporting larger datasets, tests on imbalanced datasets, and experimentation with more complex algorithms to build more realistic models. Finally, data was split into 80/20 training/testing datasets and the standard model was fit onto the training data and tested against the test data.

The evaluation method used (both in preliminary and final assessment) were the *F1-Score*, *precision*, *recall*, and overall *accuracy*. Detailed definitions of the formulae comprising these industry-standard methods is beyond the scope of this paper. Once the predictive model had been trained and evaluated, a reference file of pre-populate predictions was created. This extensive database consisted of predicted occupancy for each period. Predicted values are re-calculated at regular intervals (when deployed) to incorporate new time-series data. Though this evaluation method was limited, with zero error analysis for failure analysis conducted, it was considered sufficiently rigorous for the proof-of-concept demonstration sought.

The database of predicted values was visualised by a bespoke user interface to support a human-centric understanding of opportunities presented by predicted vacancies within clinical spaces. This 'data dashboard' was created using the proprietary data analysis platform *Qlik Sense* accessed through a custom webpage using *Php Storm* to host the dashboard and maintain interactivity. The final complete suite of software was incorporated into a *Docker* container for ease of deployment and future maintenance.

3 Results

As described above, multiple basic machine learning models were trialled using the suite of Python scripts contained in in *scikit-learn* with improving success through an iterative process. The final classification and regression model using a KNN provided the most successful predictions at 82% accurate against the training dataset (see Table 1). The F1 score is the harmonic mean of the precision and recall of the model (Taha and Hanbury, 2015). The highest possible value for F1-score is 1, the lowest possible is 0.

Table 1 – Final confusion matrix exported from scikit-learn Python package

	Precision	Recall	F1-Score
Vacant	0.83	0.79	0.81
Occupied	0.80	0.84	0.82
		Accuracy	**0.82**

The r*andom forest* algorithm by comparison performed a close second with 78% accuracy. As noted by (Boateng et al., 2020) , KNN is relatively *"easy to implement and understand but has a major drawback of becoming significantly slow as the size of the data in use grows*". The limitation of KNN was reinforced by the hardware limitations available within the corporate computing envelope of the supporting hospital. The final bespoke program hard-coded the KNN classifier use, however allowances were made to substitute other classifiers as the dataset grows if computational resources remain constricted.

A custom data dashboard was created to allow non-technical staff to visually identify opportunities to optimise clinical space utilisation supported by humans providing local context to interpret the predicted outcomes. An example of Part 1 of the dashboard (historical data) is shown in Figure 2, demonstrating an ad-hoc data-matrix comparison of historical utilisation data for select consult rooms. Historical data was presented in the dashboard as a guide to support intuitive human querying of the large prediction dataset. Visual cues highlight potential opportunities for clinical space utilisation improvement. The relative percentage occupancy for the period shown is illustrated as gradations of colour within a matrix of all consult rooms in the clinic, with low-to-high utilisation visualised as lighter-to-darker colours.

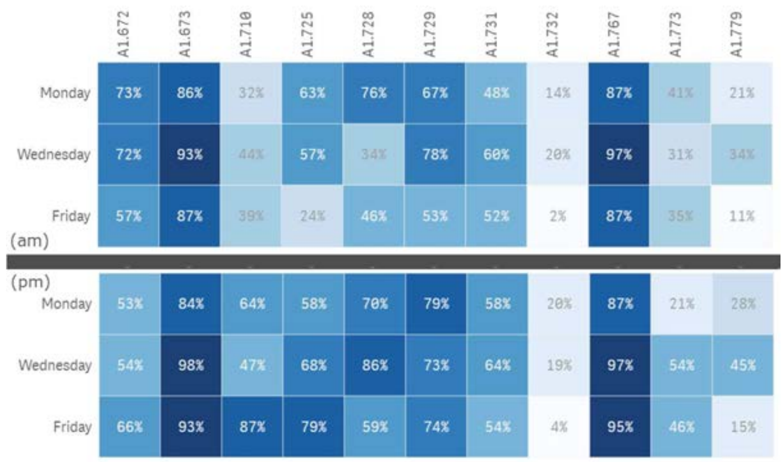


Figure 2 – Visual comparison of predicted occupation patterns for 11 clinical consult rooms, 3x days per week, separated into morning and afternoon sessions.

Part 2 of the dashboard presents predicted future utilisation rates based on user-defined parameters for room number, morning or afternoon clinic, day of the week, etc. A filtered sub-set of predictions for three consult rooms on Friday afternoons is presented in **Error! Reference source not found.**. Based on these filters, the model predicts an 85% chance that the three target spaces space will be vacant on Friday afternoons for the next year (15% utilisation), based on the previous 12 months of data.

Context provided by human operators is critical to accurately interpreting output from the current system. For example, operational reasons may exist for low occupancy rates (i.e., operational flexibility allowances) that can be then explored together for potential optimisation opportunities. This system allows front-line and executive decision-makers to manage demands for clinical space across or between

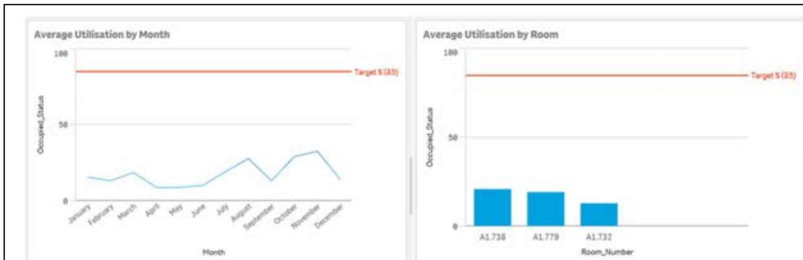


Figure 3 - Sample query results for 'average utilisation per month' and 'average utilisation by room' for 3x clinical consult rooms selected in the dashboard.

healthcare systems by using a data dashboard to identify predicted over or underutilised clinical spaces and adjust future planning accordingly.

4 Discussion

The combined capabilities of and machine learning algorithms and human operators can now be applied to the challenges of optimising clinical space utilisation within operational healthcare systems. Machine learning algorithms can be used to predict optimisation opportunities in large datasets that would otherwise be impossible for humans alone to identify. Similarly, the output from these algorithms is challenging to interpret without local operating knowledge providing context to the results. Without extensive experience in the field of Data Science, some experimentation and results analysis were required to determine the best 'fit' between these elements for each research project. However, the complexity of this experimentation and the knowledge required to train models is becoming easier as the tools become more powerful. The experimentation stages in the methodology above will increasingly become unnecessary as these tools develop.

The potential for service optimisation can be quantified to highlight its beneficial impact. Based on an average 'occasion of service' length of 15 minutes across the three consult rooms identified in Figure 2, the potential improvement equates to 39 additional occasions of service per week. Over the course of a year, the data suggests an additional 2,028 occasions of service are possible for a single outpatient clinic, in a single hospital. The costs to maintain these spaces are realised regardless of their relative occupation, in addition to human resources, consumables, and equipment costs. Also, additional occasions of care will improve access to healthcare services, potentially preventing deterioration leading to more expensive presentations in emergency departments, inpatient admissions, or ambulance callouts (Sheehan et al., 2022).

Researchers are encouraged to consider incorporating the power of machine learning into their data analysis toolkit as ML tools become increasingly powerful and easier for non-technical users to implement. Interdisciplinary research is a powerful approach to solve 'wicked problems' that single disciplines alone cannot resolve (Kumlien; and Coughlan, 2018). Research funding bodies and tertiary governance systems should foster these collaborations by providing networking and funding incentives to offset the additional complexity inherent in such endeavours (Stichler, 2009, Periyakoil, 2007).

For future research, additional machine learning models and larger datasets can be explored when additional computational resources are made available. If datasets were expanded across multiple years, it may be possible to account for seasonal or annual variability such as:

- reduced clinical bookings during school holidays,
- full-team absences during annual specialist conferences, and
- annual leave patterns of individual clinicians.

The methodology presented above resulted in a machine learning model that predicts future occupancy of target spaces through a human-friendly dashboard interface considered critical to the implementation of the algorithms. The CRISP-DM methodology could be applied to many sufficiently sized, robust datasets using preprocessing appropriate to the available data types (Schröer et al., 2021). The accuracy of the prediction model demonstrated through this paper is considered sufficient to fulfil the proof-of-concept intent. Improved prediction accuracy is expected if increased computational capacity (hardware) is applied, thereby increasing scope to explore the application of more advanced modelling and larger datasets.

5 Conclusion

Both frontline and executive decision-makers now have the tools to be able to query the use of their historical clinical space utilisation and predict future capacity for service delivery improvements. Baselines for minimum utilisation can be established and adjusted for local conditions. As demonstrated in this paper, clinical resource utilisation can be predicted. It is now possible to optimise clinical space utilisation, and the relative success of quality improvement initiatives can be objectively measured. Optimising the use of spatial clinical resources increases access to healthcare services, reduces wait times, improves the patient experience, and reduces the pressure on more expensive safety net services such as ambulance, emergency department, and inpatient care.

References

BOATENG, E. Y., OTOO, J. & ABAYE, D. A. 2020. Basic Tenets of Classification Algorithms K-Nearest-Neighbor, Support Vector Machine, Random Forest and Neural Network: A Review. *Journal of Data Analysis and Information Processing,* 8**,** 341-357.

GIUNTA, D. H., HUESPE, I. A., ALONSO SERENA, M., LUNA, D. & GONZALEZ BERNALDO DE QUIRÓS, F. 2023. Development and validation of nonattendance predictive models for scheduled adult outpatient appointments in different medical specialties. *The International Journal of Health Planning and Management,* 38**,** 377-397.

KUMLIEN;, A. C. D. A. & COUGHLAN, P. 2018. *Wicked problems and how to solve them* [Online]. TheConversation.com. Available:

https://theconversation.com/wicked-problems-and-how-to-solve-them-100047 [Accessed 30-03-2021 2021].

LI, C. 2019. Preprocessing methods and pipelines of data mining: An overview. *arXiv preprint arXiv:1906.08510*.

MCNABB, T., KRISTIN WICKING, D., TRINA MYERS, A. P. & LEI LEI, D. Optimizing Clinical Spatial Resources with IoT. Proceedings of the Australasian Computer Science Week Multiconference, 2020. 1-6.

MCNABB, T., MYERS, T., WICKING, K., LEI, L. & XIANG, W. 2018. Optimizing spatial healthcare assets with Internet of Things. *Health information science and systems,* 6**,** 11.

PERIYAKOIL, V. S. 2007. Taming wicked problems in modern health care systems. *Journal of palliative medicine,* 10**,** 658-659.

SCHRÖER, C., KRUSE, F. & GÓMEZ, J. M. 2021. A systematic literature review on applying CRISP-DM process model. *Procedia Computer Science,* 181**,** 526-534.

SHEARER, C. 2000. The CRISP-DM model: the new blueprint for data mining. *Journal of data warehousing,* 5**,** 13-22.

SHEEHAN, S., WICKING, K., CHAPMAN, M. & BIRKS, M. 2022. Profiling risk factors of patients diagnosed with type 2 diabetes awaiting outpatient diabetes specialist consultant appointment, a narrative review. *Collegian,* 29**,** 109-118.

STICHLER, J. F. 2009. Wicked problems in designing healthcare facilities. *JONA: The Journal of Nursing Administration,* 39**,** 405-408.

TAHA, A. A. & HANBURY, A. 2015. Metrics for evaluating 3D medical image segmentation: analysis, selection, and tool. *BMC medical imaging,* 15**,** 1-28.

TU-SAN, P., LEGRAIN, A., DE CAUSMAECKER, P. & LOUIS-MARTIN, R. 2022. A prediction-based approach for online dynamic patient scheduling: a case study in radiotherapy treatment. Ithaca: Cornell University Library, arXiv.org.

APPENDIX 6: *INTERVIEW INFORMATION SHEET AND CONSENT FORM*

Appendix Contents:

1) Information Sheet
2) Consent Form

INFORMATION SHEET

PROJECT TITLE: Improving Outpatient Experience and Reducing Operational Costs Through the use of Internet of Things Technology

You are invited to take part in a research project about your experiences as either a direct or indirect participant in research focused on how clinical spaces are used within the Townsville Hospital and Health Service (THHS), and the experience of occupants of clinical spaces about being observed by two different types of data gathering techniques: human observation and manual data recording vs. electronic sensor device observation and automatic data recording.

This study is being conducted by Principal Investigator Tim McNabb, and an inter-disciplinary professional team of educators at James Cook University and was funded by a grant from the THHS' Study, Education, Research Trust Account Funding Scheme (SERTA).

If you agree to participate in this research, you will be invited to be interviewed. With your consent, interviews will be digitally recorded and transcribed, and should only take approximately 30 minutes. The interview will be conducted in a designated meeting room within the THHS. Taking part in this research is voluntary and you can stop taking part in the research at any time without explanation or prejudice.

There are no foreseeable risks to the participants, other than the time and inconvenience of participating in an interview.

Your responses and contact details will be strictly confidential. The de-identified data from the interview will be used in research publications, presentations at professional conferences and reports to the funding body (THHS SERTA administrators). You will not be personally identified in any way in these publications.

If you have any questions about the study, please contact the Principal Investigator, Tim McNabb or call on

Principal Investigator: Mr. Tim McNabb
PhD Candidate, James Cook University
Phone:
Email: tim.mcnabb@my.jcu.edu.au

IMPROVING OUTPATIENT EXPERIENCE AND REDUCING OPERATIONAL COSTS THROUGH THE USE OF INTERNET OF THINGS (IOT) TECHNOLOGY

THHS Approved Ethics Application: HREC18QTHS109_1

Consent to take part in research

- I ___________________ voluntarily agree to participate in this research study.
- I understand that even if I agree to participate now, I can withdraw at any time or refuse to answer any question without any consequences of any kind.
- I understand that I can withdraw permission to use data from my interview within two weeks after the interview, in which case the material will be deleted.
- I have had the purpose and nature of the study explained to me in writing and I have had the opportunity to ask questions about the study.
- I understand that participation involves participating in a one-on-one interview with the researcher in a quiet space requiring approximately 15 minutes of my time
- I understand that I will not benefit directly from participating in this research.
- I agree to my interview being audio-recorded.
- I understand that all information I provide for this study will be treated confidentially.
- I understand that in any report on the results of this research my identity will remain anonymous. This will be done by changing my name and disguising any details of my interview which may reveal my identity or the identity of people I speak about.
- I understand that disguised extracts from my interview may be quoted in upcoming publications such as conference presentations, published papers, a written thesis of the researcher and similar academic purposes.

- I understand that if I inform the researcher that myself or someone else is at risk of harm they may have to report this to the relevant authorities - they will discuss this with me first but may be required to report with or without my permission.

- I understand that signed consent forms and original audio recordings will be retained on THHS servers, located on the Douglas Campus of the Townsville Hospital protected by eHealth standard firewalls with access limited to the researcher and co-investigators for five years as per NHMRC requirements.

- I understand that a transcript of my interview in which all identifying information has been removed will be retained for five years

- I understand that under freedom of information legalisation I am entitled to access the information I have provided at any time while it is in storage as specified above.

- I understand that I am free to contact any of the people involved in the research to seek further clarification and information.

Tim McNabb, BArch, PhD Candidate, James Cook University (JCU)
Dr. Kristin Wicking, Senior Lecturer, College of Healthcare Sciences, JCU
A/Professor Trina Myers, Head – Information Technology, College of Science & Engineering, JCU

Signature of research participant

-- ----------------

Signature of participant Date

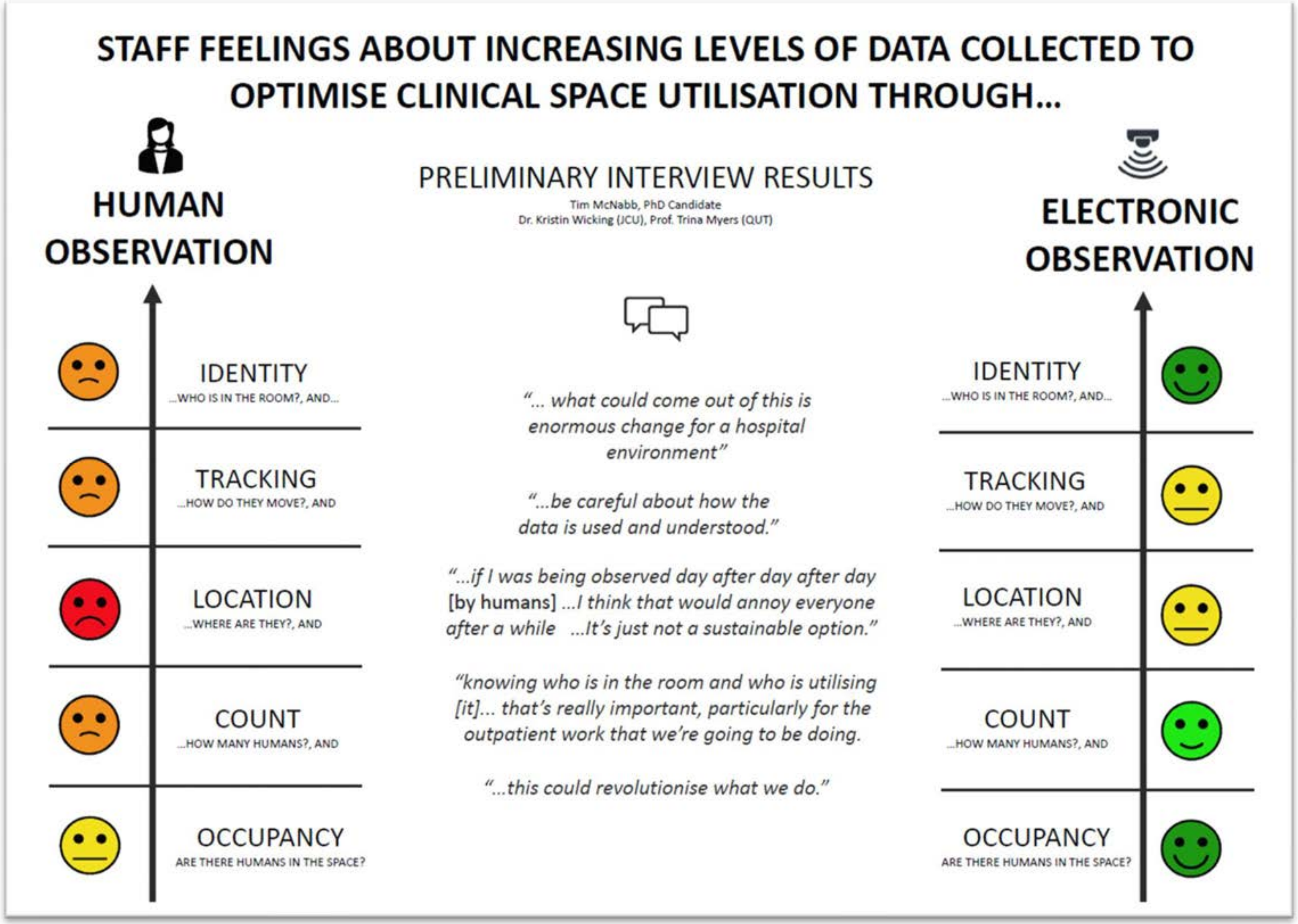
Signature of researcher

I believe the participant is giving informed consent to participate in this study

--- ----------------------

Signature of researcher Date

APPENDIX 7: PRELIMINARY INTERVIEW RESULTS ABOUT WORKING IN SMART HEALTH BUILDINGS: HOW DO HEALTH STAFF FEEL ABOUT ELECTRONIC AND MANUAL DATA GATHERING IN HEALTHCARE SPACES? (PRESENTATION)



APPENDIX 8: *FULL SURVEY* (OPTIMISED FOR ELECTRONIC DEVICES)

Title Page

USING TECHNOLOGY TO OPTIMISE USILITASION OF HEALTHCARE SPACES
(Survey Version 3 on 25 July 2020)

SURVEY INFORMATION SHEET (Version 2 on 25 July 2020)
You are invited to take part in a survey exploring how healthcare staff feel about working in Clinic Rooms being observed by various sensor technologies to understand patterns of use. The goal of this research is to improve the utilisation of Clinic Rooms while balancing the need for information versus the experience of staff.

This survey is being conducted by Principal Investigator Tim McNabb as part of his Doctorate of Philosophy, supervised by an inter-disciplinary team comprised of Dr. Kristin Wicking and Professor Trina Myers of James Cook University (JCU). This research has received funding from the THHS' Study, Education Research Trust Account Funding Scheme (SERTA). This research is being undertaken in accordance with an approved Ethics proposal (THHS HREC18QTH109-1) and JCU (H6999).

No personally identifiable information will be collected in this survey. Data collected will be used in the doctoral thesis, research publications, presentations at professional conferences, and reports to funding bodies. If you have any questions about the survey or research, please contact the Principal Investigator:

Tim McNabb
PhD Candidate, James Cook University
Phone:
Email: tim.mcnabb@my.jcu.edu.au

If you have any questions about the ethical conduct of this study, please email the THHS Ethics committee: TSV-Ethics-Committee@health.qld.gov.au for assistance.

If you consent to participate in this survey after reading this information sheet, please indicate 'yes' to the first question in the survey.

Thank you for your time.

Do you agree to participating in this survey?

Yes

No

Block 7

USING TECHNOLOGY TO OPTIMISE UTILISATION OF CLINICAL SPACES

The aim of this research is to optimise the use of clinical spaces using technology (sensors). Improving how clinic rooms are used may result in improved access to healthcare services by our consumers, and may reduce pressure to build or renovate new clinical spaces.

Human activity data in clinical spaces can be gathered through a variety of sensors, though not all are appropriate for use in clinical environments. These sensors can be broadly placed into (at least) five categories, each one gathering data to answer increasingly complex questions, such as:

SENSOR CATEGORY	QUESTIONS ANSWERED
1. Presence	Is the room occupied or vacant?

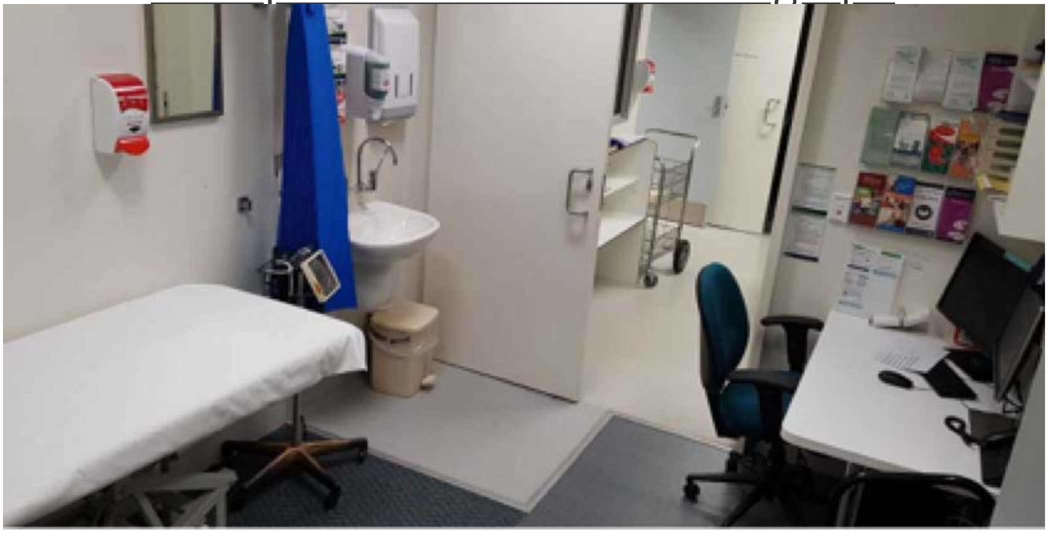
2. Count	How many people are in the room?
3. Location	Where are the people in the room?
4. Tracking	How do people move in the room?
5. Identity	Who are the people in the room?

The answer in each category contains the answers to all previous categories. For example, if you know how many people are in the Clinic Room (i.e. Count = 3) you also know if the room is occupied or not (i.e. Occupation Status = occupied).

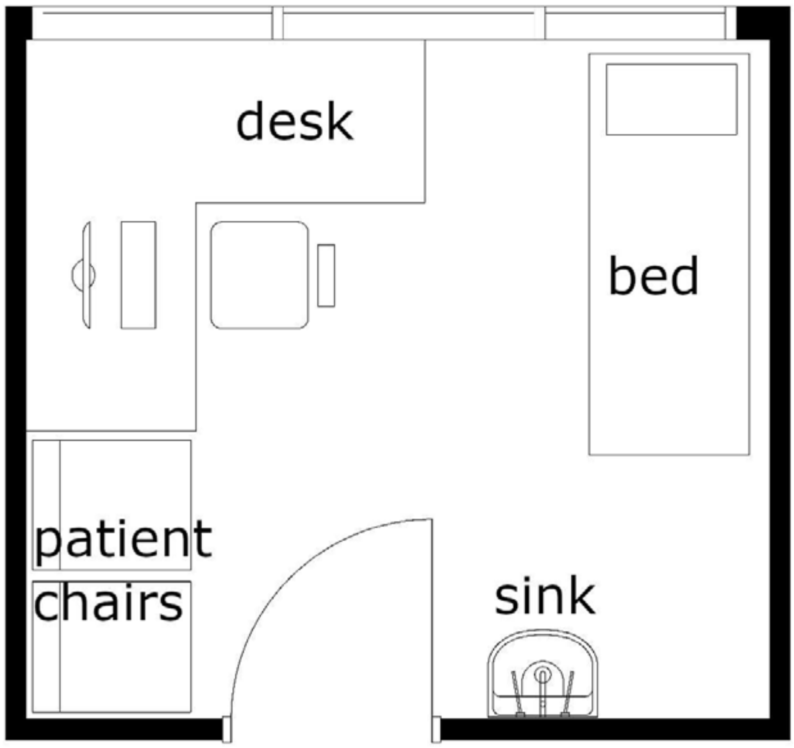
This survey seeks to identify how THHS staff feel about technologies in these categories being used in clinic rooms. Two questions will be asked about each category of sensor technology, seeking to understand:

How appropriate do staff feel the sensor technology in each category is for use in clinical environments?
How comfortable are staff working in clinic rooms being monitored by each category of sensor technology?

Example Clinic Room 1: Photograph



Example Clinic Room 2: Floor Plan

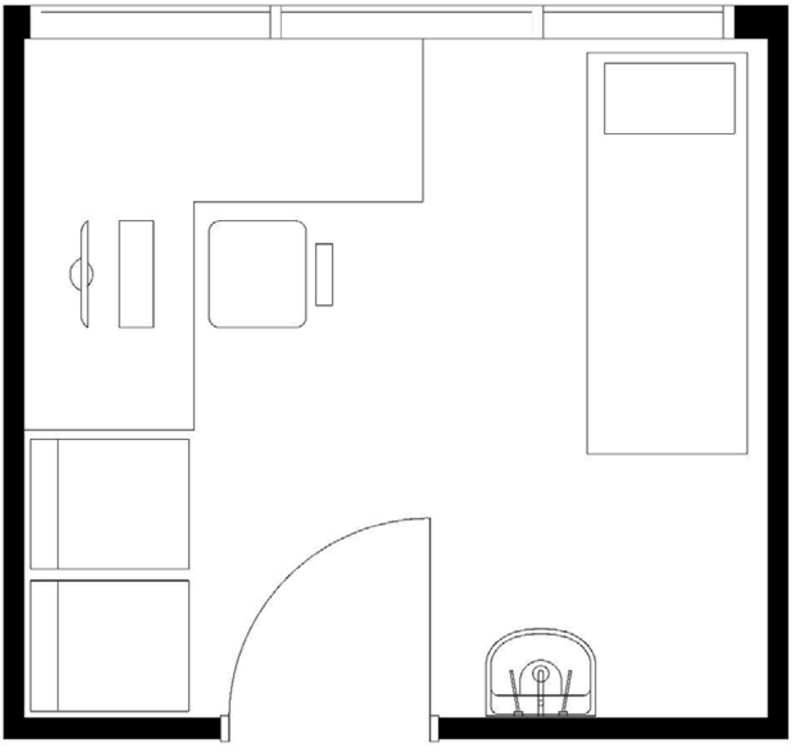


Category 1 - Presence

PRESENCE

Presence sensor technology can identify (only) if a clinic room is 'occupied' or 'vacant'

(sensors report that the clinic room below is occupied by one or more people)



How appropriate do you feel it is to use this sensor technology to determine if clinic rooms are *occupied* or *vacant*?

Extremely appropriate

Somewhat appropriate

Neither appropriate nor **in**appropriate

Somewhat **in**appropriate

Extremely **in**appropriate

How comfortable would you be working in clinic rooms that are monitored by this sensor technology which can determine if rooms are *occupied* or *vacant*?

Extremely comfortable

Somewhat comfortable

Neither comfortable nor **un**comfortable

Somewhat **un**comfortable

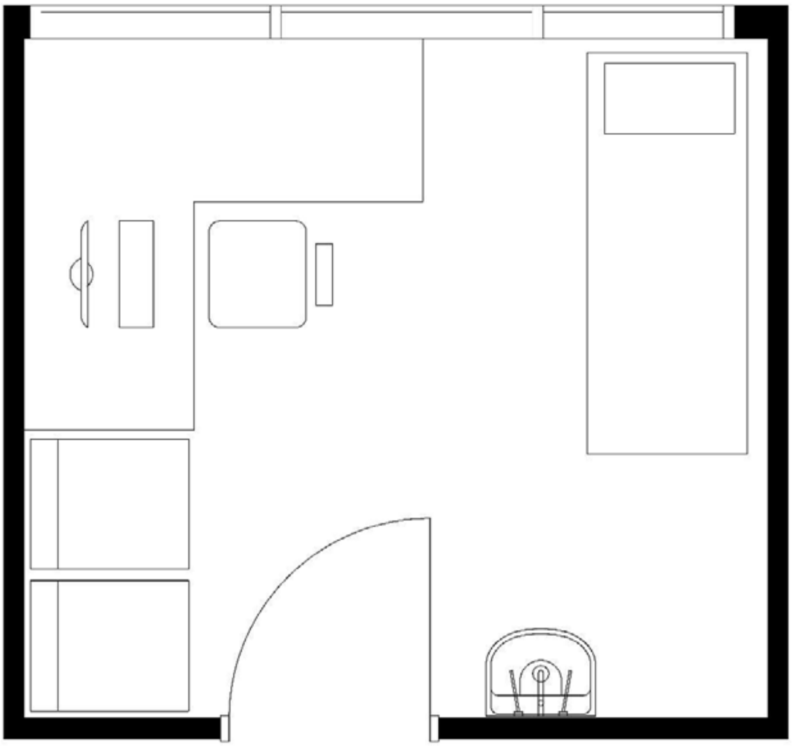
Extremely **un**comfortable

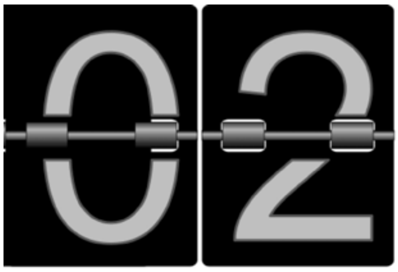
Category 2 - Count

COUNT

Counting sensor technology can identify how many people are present in clinic rooms.

(sensors report this room is occupied by two people)





How appropriate do you feel it is to use counting sensor technology to determine how clinic rooms are used?

Extremely appropriate

Somewhat appropriate

Neither appropriate nor **in**appropriate

Somewhat **in**appropriate

Extremely **in**appropriate

How comfortable would you be working in clinic rooms that are being monitored by counting sensor technology?

Extremely comfortable

Somewhat comfortable

Neither comfortable nor **un**comfortable

Somewhat **un**comfortable

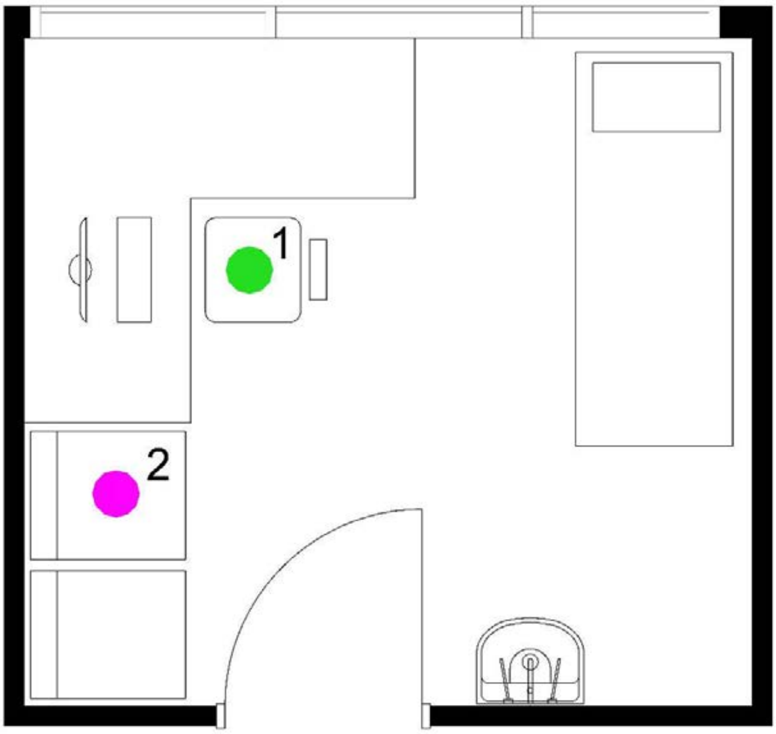
Extremely **un**comfortable

Category 3 - Location

LOCATION

Location sensor technology can identify where each person is in the clinic room.

(eg. There are humans in this room at locations 1 (green) and 2 (purple.))



How appropriate do you feel it is to use location sensor technology to determine how clinic rooms are used?

Extremely appropriate

Somewhat appropriate

Neither appropriate nor **in**appropriate

Somewhat **in**appropriate

Extremely **in**appropriate

How comfortable would you be working in clinic rooms that are being monitored by location sensor technology?

Extremely comfortable

Somewhat comfortable

Neither comfortable nor **un**comfortable

Somewhat **un**comfortable

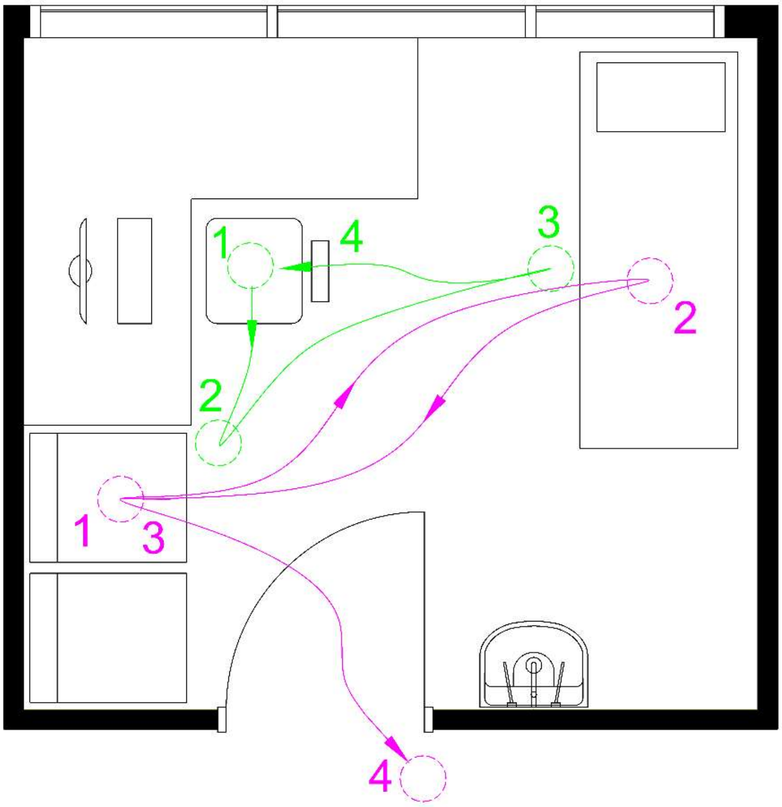
Extremely **un**comfortable

Category 4 - Tracking

TRACKING

Tracking sensor technology can identify human travel paths in the clinic room

(eg. Two humans traveled along the green and purple paths in the room below)



How appropriate do you feel it is to use tracking sensor technology to determine how clinic rooms are used?

Extremely appropriate

Somewhat appropriate

Neither appropriate nor **in**appropriate

Somewhat **in**appropriate

Extremely **in**appropriate

How comfortable would you be working in clinic rooms that are being monitored by tracking sensor technology?

Extremely comfortable

Somewhat comfortable

Neither comfortable nor **un**comfortable

Somewhat **un**comfortable

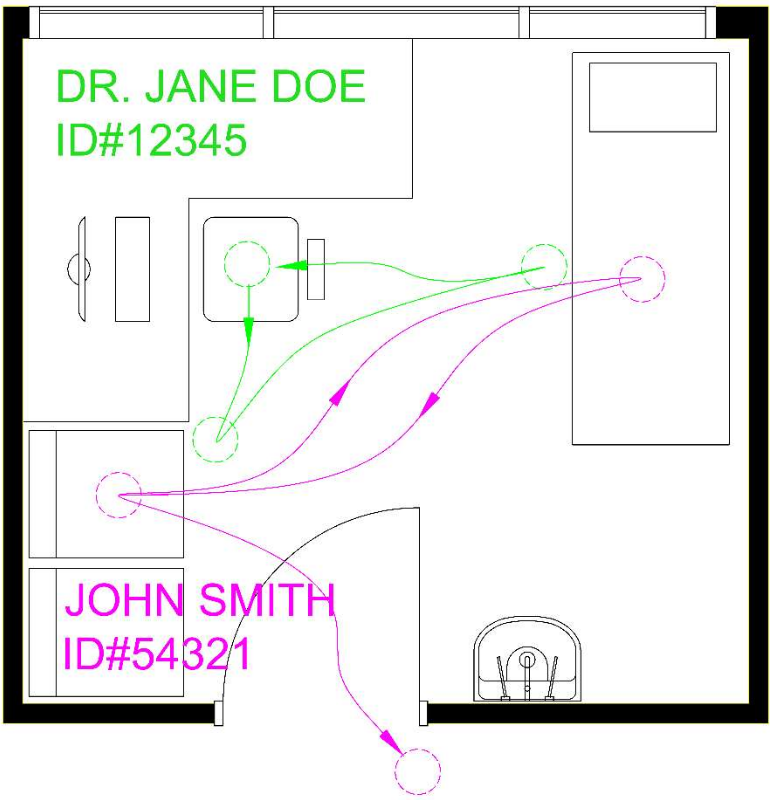
Extremely **un**comfortable

Category 5 - Identity

IDENTITY

Identity sensor technology can identify the specific individuals in the room while also tracking their paths of travel.

(eg. Dr. Jane Doe and consumer John Smith traveled along the green and purple paths in this room)



How appropriate do you feel it is to use identity sensor technology to determine how clinic rooms are used?

Extremely appropriate

Somewhat appropriate

Neither appropriate nor **in**appropriate

Somewhat **in**appropriate

Extremely **in**appropriate

How comfortable would you be working in clinic rooms that are being monitored by identity sensor technology?

Extremely comfortable

Somewhat comfortable

Neither comfortable nor **un**comfortable

Somewhat **un**comfortable

Extremely **un**comfortable

Demographics

DEMOGRAPHICS

This last section of the survey contains demographic questions to help us understand how opinions vary across groups of individuals.

Which answer best describes your primary role/department at the Townsville Hospital and Health Service?

Doctor

Nurse

Administration

Operational Services

Engineering and Maintenance Services

Information Communication Technology

Other (please describe)

What is your age?

0 10 20 30 40 50 60 70 80 90 100

What is the highest level of education you have completed?

(*categories from the Australian Public Service Commission)*

Less than Year 12 or equivalent

Year 12 or equivalent (HSC/Leaving cert)

Vocational Qualification

Associate Diploma

Undergraduate diploma

Bachelor degree (including honours)

Postgraduate diploma (includes graduate certificates /graduate diplomas)

Masters Degree

Other (please describe)

What gender to you identify with?

Male

Female

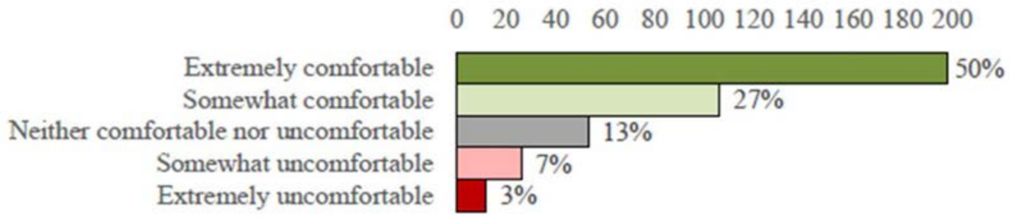
Other (please describe)

Prefer not to answer

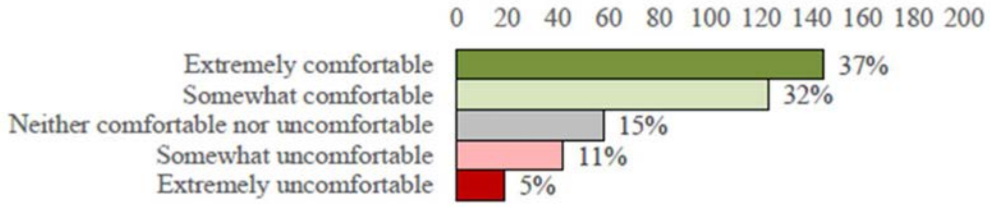
APPENDIX 9: *SURVEY RESULT DATA*

Survey Outcomes – Acceptability (comfort)

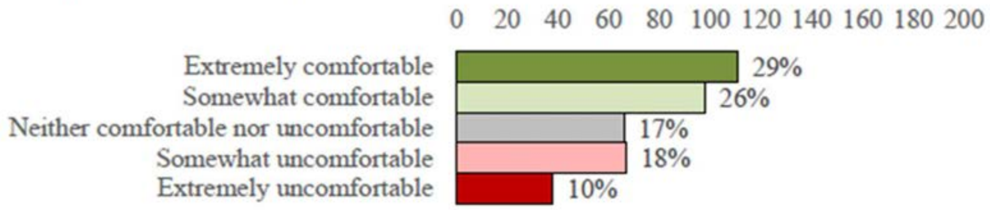
a) *acceptability* (comfort), occupancy data:



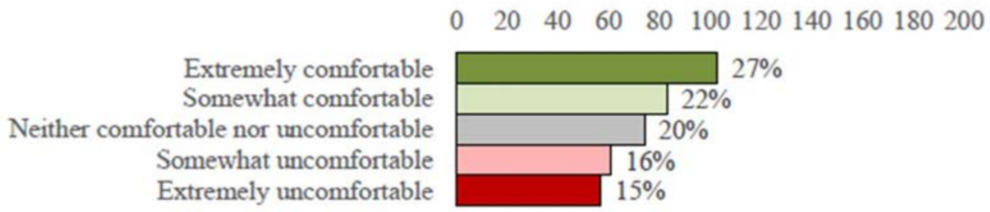
b) *acceptability* (comfort), count data



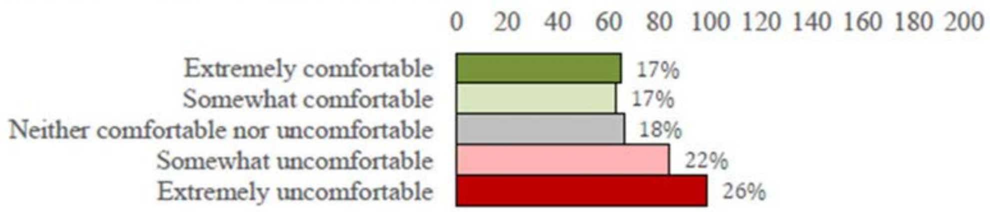
c) *acceptability* (comfort), location data



d) *acceptability* (comfort), tracking data

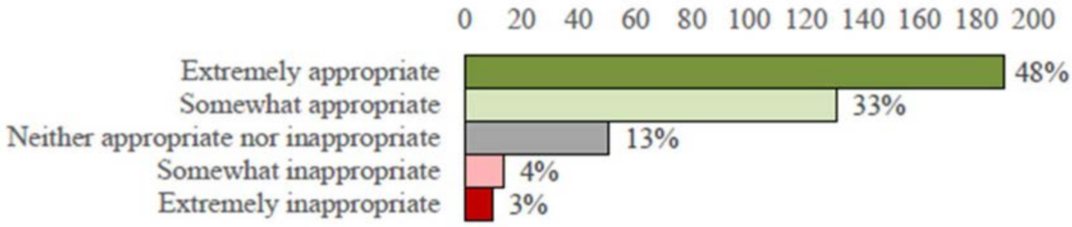


e) *acceptability* (comfort), identity data

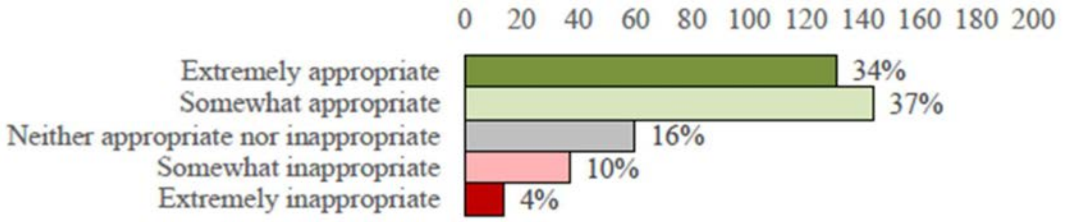


Survey Outcomes – Appropriateness

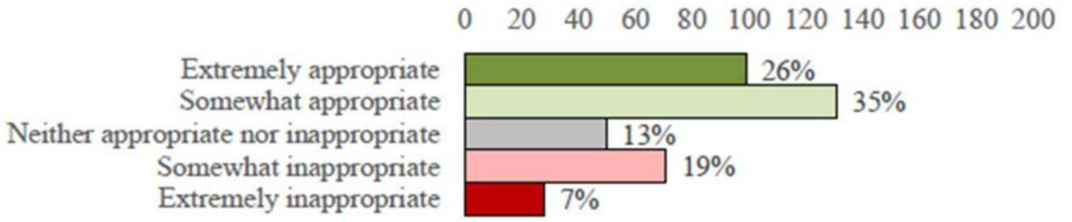
a) *appropriateness* of occupancy data gathering



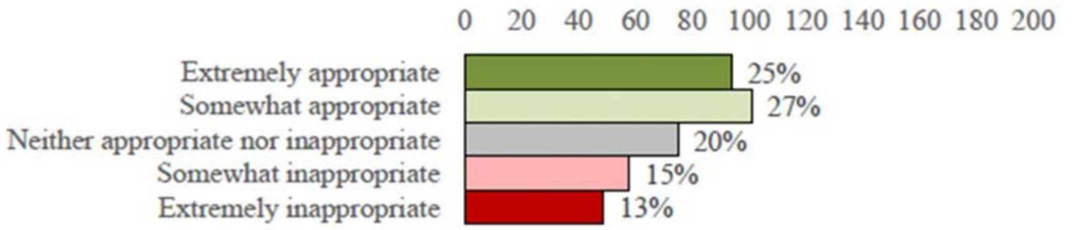
b) *appropriateness* of count data gathering



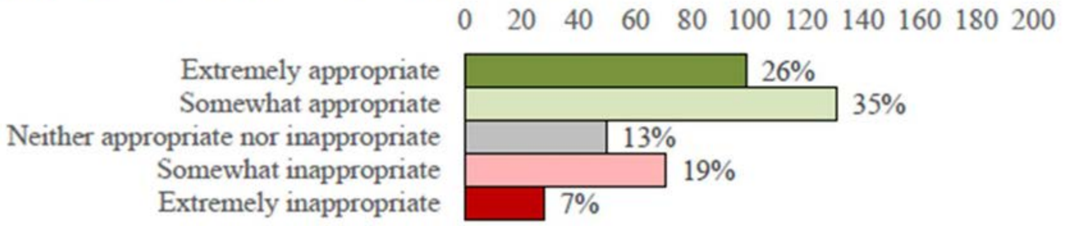
c) *appropriateness* of location data gathering



d) *appropriateness* of tracking data gathering

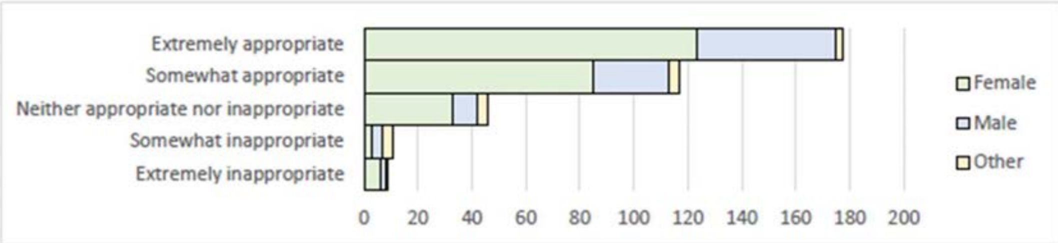


e) *appropriateness* of identity data gathering

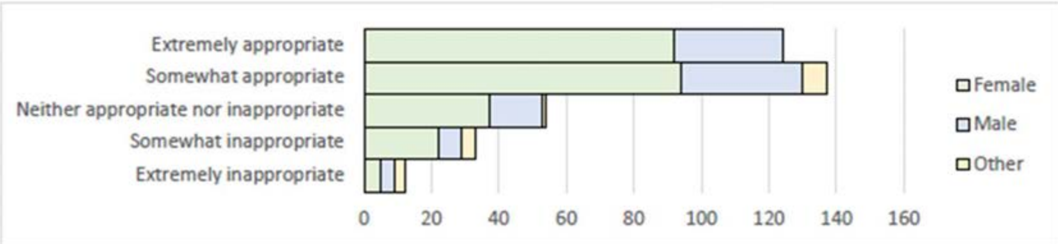


Survey Outcomes – Demographics Comparison

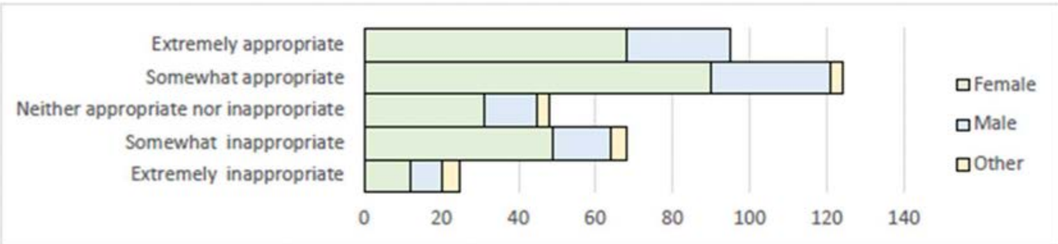
OCCUPANCY – APPROPRIATE / GENDER IDENTITY



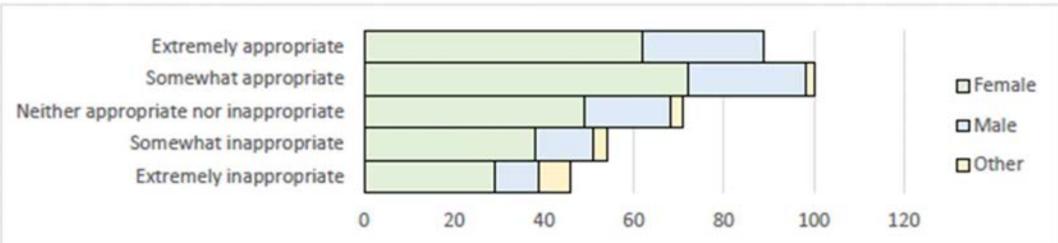
COUNT – APPROPRIATE /GENDER IDENTITY



LOCATION – APPROPRIATE/GENDER IDENTITY

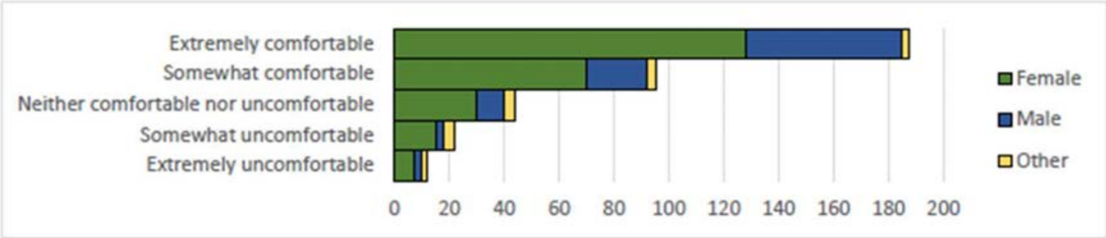


TRACKING – APPROPRIATE/GENDER IDENTITY

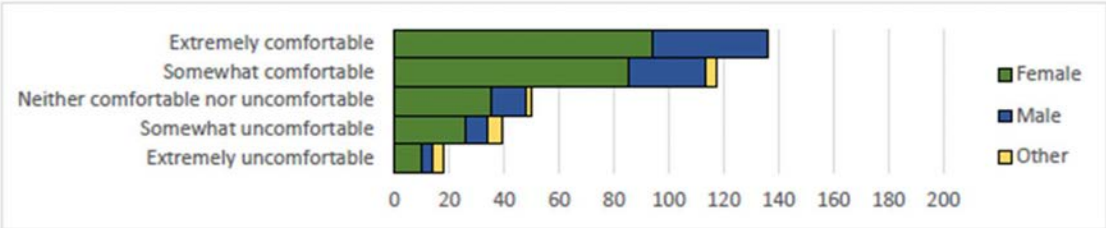


IDENTITY – APPROPRIATE/GENDER IDENTITY

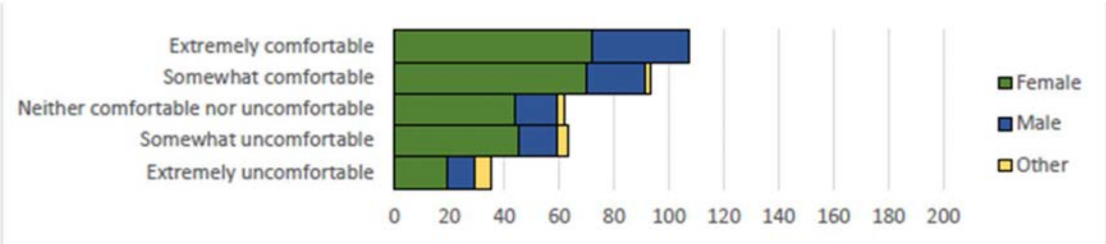
OCCUPATION – COMFORTABLE/GENDER



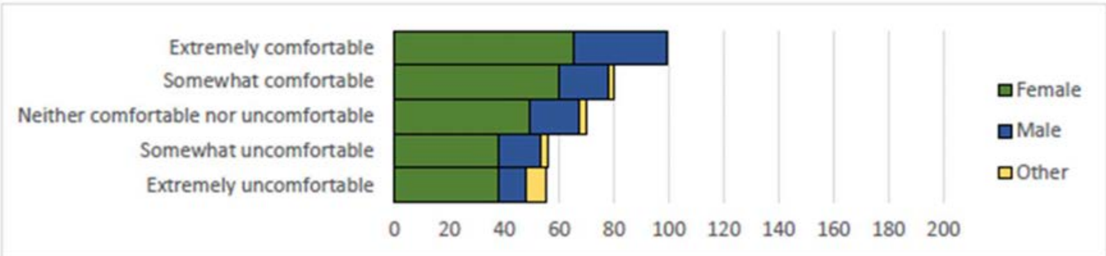
COUNT – COMFORTABLE/GENDER



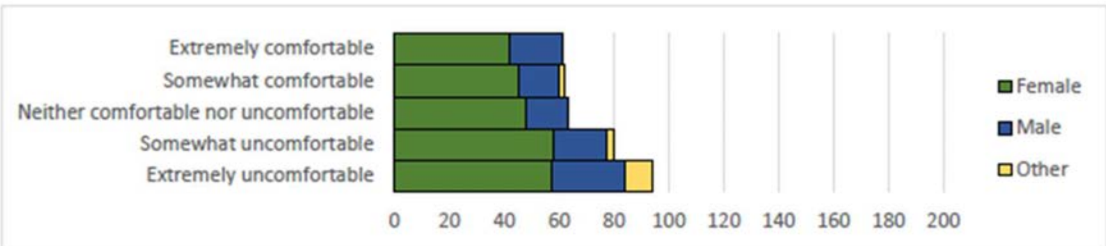
LOCATION – COMFORTABLE/GENDER



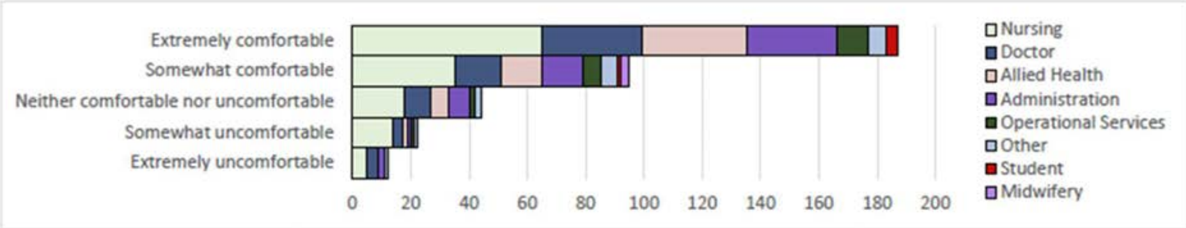
TRACKING – COMFORTABLE/GENDER



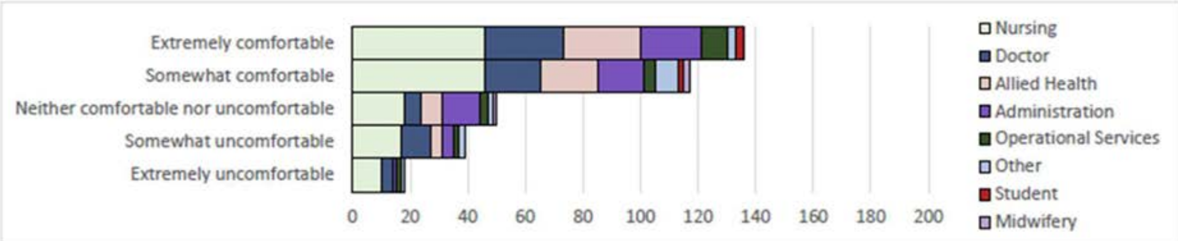
IDENTITY – COMFORTABLE/GENDER



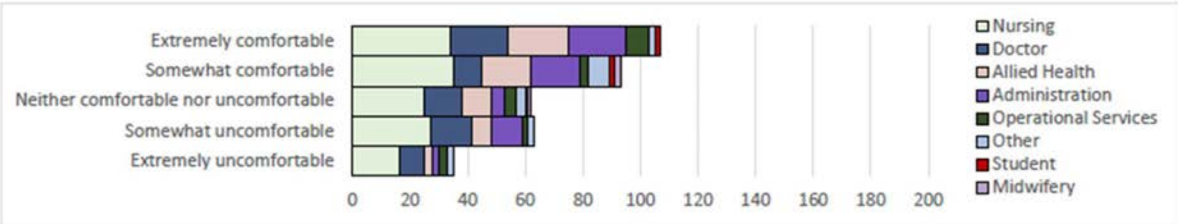
OCCUPATION – COMFORTABLE/ROLE



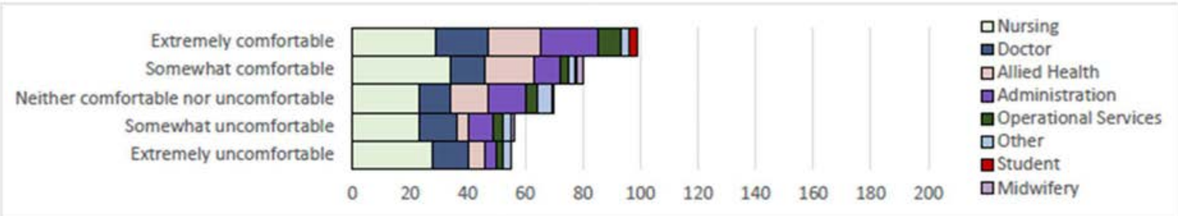
COUNT – COMFORTABLE/ROLE



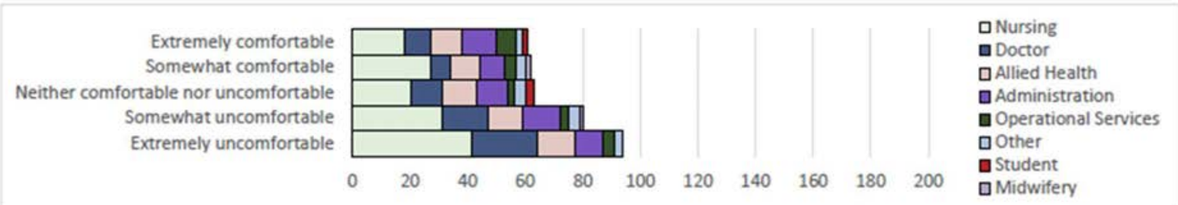
LOCATION – COMFORTABLE/ROLE



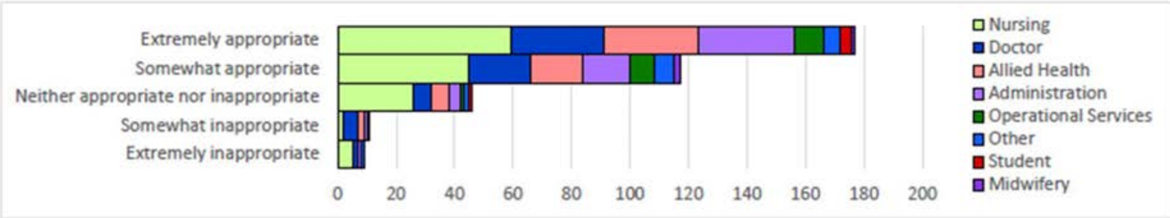
TRACKING – COMFORTABLE/ROLE



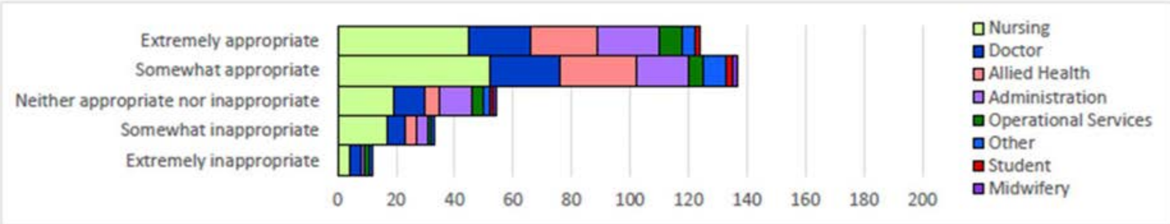
IDENTITY – COMFORT/ROLE



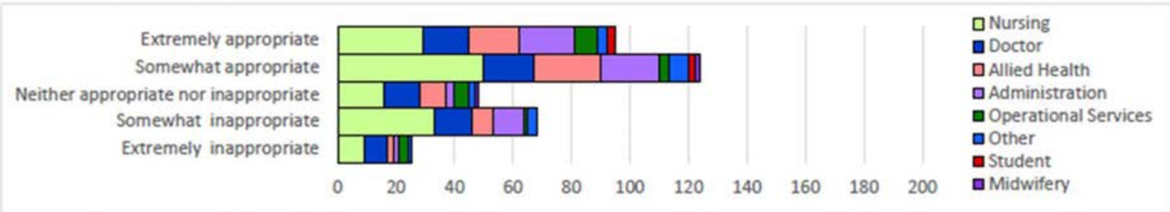
OCCUPATION – APPROPRIATE/ROLE



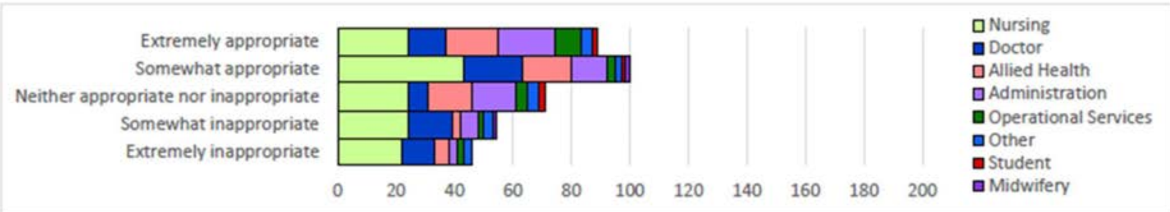
COUNT – APPROPRIATE/ROLE



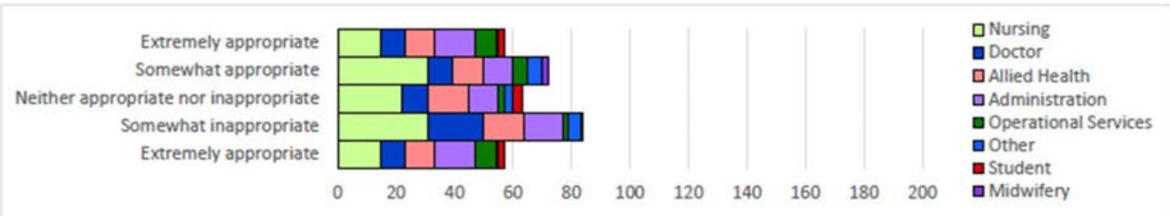
LOCATION – APPROPRIATE/ROLE



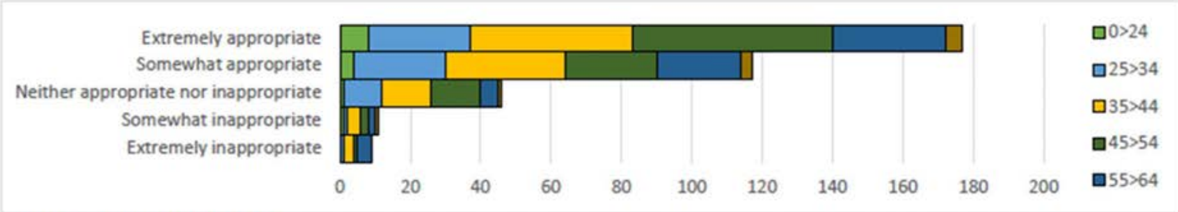
TRACKING – APPROPRIATE/ROLE



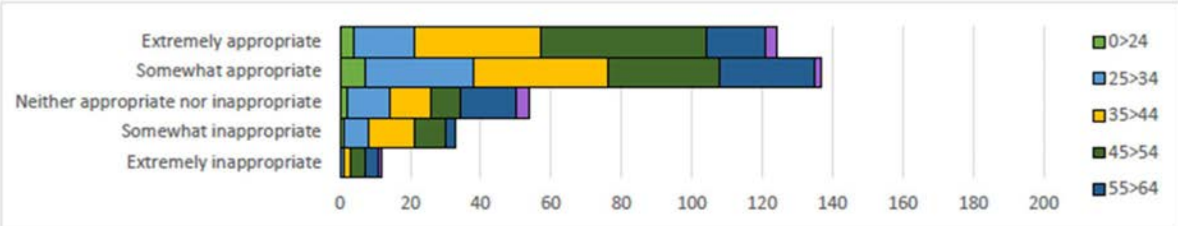
IDENTITY – APPROPRIATE/ROLE



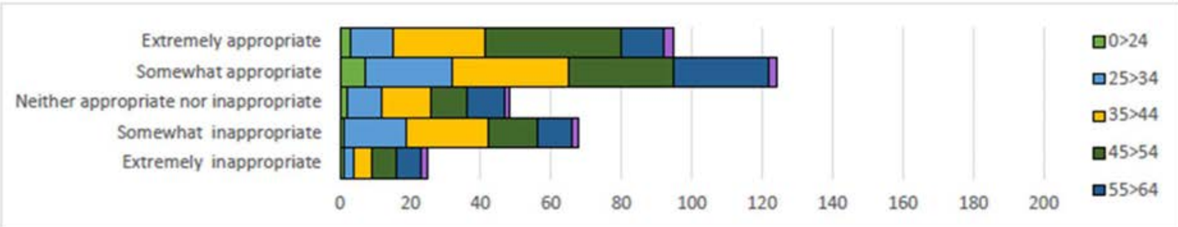
OCCUPANCY – APPROPRIATE/AGE - PARTICIPANTS



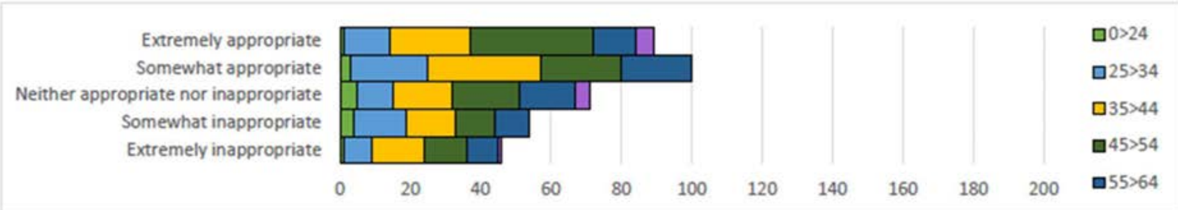
COUNT – APPROPRIATE/AGE



LOCATION – APPROPRIATE/AGE



TRACKING – APPROPRIATE/AGE



IDENTITY – APPROPRIATE/AGE