Mackenzie Health: An Analysis of a “Smart” Internet of Things Approach to Healthcare

by

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Institute of Biomaterials & Biomedical Engineering
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Abstract

Background: Providing good quality patient care is challenging in today’s busy healthcare environment. Faster response times to patient calls have been shown to reduce the risk of falls, length of stay (LOS), and improve patient satisfaction. One hospital, Mackenzie Health has implemented a new “smart’ pilot unit with various Internet of Things (IOT) connected technologies with the goal of improving care. **Methods:** Data collected by the new system was statistically compared to historic data to determine the impact. A discrete simulation model was also built to explore further potential improvements in how patient calls could be routed. **Results:** Mean and median call response times improved by ~5% and ~31% respectively. Employing alternative call routing strategies can further improve response times and nurse travel distances. **Conclusion:** This study lends evidence to the argument that the adoption of ubiquitous smart technology in healthcare can improve operations and reduce inefficiencies.

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List of Abbreviations

Abbreviation	Explanation
CAP	Call Alternate Pod
CDF	Cumulative Density Function
CPOE	Computerized Physician Order Entry
DES	Discrete Event Simulation
EMR	Electronic Medical Records
HOB	Head of Bed
IOHT	Internet of Health Things
IOT	Internet of Things
KPIs	Key Performance Indicators
LOS	Length of Stay
PCA	Personal Care Aid
PDA	Personal Data Assistant
RFID	Radio Frequency Identification
RN	Registered Nurse
RPN	Registered Practical Nurse
WOW	Workstation-On-Wheels

Chapter 1

1 Introduction

Hospitals all face the challenges of providing effective, safe, and high-quality patient care with the limited resources available to them. Hospitals also must contend with further considerable constraints on the healthcare system: increasing costs, public health budget freezes or reductions, nursing shortages, as well as an aging population and increasing demand for hospital services [1][2][3].

As a result, many hospitals are forced to try and do more with less – this in turn leads to greater workload demands placed on clinical staff, particularly nurses. Nurses spend the majority of their time dealing directly with patients [4], and are thus often referred to as on the "front lines" of healthcare. This increase can result in lower job satisfaction and staff retention; Aiken et. Al found a 15% reduction in job satisfaction per additional patient added to a nurse's care, greater burnout (23% greater burnout rate per additional patient), increased risk of errors and, as expected, a decline in the overall quality of care provided (there is a 7% greater risk of mortality and "failure to rescue" for each additional patient added to a nurse's care) [5],[6].

Nursing work is complex and requires a variety of different tasks to be completed. Nurses perform tasks such as: patient assessments, measuring vitals, documentation, administering medications, toileting, communicating and coordinating care with other clinicians [7].

Patient Call bell systems have been in use for decades and are a crucial tool for a patient to indicate their needs to nurses or to request assistance [8]. These requests can range from something simple such as needing a drink of water or an extra blanket, to reporting pain or other symptoms to nurses. Providing timely responses to call bells (and therefore patient needs) not only has the benefit of greatly improving patient experience but also has beneficial impacts on clinical outcomes (slower response times have been linked to increased Length Of Stay (LOS) and higher risk of falls among other measures) [9].

However, traditional implementations of call bell systems may lead to inefficiencies within the operation of the unit: there is redundancy in going to a patient room to find out their needs then having to go elsewhere to fetch something or communicate to other staff and return to the patient's room. For certain activities, nurses may need the assistance of other nurses (moving or transferring a patient) and this could lead to more wasted time and effort as nurses must move around the unit to try and find someone available to help. These unnecessary trips and "hunting and gathering" activities were found to consume as much as 6.6 % of a nurse's time [7].

One hospital in Ontario, Canada – Mackenzie Health is turning to new technologies to help eliminate these inefficiencies, reduce wasted time, improve workflows and change how nurses meet patient needs, while also potentially improving patient experience and clinical outcomes. They have established an "Innovation Unit", with the goal of trialing what is being dubbed the "Internet of Health Things" (IOHT) - a healthcare-related take on the Internet of Things (IOT). This pilot medical unit contains a new integrated patient call bell system and nurse location tracking system alongside other "smart" distributed technologies and devices. The unit's goal is to serve as a testbed for new technologies – to collect data and inform future iterations of these novel connected systems [10]. The new system has the potential to reduce inefficiencies, improve response times and quality of patient care on the unit.

1.1 Background

Mackenzie Health's Innovation Unit:

Mackenzie's innovation unit is a general medical unit with 36 beds which sees approximately 1,740 patients per year. Patient rooms usually contain two beds except for 3 larger rooms closest to the centrally-located nursing station, which contains 4 beds. There are also two single-bed infection control rooms with a double-door and alcove to allow nurses to suit up into masks and protective garments before entering the room. These are used as normal patient rooms when no infectious patients are present on the hospital unit.

As part of this pilot project to study the impact of advanced technology on patient care, Mackenzie Health has worked with medical technology vendors and project partners to deploy and connect various technologies including: staff Radio Frequency Identification (RFID) badges, “smart” patient beds, wall call stations, smartphone devices, and a “smart” networked hand-hygiene solution [11]. The following subsections will describe each of these components in more detail.

1.1.1 Staff Radio Frequency Identification (RFID) Badges

All staff are equipped with RFID badges. These contain a small chip, battery and integrated antenna that transmits a small wireless signal with a unique ID code that can be picked up by sensors strategically placed throughout the unit (Figure 1.1). The network of sensors throughout the ward can be used to triangulate the wearers position within the unit to within approximately 30cm (enough to accurately determine which room the wearer is in). The chip is low-powered, and battery life is approximately 2 years. This is the same technology that has been used in retail, security, anti-theft, and manufacturing for years.

Figure 1.1 - Example RFID Sensor and RFID Chip. Source: Adapted from [12]

1.1.2 “Smart” Patient Beds

These patient beds are similar in appearance to normal patient beds; however, they contain an array of sensors that can collect and transmit data to a centralized server. Figure 1.2 shows an example of a smart bed. Some of the data points collected by the beds include:

- **Guardrail state** (raised or lowered) – raised guardrails are important for preventing bed-related falls.
- **Head of Bed (HOB) angle measurement** – this is important for patients with respiratory difficulties as elevation can ease breathing effort.

Figure 1.2 - A "Smart" Patient Bed, and Touchscreen Interface. Source: Adapted from [13]

- **Patient weight** – the bed is equipped with pressure sensors that can automatically weigh patients, eliminating the need for a separate patient scale system and reducing the risk of lifting-related injuries by nursing staff.

The bed can also provide automatic notifications and alerts to staff:

- **Patient turn frequency reminder** – the bed can send reminders to nurses at regular intervals to shift a patient’s position to reduce the risk of pressure ulcers (bedsores).

- **Bed exit alarm** – A patient can be placed on “falls alert” meaning they are at high risk of falling and injuring themselves if they try to move about the unit unassisted. The bed can automatically detect (through its pressure sensors) if the patient begins to try and sit up or climb out of bed. At this point, the bed will activate an audible alarm as well as triggering the ceiling dome light and sending an alert to nurses in order to draw rapid assistance and hopefully prevent a possible fall.

- **Auto bed exit alarm disable/cancellation in nurse presence** – In order to prevent false bed exit alarms when nurses are moving or assisting patients a bed can suspend it’s falls alarm if it detects nursing staff in close proximity. The bed will then automatically re-engage the alarm after it detects staff have left the vicinity.

- **Integrated call button** – the final key piece of the bed system is an integrated patient call bell, referred to as the “pillow speaker”. This device allows patients to request assistance from their nursing staff. It also contains a speaker/intercom system, so nurses can remotely contact patients who have called and find out more about their needs, provide information about how soon they will be available to help, or even completely address the purpose of the call remotely (for example, if the patient just has a question that can be answered quickly). Figure 1.3 shows the pillow speaker call bell and its 3 types of call buttons for normal, bathroom or pain calls.

Figure 1.3 - The "Pillow Speaker" Call Bell with Instructional Card

1.1.3 Wall Call Stations & Mobile Devices

There are two ways for nurses to receive patient calls – through wall call stations located throughout the unit and at the nursing station, as well as through mobile devices issued to each staff member. These wall stations appear as large touch-screen intercom-style devices which light up and display which patient has called, the type of call, and their room/bed number (seen in Figure 1.4).

An advanced feature of the call stations is their integration with the RFID location system. This allows the system to send the call alert directly to the station that is closest to the assigned nurse of the patient who initiated the call. If that nurse moves to a different location before noticing or answering the call then the new nearest station will light up (i.e., effectively the call alert will “follow” the patient’s assigned nurse around the unit).

Figure 1.4 - Wall Call Station

The wall stations allow nurses to answer, “hold”, or dismiss or a call. When a nurse answers a patient call they have the option to talk to the patient via the integrated pillow speaker. This allows the nurse to find out the patient’s needs in advance without having to walk into the room directly. If the call has been dealt with remotely (e.g. just answering a quick question) the nurse can then dismiss the call – recording it as successfully answered.

The “hold” feature is meant for when nurses are busy and cannot answer the call immediately, they can temporarily silence the alerts. If the primary assigned nurse – a Registered Nurse (RN) or a Registered Practical Nurse (RPN), does not respond to a call alert within 60 seconds then the call is sent to the secondary assigned caregiver – usually the Personal Care Aid (PCA) working with that nurse. If the secondary caregiver does not respond within 60 seconds then the alert cycles back to the primary nurse, and this continues until the call is finally answered or dismissed. Furthermore, a call will automatically be recorded as answered if the nurse walks into the patient room.

Additionally, this new system allows nurses to contact each other directly; they can locate one another on the wall stations and either just view the other’s location, or also trigger a call to that nurse and use the intercom to communicate directly. This feature was particularly well-received by the many nurses the author spoke to during the course of this project, as it quickly allows them to request assistance from one another when, for instance, they need to move a patient or consult another nurse.

Working in conjunction with the wall stations are mobile smartphone devices. These devices provide the same functionality as the wall call stations, while also allowing nurses to receive lab test/bloodwork results remotely and more easily keep in contact with physicians and patient family members. The phones also allow nurses to be able to send text messages to physicians to report on patients or message other nurses.

According to nurses on the unit, the smartphones are used less frequently for answering patient calls, due to the fact that the phones are secured with a 16-digit passcode (the same unique one used by a nurse to log into the electronic medical record). The nurses stated that because of the smaller size of the unit it is often quicker to answer on the numerous wall stations, walk directly into the room if they are close by. This means that the phones have taken on the role of communicating and checking results externally with the unit, while the stations are used to communicate more within the unit. Nevertheless, these devices and their associated improvement in communication ability have the potential to reduce unnecessary travel around the unit.

1.1.4 Ceiling Dome lights

Ceiling dome lights are located above the door outside each patient room and are synced with the call bell system and will light up to indicate when a patient has requested assistance. They also have a “N” symbol as a quick indicator which lights up when a staff member is present in that room (seen in Figure 1.5). These provide an alternative way for nurses to be informed about patient calls without having to check their phones or the wall call station, however they are only effective if the nurses are in close visual proximity to the outside of the patient room.

Figure 1.5 - A Ceiling Dome Light

1.1.5 “Smart” Hand-hygiene Dispensers

The last part of the system is aimed at improving staff’s hand hygiene compliance is the use of “smart” hand hygiene stations located by the entrance to each patient room as well as inside. These are equipped with close-range motion and RFID sensors (as seen in Figure 1.6) to detect when the hand pump is used, and which staff member used it. The system not only records hand hygiene events, but also “missed” opportunities (i.e. if a nurse entered a patient room but did not wash their hands). Though there is additional logic built into the system so that multiple redundant hand washes are not required (e.g. if the nurse uses the station as they leave one patient room before immediately entering another they will not be counted as missing the second hand hygiene event.

Figure 1.6 – A “smart” Hand Hygiene Sensor

The impact of this part of the system on hand hygiene compliance is being covered by a separate piece of concurrent work, and as such will not be analyzed or discussed in further detail in this study.

As the unit is a testbed, the system was continuously undergoing updates, software patches, and various improvements over the course of the research project. Due to this the system's capabilities, accuracy and reliability improved over time.

1.2 Problem Definition

While this new system has the potential to improve operations on the unit and reduce wastes, the actual efficiency gains had yet to be quantified and compared to historic data. Furthermore, a new challenge brought to light by the system was the fact that nurses may have 5-6 (or more if night time) patients to attend to (as well as their many other tasks and duties), and often may be too busy to immediately answer a call.

As mentioned, if the primary care nurse does not respond to a call within 60 seconds the secondary caregiver is sent the call. However, if this staff member is also preoccupied then unfortunately the calling patient must wait until either the primary RN/RPN or PCA becomes available which could take some time. The risk here is that the patient may decide to get out of bed and move about unattended (particularly if it was a bathroom call) and greatly increase their risk of falls and injuries.

Additionally, the current call strategy does not take advantage of the full "smart" capabilities of the system, which could be further utilized. Alternative call routing strategies may be more effective at improving response times and the amount of direct care time nurses are able to provide, while reducing unnecessary travel.

The hospital management are particularly interested in potential solutions that can improve call response times and thus, patient satisfaction and quality of care while also reducing the chances that patients are waiting for long and then may decide to get out of their bed, risking a fall.

1.2.1 Key Metrics

Hospitals often utilize certain metrics or Key Performance Indicators (KPIs) to better quantify, understand and evaluate their processes [14][15]. Three key measures will be used to evaluate the impact that this new system has had on care in the unit, these are defined as follows:

1) ***Mean Response Time (t_r)*** [minutes] = Total time elapsed from the moment a patient call is placed to the time a nurse either enters patient room or answers the call remotely, averaged across all calls. The diagram shown in Figure 1.7 displays response time visually (Note: the diagram is illustrative, and the lengths shown do not indicate actual proportions of time that each stage takes).

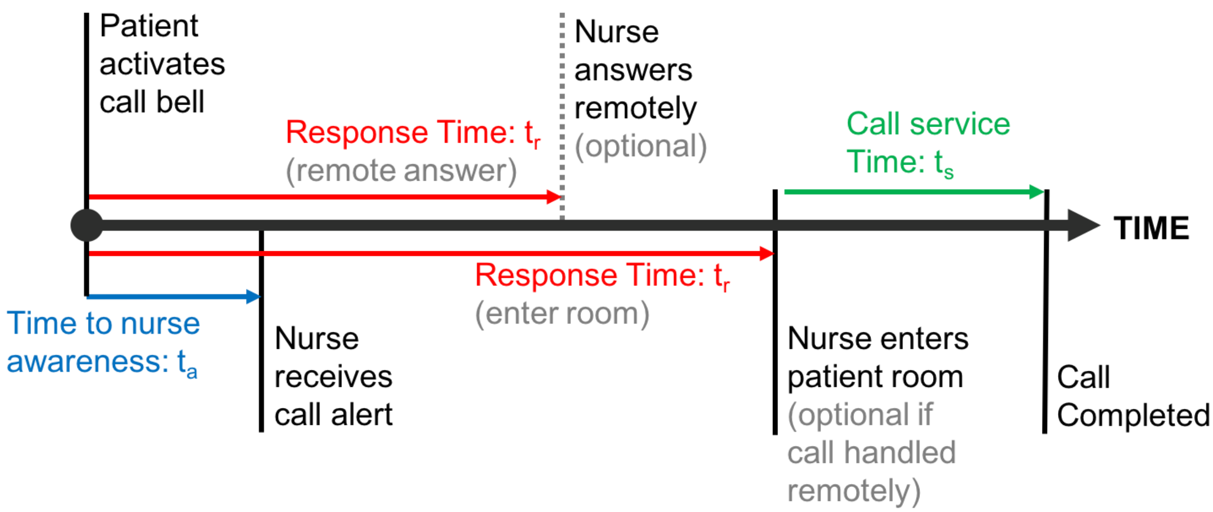


Figure 1.7 - Response Time KPI

2) ***Mean Direct Care Time*** [%] = % of total shift time spent on direct patient care activities, averaged over all shifts.

3) ***Mean Distance Travelled per Shift*** [km] = total average distance travelled by a nurse per 12-hour shift, averaged over all shifts.

These metrics will be used to compare and evaluate the impact that this new system has had on the unit as well as any potential further improvements proposed.

1.3 Research Objectives

Overall, this study aims to evaluate the impact of this “smart” technology on the care of the unit as well as develop and test more efficient call routing strategies for Mackenzie Health’s innovation unit.

1.3.1 Research Question

Our research objective leads us to two key Questions:

RQ1) What impact has the implementation and use of this new IOT “Smart” call system had on nurse ***Mean Response Times***, ***Mean Direct Care Times*** and ***Mean Distance Travelled***?

RQ2) Can these response times and direct care times be improved further through the use of an alternative call routing strategy in Mackenzie Health’s innovation ward?

Chapter 2

2 Literature Review

This chapter explores previous findings on the relationship between nursing staff and quality of care delivered to patients, as well as how response times impact patient satisfaction. It will also look at past work done in the fields of patient call bells and the impact of healthcare technology. Finally, we will discuss the use of Discrete Event Simulation (DES) in healthcare operations.

2.1 Quality of Care and Nurse Staffing

While it can be difficult to define exactly what constitutes “quality of care”, researchers agree that it is comprised (in large part) of both clinical outcomes as well as patient experience and satisfaction [16][17]. Clinical outcomes are affected by measures such as: rates of nosocomial urinary tract infections, gastrointestinal bleeding, pneumonia, and adverse events such as: shock or cardiac arrest, respiratory failure, sepsis, or deep venous thrombosis [9][18].

Patient experience is derived from the many interactions and communications a patient has with their care providers and the care process, while patient satisfaction is the overall lasting impression a patient has of their experiences with a course of care. J. Ware et al. states that “a patient satisfaction rating is both a measure of care and a measure of the patient who provided the rating” [19] (incorporating a patient’s own expectations, preferences as well as past experiences into the measure). Particularly, nursing care has the greatest impact on patient satisfaction, discomfort and frustration [20].

These studies [9],[18] have established that greater nursing care time per patient and direct care time are associated with reductions in all the previously stated adverse events and measures. Supporting these findings, Cho et al. found evidence that less nursing hours and lower nurse-to-patient ratios leads to increased risk of pressure ulcers and pneumonia, which in turn results in increased Length of Stay (LOS) by ~6.2 and 5.4 days respectively, with an increase in hospital costs of ~$28,000 for pneumonia [21].

2.2 Response Times and Patient Satisfaction

Response times have been found to have a large impact on a patient's perception of their care and their overall patient satisfaction – with better response times leading to better reported pain management and higher patient satisfaction scores [22].

An interesting study by G. Gardner et al. [8] states that "the greatest demand from call bells is before and after meals and at change of shift, times when staff are already busy" – we agree with this assessment, however it should be noted that we believe that change of shift or nurse handover activities do not contribute to increased patient calls, simply that traditionally nurse handover takes place during mealtimes and when patients are first waking up. They also found that slow response times to call bells lead to increased risk of falls (and thus increased LOS) and confirmed that slow response times have large negative impact on patient satisfaction [8].

In short, both clinical outcomes and overall patient satisfaction can be improved with reduced response times, leading to a greater quality of care. Intuitively this makes sense; on the clinical side if clinicians are spending more time with each patient they may be able to prevent or catch early warning signs of degrading health, before it's too late. On the patient satisfaction side, patients feel that the more "face time" they have with clinical staff means that more effort and attention are being directed to them and their care [23][24].

2.3 Patient Call Bell Systems

Hospitals in the past have trialed and/or implemented mobile call systems, or RFID location tracking for medical devices, nurses or patients. Previous studies in hospitals in the US that have implemented the nurse mobile devices and wireless automated call routing component have shown an immense impact of routing patient calls to nurse wireless devices - a 70-80% reduction in response times; demonstrating how routing can have dramatic impacts on patient care [25][26]. However, the combined use of (a permanent) RFID system to track nursing staff, tied into a set of connected beds, mobile devices, hand hygiene and wall call stations, is to the extent of the authors knowledge, unique in Canada (at least as far as the literature indicates). Mackenzie Health's setup is special as it combines these many different capabilities together into one system.

2.4 "Digital Hospitals" and Healthcare Technology

Mobile technology is highly pervasive in everyday life yet hasn't gained widespread use within the healthcare sphere. Yet some small pilot studies which have trialed mobile devices for communication have shown them to be effective at improving response times and importantly mitigating errors [27].

One notable large-scale time-motion study carried out across 36 hospital units in the US, utilized a RFID location tracking system to measure nurse's locations and time spent in each location [7]. This setup sounds very similar to Mackenzie Health's system, but was only installed in each unit for one week (the duration of the study). The authors of this study then used the location data to calculate distances traveled and physically where nurses spend their time - indicating potential directions for this research project.

Increasingly hospitals have turned to other new technologies as well to help solve their problems; Electronic Medical Records (EMR), Computerized Physician Order Entry (CPOE), and more complex medical devices. However, if not carefully designed and implemented, these systems can add to the workload and create their own technical and human factors issues - outweighing the potential benefits they could provide. It is estimated that nurses spend around 35% of their time on documentation (such as EMR use) compared to only 19% on patient care time [7][28]. The promise of greater efficiency, faster, accurate and more "intelligent" care is driving innovation and the development of "smart" medical devices and systems.

2.5 Discrete Event Simulation

A discrete event simulation (DES) approach has been selected for analysis (used in conjunction with other data mining and analysis methods), as simulation modelling offers significant advantages in terms of time and cost when testing out large scale workflow changes. There is minimal risk to testing novel improvements or changes in a computer model compared to implementing those changes in real life and then seeing if they work.

Simulation also allows built-in detailed metrics and statistics to be captured, and has been shown to be a powerful and valid method for modelling complex situations in healthcare [29][30].

Chapter 3

3 Methodology

This chapter will discuss the steps taken in conducting data analysis and in developing a discrete event simulation (DES) model of Mackenzie's Innovation unit. We start with an overview of the available datasets, the processes used to clean, join, and finally statistically analyze them. The latter half of the chapter will describe the simulation model development including; model inputs, outputted KPIs, model validation and finally assumptions and limitations of the model.

3.1 Data Analysis

The data used in this study is broken down into two categories: "Pre-innovation" and "Post-innovation". The Pre-innovation data available is in the form of a previous time-motion study conducted in December 2013 on the unit by an external process improvement consulting company. This study collected and presented various summary statistics about the operation of the unit at that time. Post-innovation refers to the data gathered by the new patient call bell and nurse location system after installation was completed in July 2014. Figure 3.1 displays how the pre and post-innovation study phases relate to our research questions.

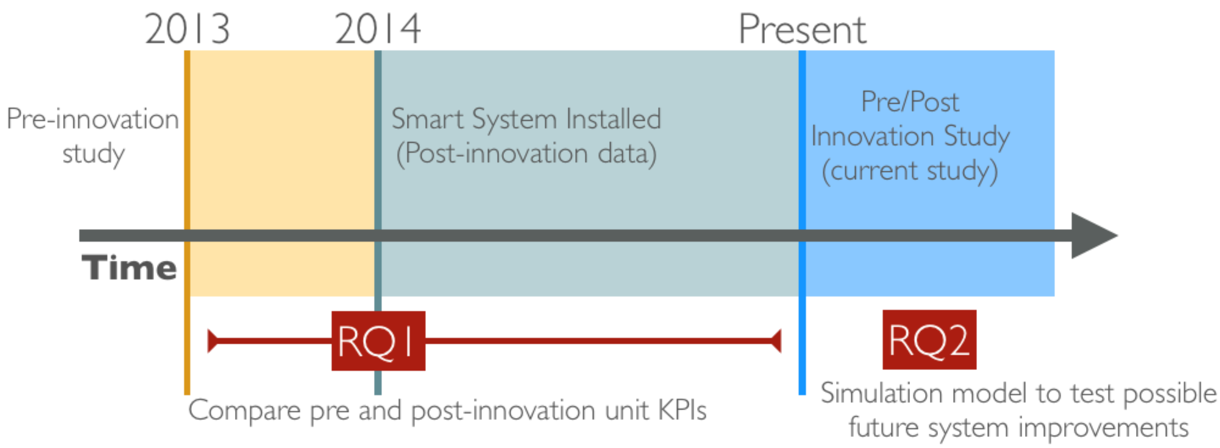


Figure 3.1 - Study Phases

In order to determine if implementation of this new “smart” system had an impact on the selected KPIs, the results from the pre and post data analysis were compared as closely as possible.

3.1.1 Pre-innovation Data

The 2013 time-motion study used work sampling techniques to collect information on nurse locations and tasks being performed. The work sampling included use of personal data assistant (PDA) devices which at random intervals alerted the nurse to input information on their location and the task they were performing at that moment. This was used in conjunction with traditional time-motion practices of nurse “shadowing” – following nurses around the unit as they go about their work while observing and noting their actions. Summary results available from the pre-innovation study include: Call bell response times, direct care times, nurse task breakdowns as well as nurse travel distances and location. These are discussed further in the following sections.

3.1.2 Post-innovation Data

Three datasets were collected by the new “smart” system: patient calls, nurse locations and staff assignment (nurse-patient) data. This data includes a 3-year period from July 2014 - July 2017. For the patient calls analysis, the full dataset was utilized, however for the nurse location and staff assignment data a more recent subset of December 2016 – July 2017 was used. This was due to the fact that the location system underwent a few updates and changes in data structure as early implementation and reliability challenges were resolved over the course of the project – this latter subset represents a more stable and complete set of location data. The three datasets were anonymized, cleaned and joined for analysis (this process will be discussed further in the latter parts of this section).

The data is stored on hospital servers and was periodically exported by the researchers for analysis. The main data fields for each dataset are outlined in Table 3.1.

Table 3.1 - Post-innovation Dataset Fields

Calls Data	Nurse Location Data	Nurse-Patient Assignment Data
Patient ID	Nurse ID	Nurse ID
Type of Call (e.g. Pain, Normal, Bathroom etc.)	Timestamp	Assigned to: Patient ID
Timestamp	Room # / Location	Timestamp (Assigned & Unassigned)
Room # / Location		

Samples of each dataset can be seen in Appendix A.

3.1.3 Call Bell Data

The calls bell data includes both the pre-innovation data summary statistics as well as the raw calls data collected by the post-innovation system. The pre-innovation summary statistics were based off of a sample size of N=115, whereas the post-innovation data captured by the new system contains N=258,848 – significantly more. These will be statistically analyzed and compared to determine the impact of implementing the smart call bell system on response times.

	Dec-13
Max	32.95
Average	4.44
Median	2.83
Min	0.03
SD	5.57
Count	115

Table 3.2 - Pre-innovation Summary Statistics

3.1.3.1 Call Bell Response Times (Pre-innovation)

The pre-innovation study provides us with some aggregated summary statistics of nurse response times to patient calls. This study reports that the mean and median response times to patient calls were 4.44 and 2.83 minutes respectively (N=115). Additional descriptive statistics are shown in Table 3.2.

3.1.3.2 Patient Calls Data (Post-innovation)

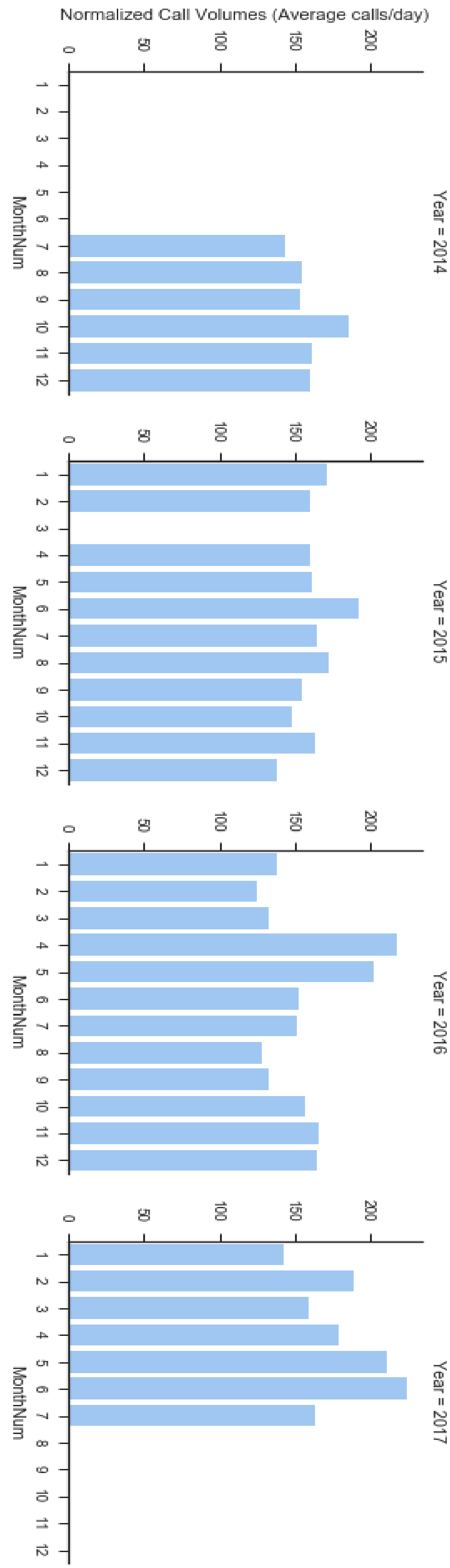
The calls system data contains a unique patient ID, a timestamp, location (patient room) and call type (e.g. bathroom) for each patient call. The system captures many different types of calls including a number that are outside the scope and focus of this research (e.g. dietary orders, bed unplugged, patient transfer orders etc.). We will instead only focus on the main types of calls which make up ~65% of all calls. After filtering the data to include only main calls types, entries with response times greater than 45 minutes were removed (this incorporated some obvious outliers such as an 8-hour response time where the system may not have recorded that the call was answered or other circumstances). With this criterion only 0.64% of the data was removed (thus minimally impacting results). Figure 3.2 shows the output of the code used to clean the dataset.

```
------------------------------------------------------------------------------------------
Whole calls dataset (all call types): N1 = 258848
Calls included in analysis (only call types of interest): N2 = 169152 (65.35% of all calls)
Response Time outlier threshold: >45 minutes
(i.e. calls with response times greater than 45 minutes will be excluded)
Outliers: 1075
Inliers (N2'): 168077
Proportion Removed: 0.64%
------------------------------------------------------------------------------------------
```

Figure 3.2 – Console Output from Data Cleaning Code

Figure 3.3 shows the call volumes captured by the post-innovation system (normalized by number of days in month); we can see there appears to be some random variation between different months. July 2014 (month 7) and January 2017 (month 1) had half as much calls data available during this period (and thus was normalized according to the number of days of available data instead) and March 2015 (month 3) had no calls. These were due to system downtimes and upgrades that took the call system offline throughout the study period. For the simulation model (discussed further later) we will use the average volume of calls per month (approximately ~4,800).

Figure 3.3 - Post-innovation Call Volumes



The histogram in Figure 3.4 shows nurse response times to patient calls and gives us a good idea of the distribution shape of the data. From this chart we can see that the majority of calls (~87%) are answered in less than 10 minutes, and ~74.5% are answered in under 5 minutes. Despite this there is a long tail, indicating instances when no one is available to answer calls and patients have to wait longer to be answered. Note: it is also possible with the new system to have response times of zero under specific circumstances. This can occur if a nurse is either in, or just entering a patient room already when one of the patients in that room triggers the call bell (e.g. they may be attending to one patient in the room when a patient in another bed pushes the call button). This only occurs in a small number of cases however.

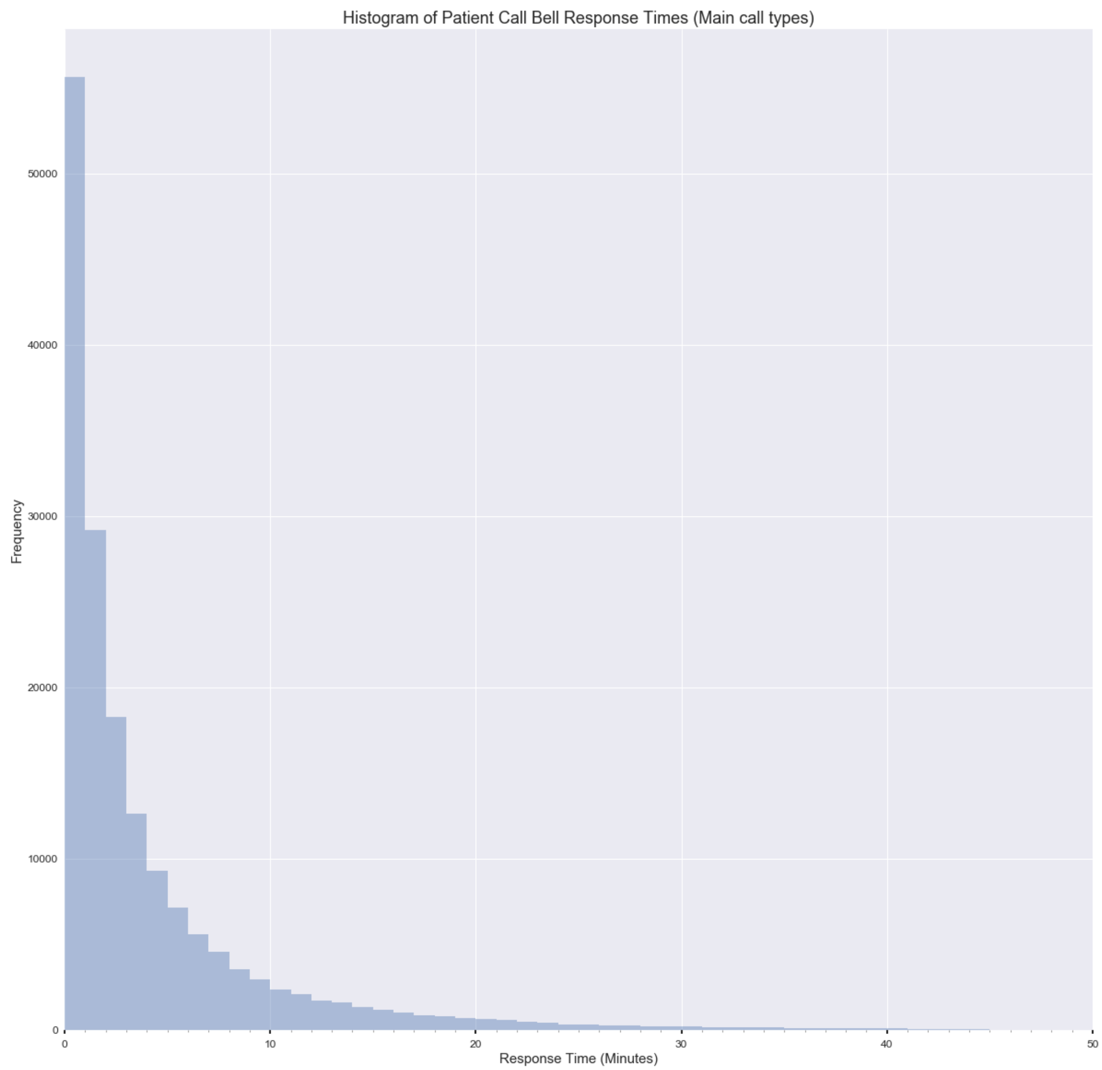


Figure 3.4 - Histogram of Nurse Response Times

3.1.4 Staff Location Data

In understanding the operations of a hospital unit, it is important to understand the activities of its nurses. The pre-innovation study differs in its approach from the way the post-innovation system collects data here. The pre-innovation study uses more traditional time-motion methods to collect their data – nurse shadowing techniques combined with the use of PDA devices. The post-innovation dataset utilized the advantages of the system to automatically record nurse locations using the RFID badge system.

3.1.4.1 Nurse Location Data (Pre-innovation)

The pre-innovation study researchers conducted nurse shadowing over 4 shifts and equipped nurses with the PDAs for another 21 shifts collectively. Table 3.3 summarizes the data collection sample.

Table 3.3 - Pre-innovation Data Sample Sizes

	Nurse Shifts	Data Points
PDA (work sampling)	21	433
Nurse Shadowing	4	1,418

While conducting the shadowing, researchers recorded nurse movements in order to calculate the total distance travelled. On average a nurse travelled approximately 2.58 km per 12-hour shift before the new system was installed. An important note is that this figure is an estimate, based on the number of location changes per hour, a "density" or measure of efficiency of that route, as well as the actual distance. Additionally, the small sample size (N=4) means there is potentially less accuracy in this measure. These factors combined means that this number should be taken with a grain of salt. Figure 3.5 illustrates the pre-innovation study's distance results.

Figure 3.5 - Pre-innovation Distance Results. Source: Adapted from [31]

3.1.4.2 Nursing Task Breakdowns (Pre-innovation)

The work sampling PDAs used in 2013 allowed detailed information to be collected on which tasks nurses perform. The 2013 research team sorted these tasks into various categories, (as can be seen in Figure 3.6). A large change that took place around the time of the 2013 study was the implementation of a new Electronic Medical Record (EMR) system. This reportedly led to an increase of 6.4% and 2.3% in the time nurses spend on documentation and chart review activities respectively [31].

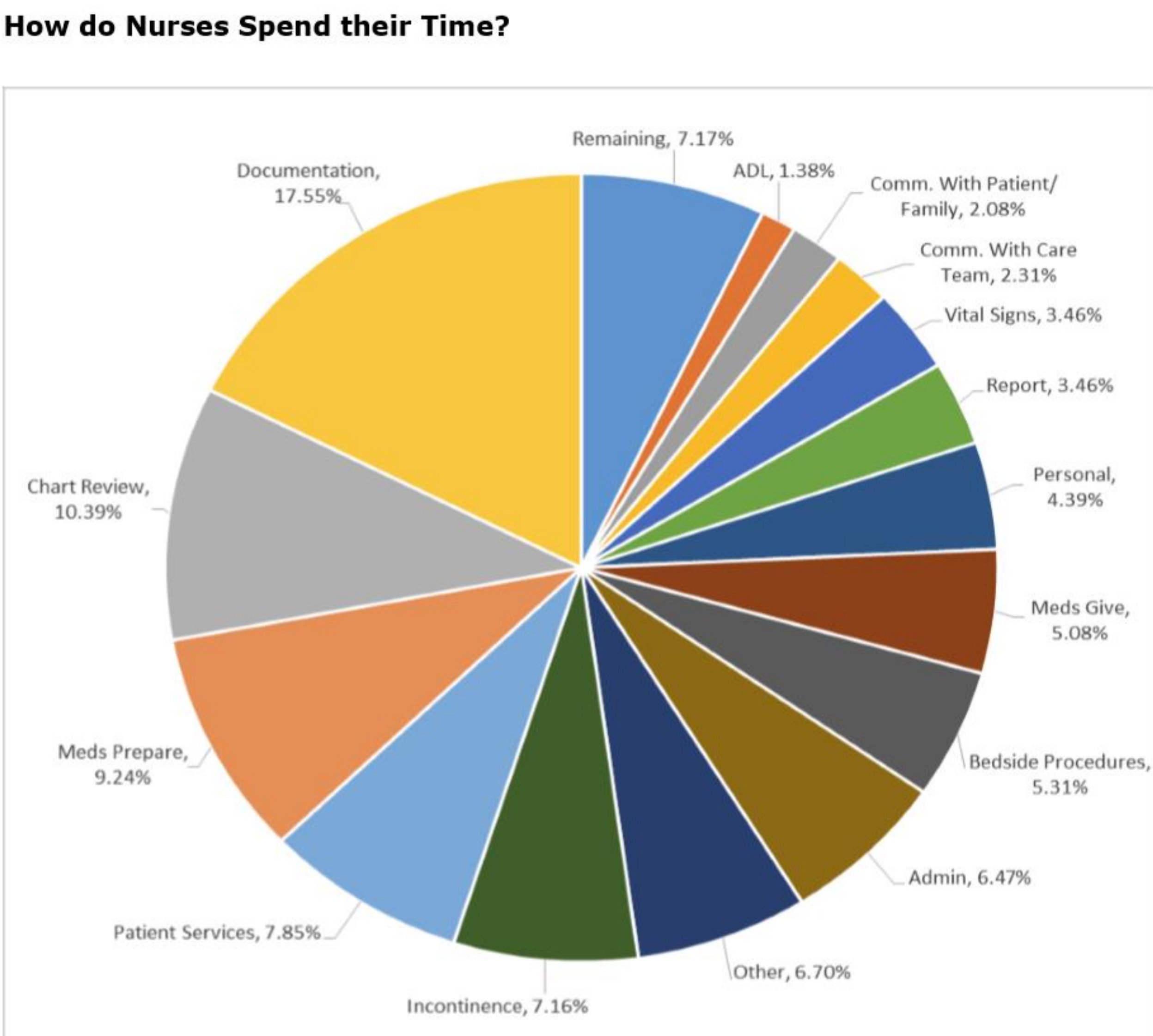


Figure 3.6 - Nurse Activity Breakdowns. Source: Adapted from [31]

3.1.4.3 Nurse Location Data (Post-innovation)

As mentioned previously, the new system enables nurse locations to be automatically recorded by picking up the unique signature of each staff member's RFID badge. This allows the system to capture information such which nurse is in which room, timestamps of when nurses entered and exited that room, and thus the duration they were in the room. The dataset includes 8 months of data from Dec 2016 – July 2017 (N=1,987,662) and covers the movements of 110 staff. Data before this period contained some missing data and inconsistencies (due to early implementation issues with the tracking system e.g. badge batteries dying early and system updates/changes) however the 8 months still consists of almost 2 million rows of data which is a sufficient sample size for our analysis.

After an initial analysis ~1.6% of the data was filtered out – movements which belonged to staff types other than PCAs, RPNs or RNs. This was because there are a small number of admin, managers and student nurses on the unit who do not answer call bells or provide direct patient care (or in the case of the student nurse are assigned to shadow a full RN). Figure 3.7 displays the data cleaning numbers.

```
Total number of location visits made by:
- All staff:                     1,987,662 [100.00% of visits]
- RNs/PCAs/RPNs staff:           1,955,188 [ 98.37% of visits]
- Managers/Admin/Other staff:       32,474 [  1.63% of visits]
```

Figure 3.7 - Nurse location data cleaning

According to hospital management there was some initial hesitancy by nurses in adopting the new system; under fears it would be used to negatively judge nurse performance. However, after reassurances that the information collected would only be used to improve the operations of the unit, nurses then began to utilize the system's features and came to favour certain features such as the ability to locate and call for assistance from one another remotely.

3.1.5 Dataset Joining - Staff Assignment Data (Post-innovation)

By joining the patient calls and nurse location datasets we can gain more insight into how nurses respond to patient calls. The use of a third dataset: Staff Assignment data allows us to accomplish this.

The staff assignment data contains nurse IDs paired with patient IDs as well as assignment and un-assignment timestamps and the caregiver role. This means we know which nurses were assigned as the primary caregiver for which patients during particular time periods. By joining these datasets, we can accurately map nurse movements to patient calls. The data joining schema can be seen in Appendix B.

3.1.6 Data Limitations

Both the pre-innovation and post-innovation datasets have their own advantages and disadvantages. For the pre-innovation data, the PDA devices captured the activities the nurses were doing at certain timepoints and the in-person nurse shadowing was used to record responses to calls. This allowed very granular data with a high level of detail to be collected. The drawback to these methods however is that they are effort intensive and require a great deal of time, and result in an overall smaller sample size and potential loss of accuracy. Another important effect to consider when conducting in-person observations or shadowing is the potential impact of the Hawthorne or “Observer” Effect – when those who are being observed or are aware they are part of an experiment alter their behavior. This effect has been shown to have a significant impact on similar healthcare situations to this research; such as for hand hygiene compliance when shadowing nurses versus data collection through an automated system [32]. These factors limit this intensive style of data collection to one-off studies and quality projects.

The post-innovation data has the advantage of automation and so was able to collect a large amount of data with very little effort. While some datasets such as the calls data have a good amount of detail and fidelity other datasets have the downside of not being in-depth. For instance, the nurse location data has good information on where and when nurses were in a location, but no information on what actual tasks they were performing. While in some cases inferences can be made (e.g. if they are in the patient room they were quite likely to be delivering patient care) in others the data is somewhat ambiguous (e.g. if they are at the nursing station they could be retrieving medications, completing documentation, communicating with managers/colleagues, or even just idle). This lack of detail restricts what analysis can be done.

Hence, it is important to recognize the strengths and weaknesses of each dataset and consider their impact on any analysis and results accordingly.

3.2 Simulation Model Development

In this subsection we will cover the simulation model structure, various input parameters, outputs, and validation of the model.

3.2.1 Model Design

The model was built using Simul8 simulation software with an Excel-based parameter interface for familiarity and ease of use for hospital staff. The layout of the model was designed to look similar to both a live display that currently is at the nursing station which can show the real-time locations of nursing staff, and the actual unit blueprints. This was done to ease future adoption of the model, which is planned to be handed off for the hospital to use after this study. Screenshots of the real-time display and the simulation model can be seen in Figure 3.8 and Figure 3.9 respectively.

Figure 3.8 - Real-time Nurse Location Display

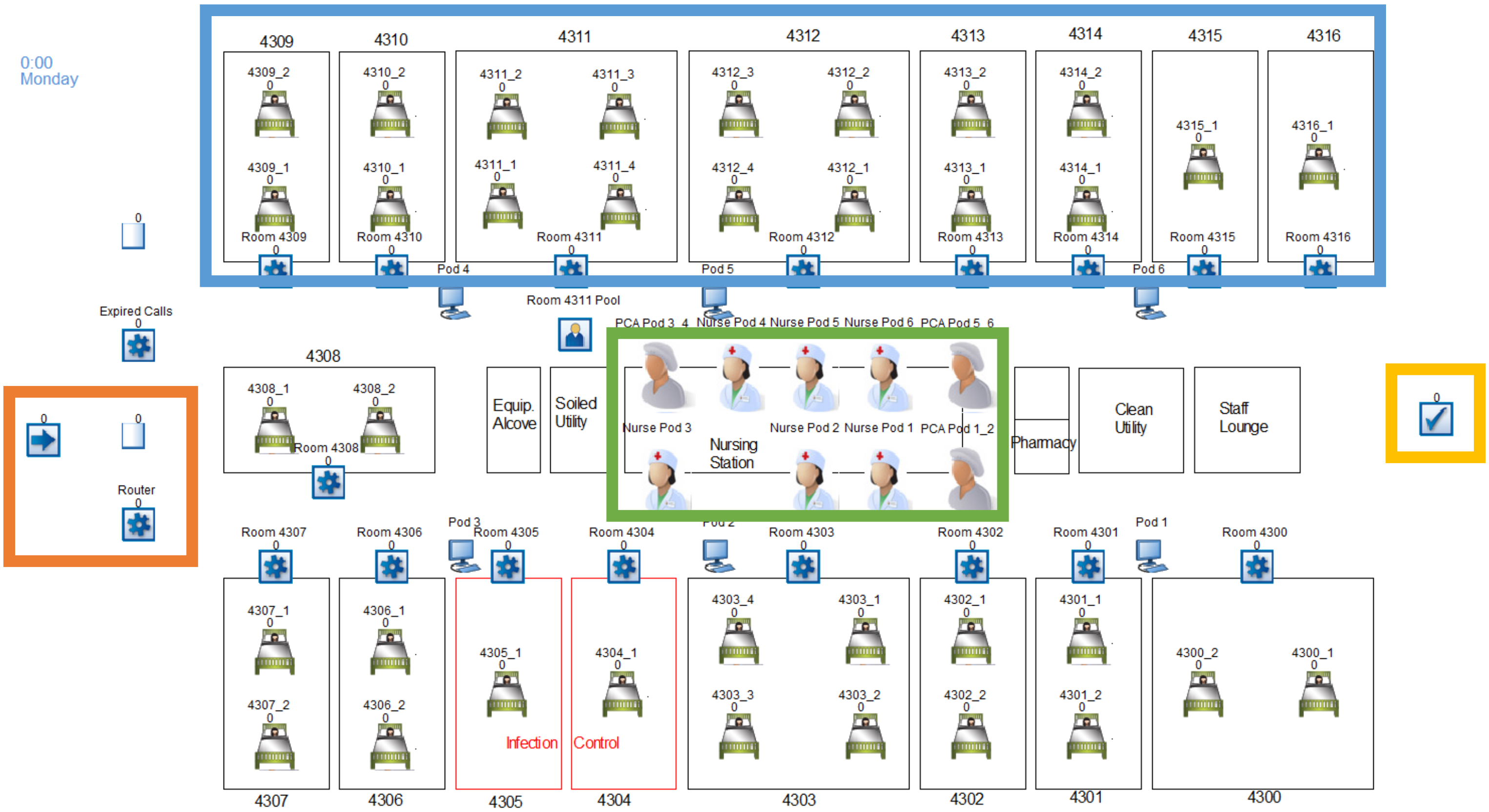


Figure 3.9 - Screenshot of the Simulation Model

3.2.2 Model Logic

Coloured boxes were added to Figure 3.9 to highlight different model components. The orange box highlights the call arrivals component where patient calls are generated according to statistical distributions (more on this later), before they move to a “router” which randomly routs the call to a patient bed depending on bed occupancy and whether or not a bed already has an outstanding call. The large blue box encompasses some patient rooms, where the routed call will wait until a free nurse comes to service the call. Each bed contains custom Simul8 Visual Logic code to capture timestamps of the arriving call and nurse arrival time allowing response time to be calculated. The beds will also have a service time for each call (based on more fitted statistical distributions), which will occupy a nurse making them unavailable for the duration of the call. After being serviced calls will finally move to the endpoint highlighted in yellow. The main final component is the key resources – the nursing staff highlighted in the green box. The simulated staff will move around the unit responding to calls as well as moving to the pods. The model captures metrics on each nurse such as the distance travelled over a shift and the utilization percentage.

3.2.3 Model Inputs

Aside from the logic a DES model requires certain inputs to accurately model the real-world situation in a unit. These inputs are primarily based on information about the operation of the unit, as well as historical data to determine arrival and processing times. Table 3.4 shows the model inputs, which include:

Table 3.4 - Model Inputs and Data Sources

Model Input	Data Sources
Calls	Arrivals distributions fitted to historic calls data as well as call type break downs
Service times	Distributions fitted to historic location data
Patients	Historic data on bed occupancy and which beds calls originate from
Staffing levels & shifts	Historic data and discussion with nurse manger about unit policy/practices
Physical Layout & Distances	Unit blueprints and unit visits

3.2.3.1 Call Arrivals

One of the most important inputs to the model is how often patients use the call button to call for nurse assistance. Figure 3.10 details the call volumes by day of week and by hour, normalized by number of patients. The blue bars are the average hourly calls per patient whereas the orange line is the average daily number of calls per patient. As can be seen, there is a rough daily cyclical pattern where the number of calls peaks at two points during the day (~8-10AM and ~5-10PM) and decreases significantly during night time hours (Midnight-7AM). The average daily number of calls/patient is fairly consistent and ranges from minimum 35.30 to maximum 36.95 average calls/patient. This is interesting as there are approximately 2 less patients present on average in the unit over the weekends vs. the weekdays (see section 3.2.3.3). This difference is likely caused by the fact that is roughly 1-2 less nurses over the weekend than during the week (see section 3.2.3.4), and so patients may need to utilize the call buttons slightly more to be attended by nurses. As this is a minor difference, (only ~1.65 additional calls/patient per day) it was decided that weekend call arrivals could be treated the same as weekdays with minimal impact.

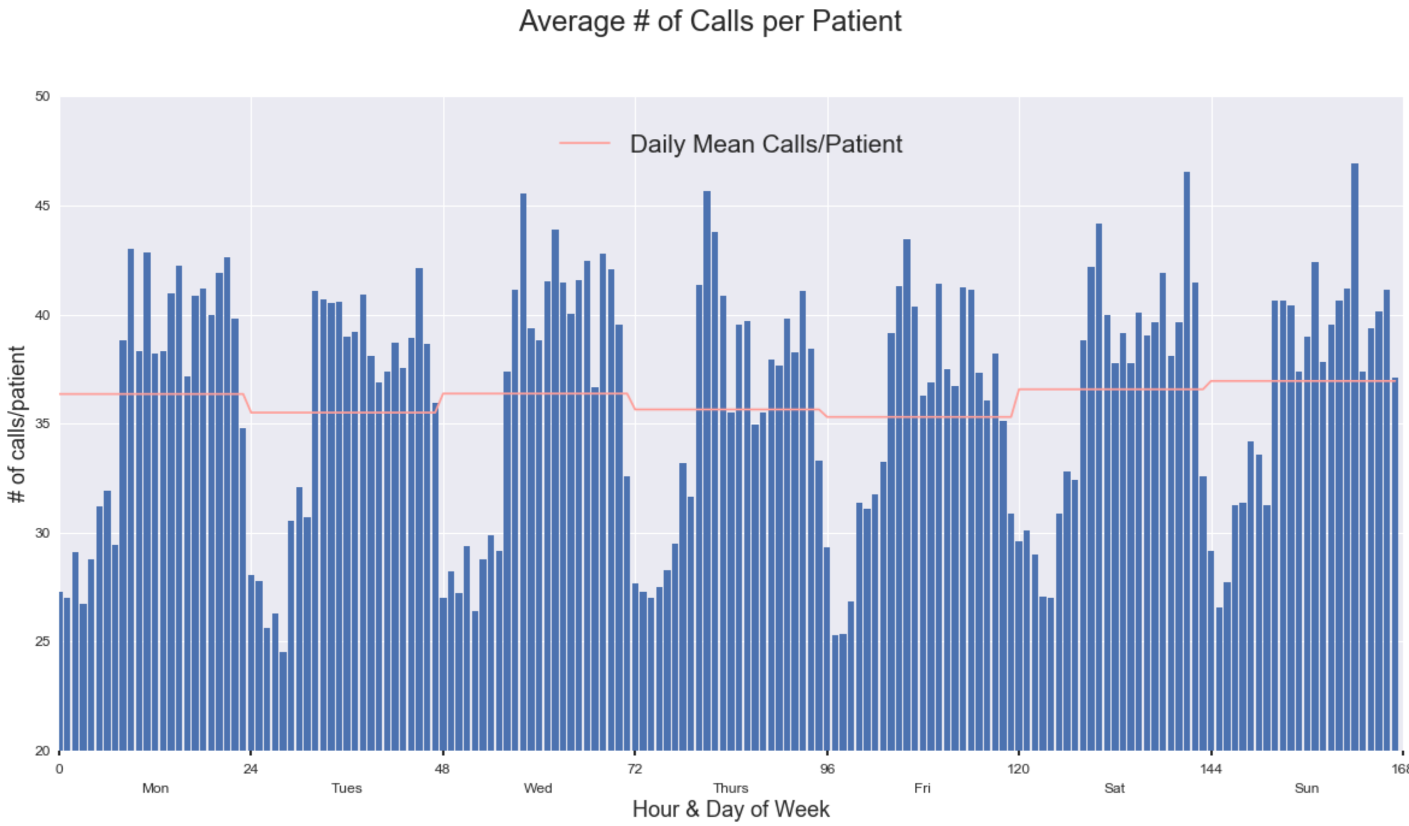


Figure 3.10 - Normalized Patient Call Volumes

Fitting a single statistical distribution to these cyclical call volumes would result in a poor fit. To deal with the cyclic nature of call volumes different distributions need to be fitted to the different peaks and lulls throughout the day. To clearly identify these periods a K-means clustering algorithm was run on the hourly average calls per patient. This algorithm effectively groups hours of the day that have similar arrival rates of calls into similar clusters. The algorithm was tested with varying numbers of clusters (K= 1 to 10) and 3 clusters was found to be a good choice for K (i.e. the fewest number of clusters that still maintain a good “inertia” measure (summated intra-cluster distances – see Appendix C).

The results of the clustering can be seen in Figure 3.11. These clusters are also intuitive as they correspond to a “quiet” night time group (cluster 0 = blue), an “average” midday group (cluster 1 = green), and “busy” peak group (cluster 2 = orange).

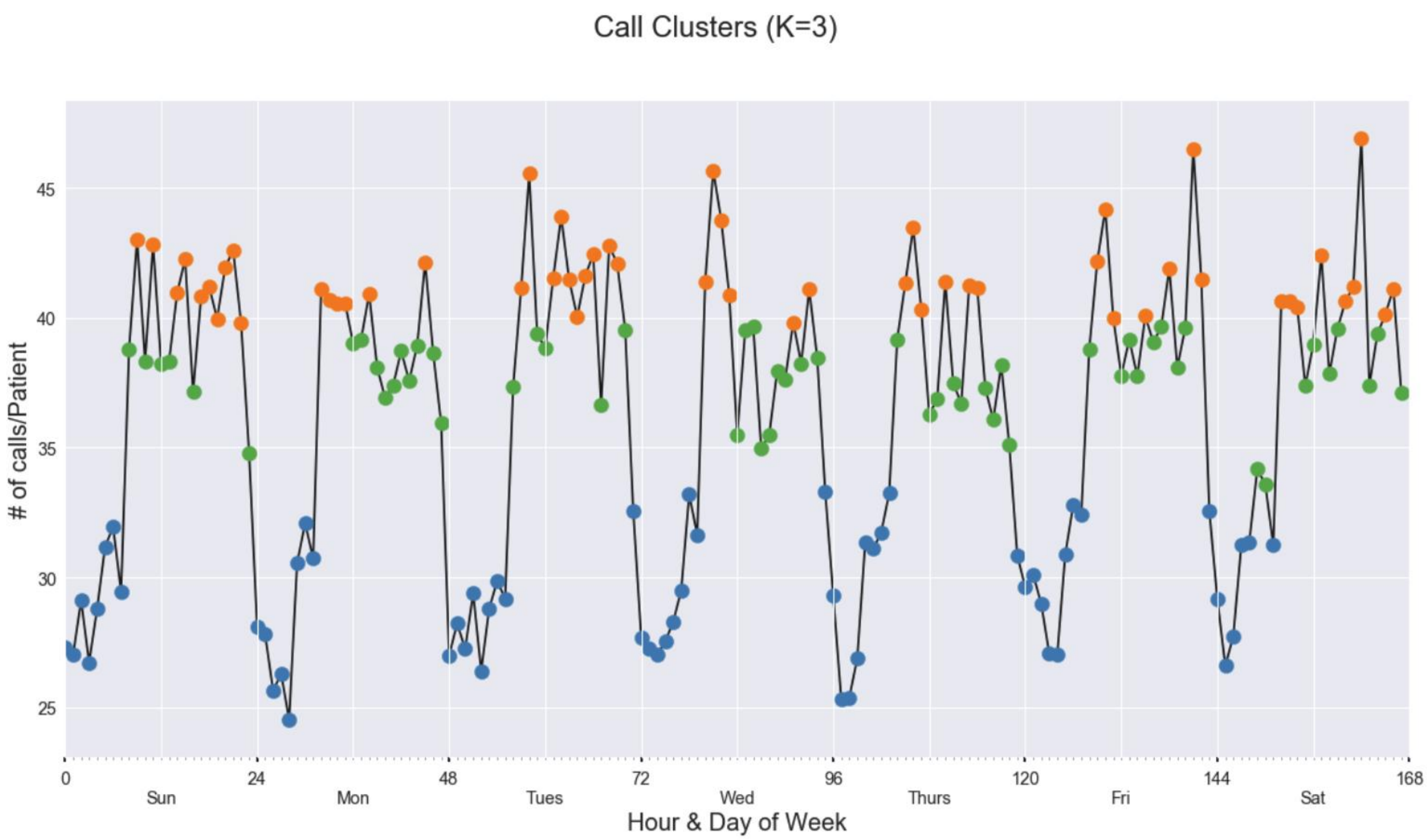


Figure 3.11 - Clustered Call Volumes

After each cluster was identified, the corresponding cluster labels were applied to the individual calls and then separate exponential statistical distributions were fitted to the interarrival times of each cluster. These were used in a Poisson arrival process with a time-dependent piecewise constant arrival function (where the hourly arrival rate depends on which cluster that hour falls in). Poisson arrival processes were used as this is a natural well-known model for call arrivals (as calls are arriving from many independent patients) [33], and also has the nice property of being relatively straightforward for later use by hospital staff (as the only parameter is the arrival rate). Figure 3.12 shows the fitted exponential distributions for each cluster. The fitted distributions were programmed into the model to generate calls during their corresponding hours. Further detail of the fits and PP-plots can be found in Appendix D.

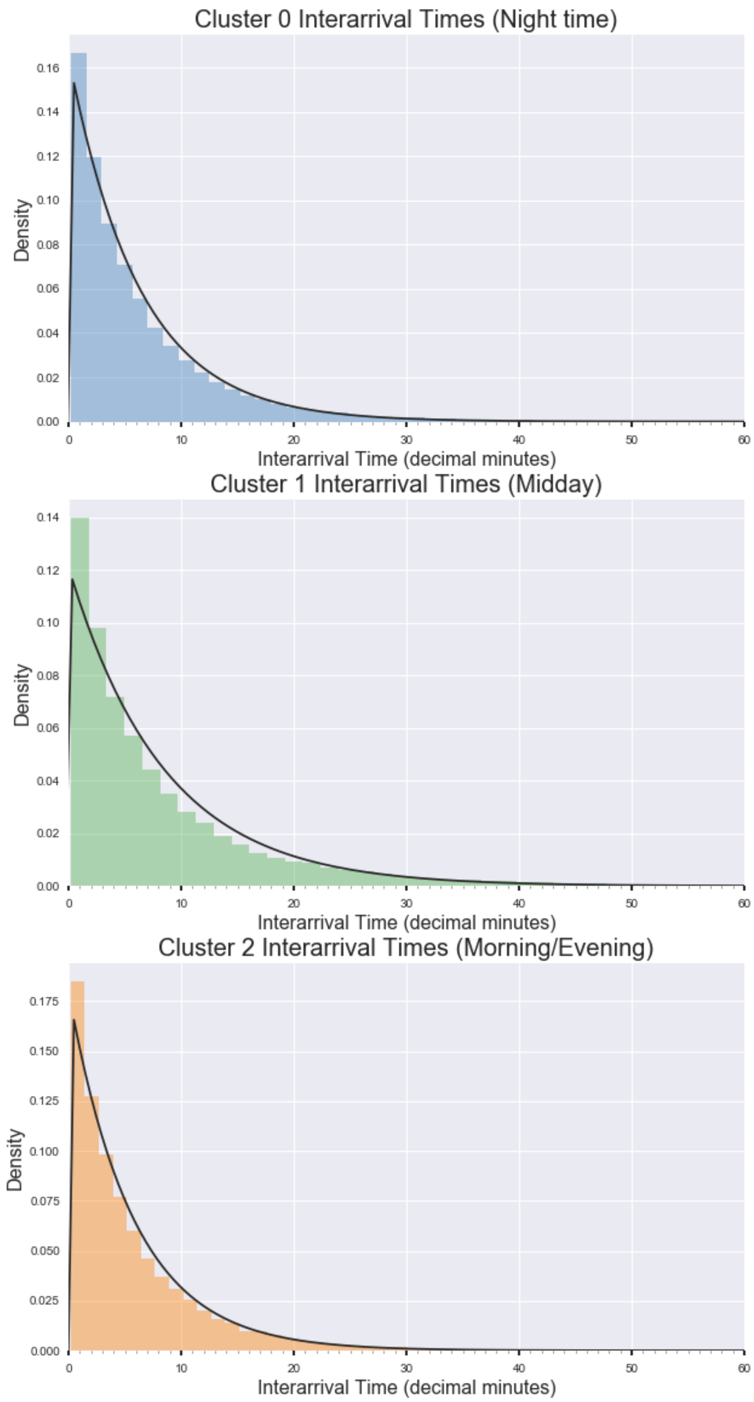


Figure 3.12 - Fitted Exponential distributions for each cluster

The final challenge with the calls was identifying the correct call type. Due to the design of the patient call button the "Normal" call button is larger and more visible, and hence easiest to press which is reflected in the data – 98.5% of calls were of type "Normal" (see Appendix E for an image of the call button). To compensate for this and to find more accurate breakdowns of the call types, a sample of patients (n=162) was identified who were using all three buttons frequently. More accurate and representative call type percentages were calculated based on the calls from these patients. Table 3.5 illustrates the original and adjusted call type percentage calculations. These adjusted ratios were used instead of the originals in the model.

Table 3.5 - Original & Adjusted Call Type Breakdowns

	Bathroom	Normal	Pain
Original	0.8%	98.5%	0.7%
Adjusted	12.7%	78.9%	8.4%

3.2.3.2 Service Times

After joining the datasets, we can determine the service times for calls by mapping the call to corresponding nurse movements and how long they remain in the patient room after answering the call. Figure 3.13 shows the services times for the different types of calls. These parameters were programmed into the simulation model.

Additionally, approximately ~22% of calls are answered remotely by nurses. Of these remote calls however, the majority still require the nurse to go to the patient's room, resulting in roughly about 5% of total calls that can be dealt with completely remotely (e.g. such as answering a patient question). These calls require no in-room service time and, thus exit the system. This is represented in-model by having 5% of calls (randomly selected) exit the model without further nurse processing.

```
Mean:
--------------------------
All types:  7.97
Normal:  7.96
Pain:  7.97
Bath:  8.08
Bathroom Request:  8.74

Std. Dev:
--------------------------
All types:  13.63
Normal:  13.54
Pain:  14.43
Bath:  12.5
Bathroom Request:  20.2
```

Figure 3.13 - Service Times

3.2.3.3 Patient Bed Occupancy

A key consideration for the simulation model is how many patients are on the unit each day; Figure 3.14 shows the average number of patients each day (July 2014 - July 2017). A pattern common to general medicine units can be seen here, where beds utilized during the week is fairly constant, but then decreases as patients are discharged before the weekend. For the model these values were rounded to the closest whole number.

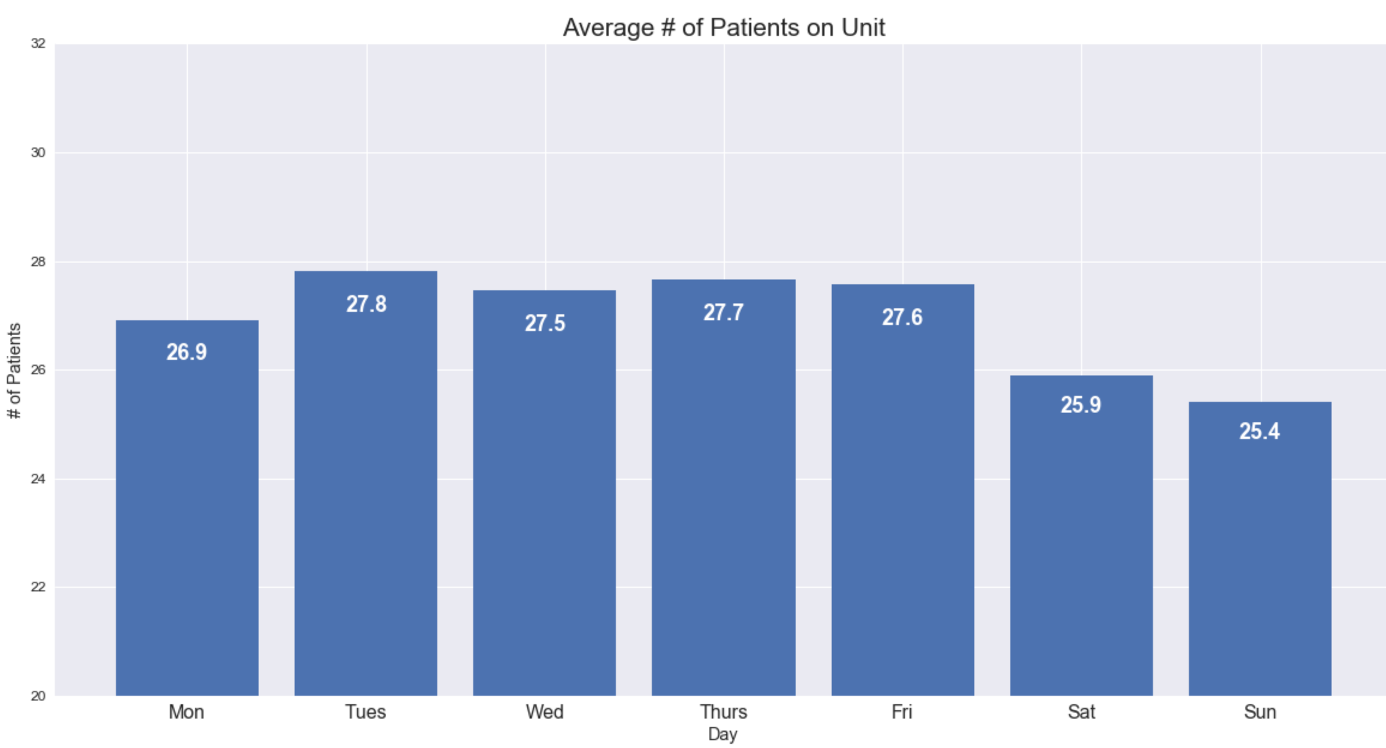


Figure 3.14 – Average patient occupancy on the unit by day

We are also interested in which beds the patients are placed in most often, and hence where calls originate from. Figure 3.15 shows us the percentage of calls which originate from each bed. The distribution of call origins is fairly even. Note: the format of the location is: [Room Number] – [bed #] e.g. 4307 – 1 indicates that the call came from bed one in room 4307. Those calls that lack a bed location originate from the washroom within each patient room (which has a built-in call bell inside).

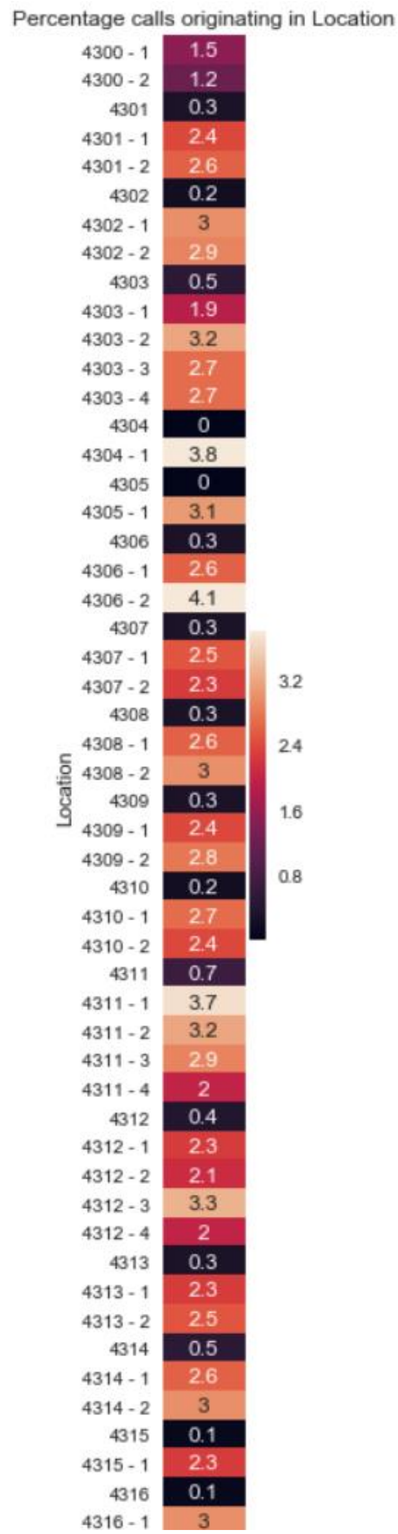


Figure 3.15 - Heatmap of call origins

3.2.3.4 Staffing Levels & Shifts

On the staff side of things, we must consider nurse shifts and the three different staff types: Registered Nurses (RNs), Registered Practical Nurses (RPNs), and Personal Care Aids (PCAs). RNs are licensed to perform all nursing duties and can take care of patients requiring complex care and/or who are unstable. They will often also work closely and supervise RPNs or PCAs. RPNs are licensed to deliver basic care such as taking patient vitals or preparing injections (under the supervision of an RN) and can perform a wider range of care on less complex patients. PCAs can deliver basic bedside care and will typically assist with bathing, feeding and toileting activities [34].

Shifts are usually 12 hours and run from 7:30AM to 7:30PM for the day and 7:30PM to 7:30AM for the night shift. There are usually 5-7 RNs/RPNs and 2-3 PCAs (and a single float nurse) on the day shift, with 3-4 RNs/RPNs and 1-2 PCAs overnight. Table 3.6 illustrates the average staffing levels by day for each staff type. The nursing staff operate in pod teams consisting of a RN and a PCA/RPN (who split their time between two pods) shared with each team.

PCA breaks are 30 mins and 45 mins for lunch, whereas RN/RPN breaks are 15 min x 2 with 45 mins for lunch. The float nurse will cover another nurse's patients when they go on break.

Weekday	PCA	R P N	REGISTERED NURSE	Total
1	4.50	8.03	7.22	19.75
2	4.71	8.10	7.45	20.26
3	4.62	8.34	7.81	20.78
4	4.67	8.88	7.64	21.18
5	4.33	8.18	7.58	20.09
6	4.30	7.73	6.82	18.85
7	4.28	7.53	6.84	18.66

Table 3.6 – Average Staffing levels by day (combined day & night shifts)

The previous study found nurses only have ~47% of their time available for direct care activities [31]. Since we do not have information on the tasks that the nurses are performing (only their locations) we will utilize the 2013 findings and restrict the simulated nurses to only having ~47% of their time for direct patient care. The staffing levels and other breaks information was incorporated into the simulation model.

3.2.3.5 Unit Layout

The unit layout consists of a single central nursing station, medication dispensary, clean and dirty utility supply rooms, and a staff break room in between two corridors lined with patient rooms. The unit map provided by the hospital can be seen in Figure 3.16.

The model layout was created (in-part) to resemble the actual layout of the unit for ease of understanding by hospital staff. From measurements taken, and the use of these blueprints the author was able to create a distance matrix (seen in Appendix F) that maps the distance from every room/point of interest to every other in the unit. Using this in conjunction with the location data we can calculate how far nurses travel each shift.

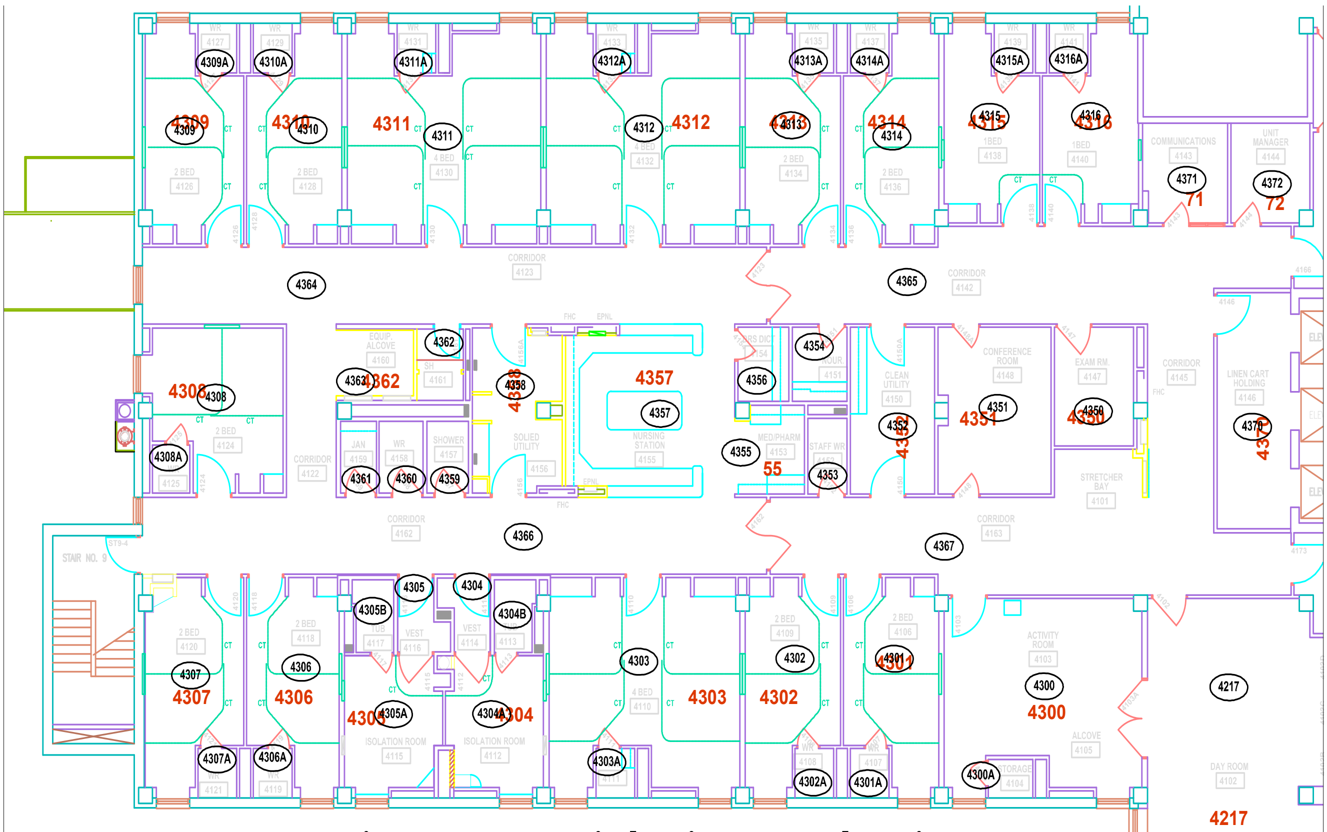


Figure 3.16 - Hospital Unit Layout Blueprints

3.2.4 Model Outputs

A single run of the model was be set up to simulate and record results from 1 month on the unit. This run length is in line with the monthly reports the hospital generates. A one-day warmup period at the beginning ensures the model reaches steady state before results are collected. The KPIs of interest defined earlier are collected by the model for evaluation:

- Response Times
- Time Spent in Patient Room (Note: this differs from direct care time – discussed further in the limitations section)
- Total Distance Travelled per Shift

Results will be based on a trial of 30 model runs.

3.2.5 Model Validation

The current-state model was be evaluated and validated against some key metrics: Hourly average response times, response time distribution proportions, and nurse travel distances.

3.2.5.1 Response Time Validation

The response times will be evaluated in two ways:

1. Compare the average hourly response times against the historic averages. shows us the historic time versus the model outputs, and Figure 3.17 shows a visual chart of the same information.

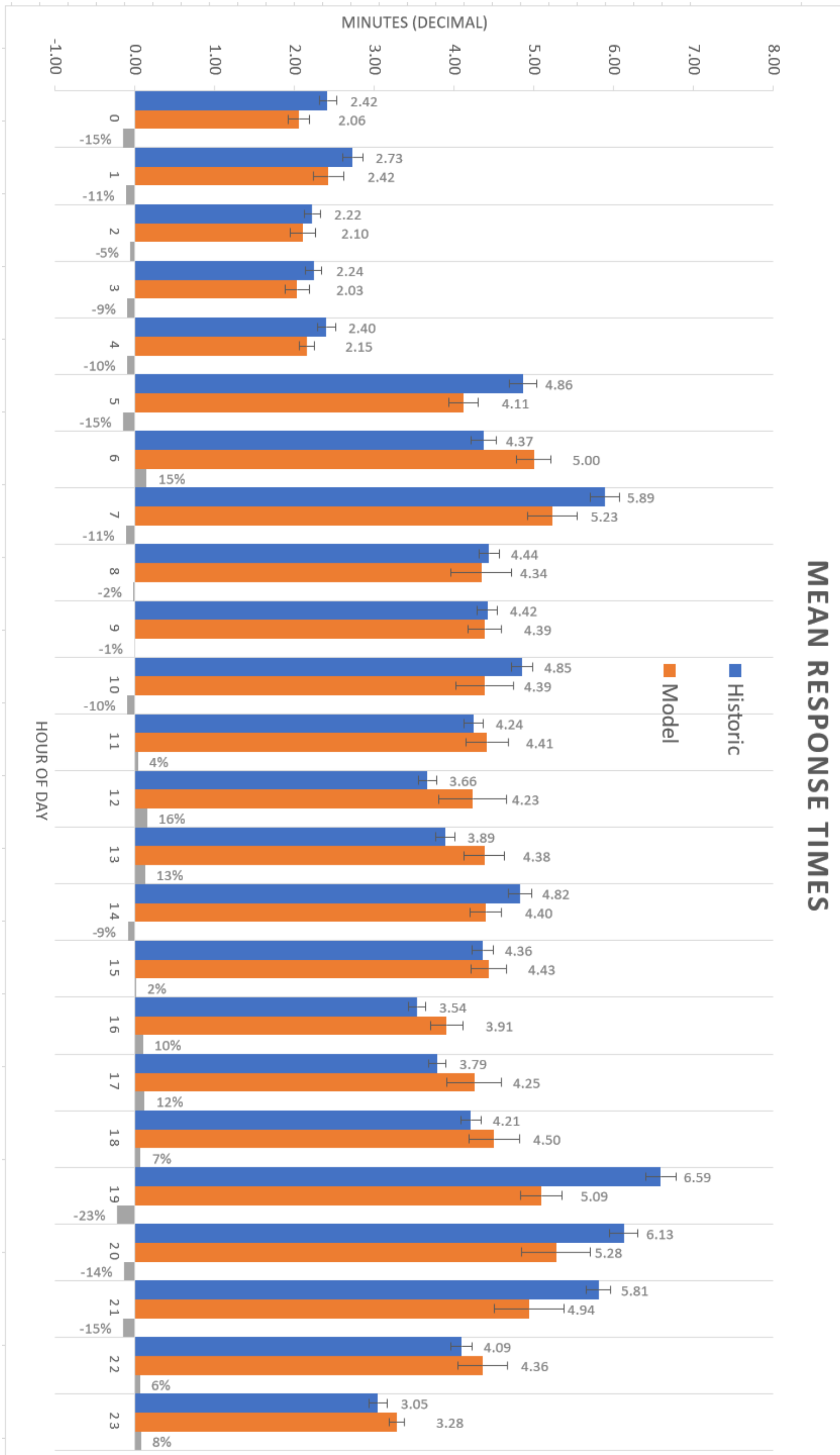
2. Compare the distributions of the response times to ensure they are close in overall shape. Figure 3.18 displays the histograms of the model and historical data together.

Table 3.7 - Average Hourly Response Times

Response (dec min)						
	Historic		Model			
Hour of Day	Mean	95% Confidence Interval	Mean	95% Confidence Interval	% Difference in Means	Absolute Difference in Means
0	2.42	0.11	2.06	0.13	-15%	15%
1	2.73	0.12	2.42	0.19	-11%	11%
2	2.22	0.10	2.10	0.16	-5%	5%
3	2.24	0.10	2.03	0.15	-9%	9%
4	2.40	0.11	2.15	0.10	-10%	10%
5	4.86	0.17	4.11	0.18	-15%	15%
6	4.37	0.16	5.00	0.21	15%	15%
7	5.89	0.18	5.23	0.31	-11%	11%
8	4.44	0.13	4.34	0.38	-2%	2%
9	4.42	0.13	4.39	0.21	-1%	1%
10	4.85	0.14	4.39	0.36	-10%	10%
11	4.24	0.12	4.41	0.26	4%	4%
12	3.66	0.11	4.23	0.42	16%	16%
13	3.89	0.12	4.38	0.26	13%	13%
14	4.82	0.15	4.40	0.20	-9%	9%
15	4.36	0.13	4.43	0.22	2%	2%
16	3.54	0.11	3.91	0.20	10%	10%
17	3.79	0.11	4.25	0.34	12%	12%
18	4.21	0.13	4.50	0.32	7%	7%
19	6.59	0.18	5.09	0.26	-23%	23%
20	6.13	0.18	5.28	0.43	-14%	14%
21	5.81	0.16	4.94	0.44	-15%	15%
22	4.09	0.13	4.36	0.31	6%	6%
23	3.05	0.11	3.28	0.09	8%	8%
Overall Mean:	**4.23**		**3.99**		**-6%**	**10%**

Looking at Table 3.7 we can see that the differences (or absolute error) ranges from 1% to 23% depending on the hour of the day. It appears the model is less accurate during the busy hours of the day but is able to model the less busy times quite accurately. The average absolute error is approximately 10% overall, which is within acceptable bounds. Figure 3.18 shows us that the distributions follow roughly the same shape but slightly more of the model's response times fall between 3 and 8 minutes when compared to the historic responses. This is somewhat expected as a simulation model is typically more consistent than the real world and would not experience the extraneous circumstances that could cause the long tail (and thus very slow responses) of the historic distribution.

Figure 3.17 - Mean Response Times by Hour



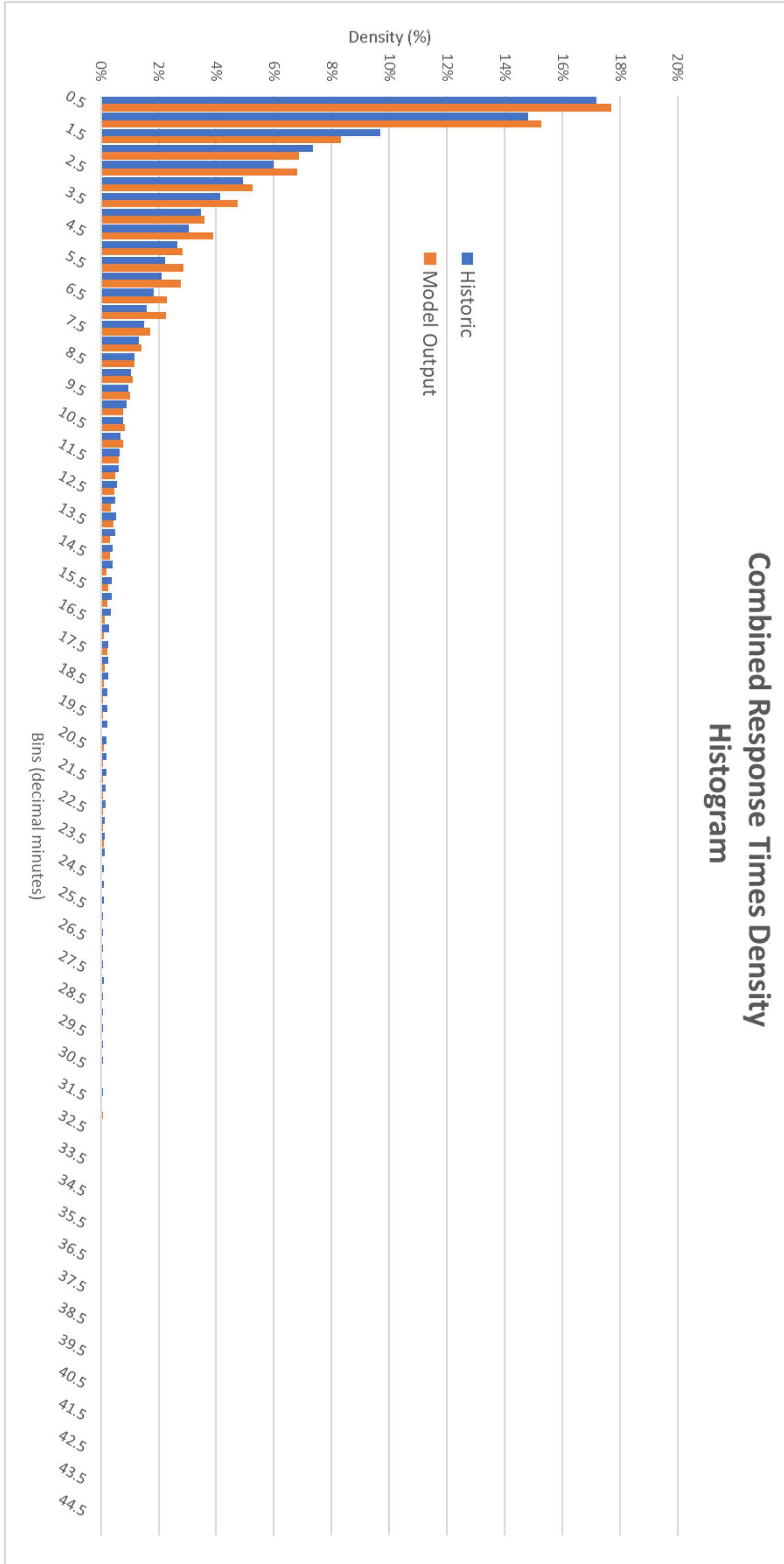


Figure 3.18 - Response Time Density Histogram

3.2.5.2 Nurse Travel Distances Validation

To validate the nurse travel distances, we compare the average travel of the simulated nurses against the historical travel distances (both pre-innovation and post). In Figure 3.19 we can immediately see a large difference between the 2018 post-innovation average travel distance (~4.26 km) and both the pre-innovation result (~2.6 km) and model output (~2.49 km). This is due to the way the 2013 study was done and how the simulation model measures distances – both of these only consider nurse motion when they are moving to (or from) answering patient calls, not the myriad of other short trips nurses make around the unit. The post-innovation system can capture every nurse trip, no matter how small, and therefore will provide a far more complete picture.

That being said, the fact that the model's outputted distance is within 5% of the 2013 study means that it at least can accurately represent the travel nurses undergo to answer patient calls, and so can still be used for insight in this regard.

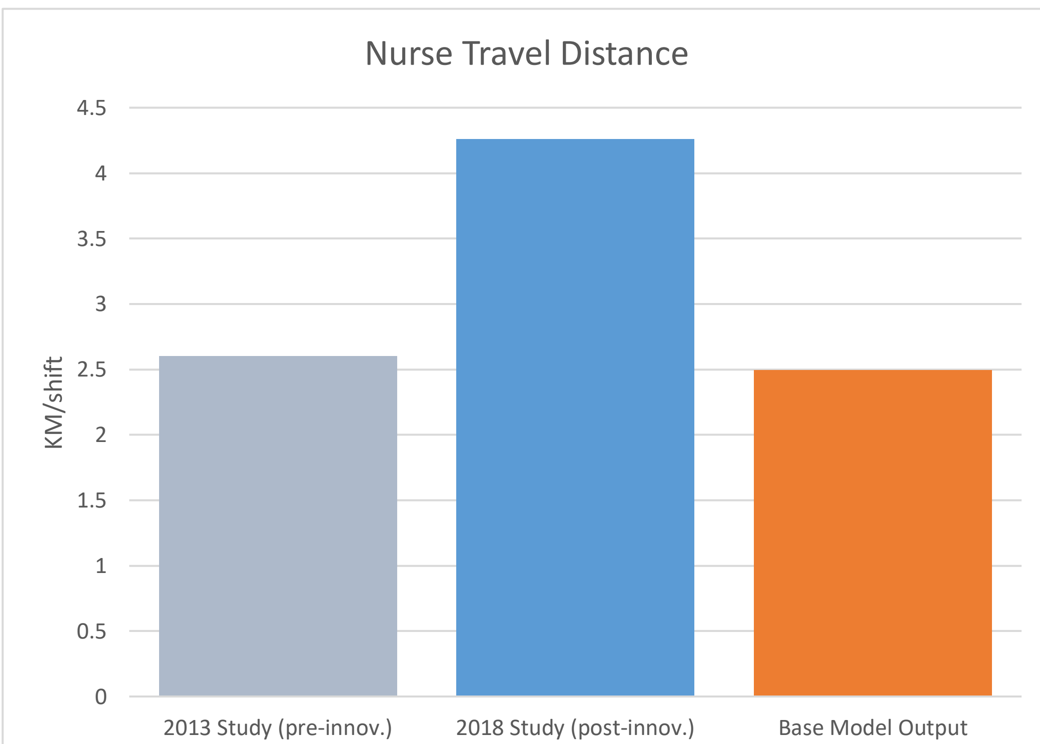


Figure 3.19 - Travel Distance Validation

3.2.6 Model Assumptions & Limitations

The base model makes some assumptions about the unit and nurse behavior including:

- Nurses will complete tending to calls before they go on break
- Nurses walk at a constant spend of 5 km/h around the unit
- The number of nurses on a shift will remain constant; no absences or extra nurses
- Nurses will only answer calls from their assigned patients
- If idle, nurses will return to the nursing station
- Nurses will always answer calls as soon as they can if they are available
- A single nurse is always able to deal with a call, assisting nurses are not required
- It is assumed that patients do not leave the bed and move about the unit

Originally, it was found that the model was systematically under-predicting the response times to calls by a small margin. This is believed to be because the simulated nurses would immediately go answer a call if they were free and able to do so, however in the real world nurses may take their time and finish up whatever they are currently doing before responding to a cell bell. This was consistent with what the authors witnessed during some visits to the unit. To compensate for this, a small buffer task of 60 seconds exponentially distributed was incorporated into the model to help offset this. This buffer task represents nurses taking a little time to complete whatever they were currently working on before they go to answer a call. In reality this task may not be exponentially distributed – however without additional task-time data to fit the actual distribution to, this assumption will have to suffice.

Another limitation of the model is that since the travel distances only account for answering patient calls (which is roughly 50% of the total travel), any improvements that the proposed scenarios demonstrate will only apply to half the distance and thus the full extent of the improvement may not be fully realized in the real unit.

Chapter 4

4 Scenario Testing

After validating the base simulation model (which represents the current state) we then developed three proposed alternative scenarios, with the goal of further improving our KPIs. The scenarios suggested below explore the potential impact of new call routing strategies, instead of always routing to the assigned nurses, calls are routed according to the following rules:

1) “Proximity”: Nearest available nurse (not within a patient room) is sent the call notification

2) “Call Alternate Pod (CAP)”: The call will be sent to a nurse in another pod to allow them to come to the assistance of a busier pod. Available nurses (not within a patient room) will be alerted to call, the first to confirm on phone/wall station is responsible for attending the call. Note: this call strategy assumes some altruistic behavior on behalf of the nurses responding to calls from patients other than their own, however this behavior may be encouraged through unit policy, incentives or recognition by managers for example.

3) “Call by Licensure”: Bathroom calls exclusively handled by PCAs, Medication calls exclusively by RNs/RPNs, normal calls can be handled by either if available.

The outputted KPIs from these scenarios will be compared to the those from the base model. A 30-run trial was run for each scenario to allow us to calculate confidence intervals and judge if any effects are significant or not.

Chapter 5

5 Results & Discussion

This section will present and discuss the results of this study – both the data analysis component, to determine the impact of implementing the “smart” system, and the simulation of alternative call routing scenarios.

5.1 Post-Innovation Data Analysis Results

To determine the impact of implementing the post-innovation “smart” system, statistical analysis was conducted on the KPIs – comparing pre-innovation and post-implementation results.

5.1.1 Call Response Times

Mean and median average response times to calls in 2013 (pre-innovation) were statistically compared to 2014-2017 (post-implementation) data. Since only summary statistics are available from the pre-innovation study (not raw data), a one-sample t-test and a sign rank test were performed on the mean and median response times respectively at the 95% confidence level. The results are summarized in Table 5.1 below:

Table 5.1 - Pre vs. Post Response Time Statistical Results

Test Statistic	Pre-implementation (2013)	Post-implementation (2014-2017)	p-value	% Change
Mean	4.44 minutes	4.22 minutes	$p \ll 0.05$*	-4.8%
Median	2.83 minutes	1.95 minutes	$p \ll 0.05$*	-31.1%

*in both cases p was much smaller than the required threshold of 0.05 therefore these results are statistically significant at the 95% confidence level.

From Table 5.1 and Figure 5.1 we can see there was marginal improvement post-implementation of the mean (4.8% decrease) and a large improvement in the median (31.1% decrease). Figure 5.2 displays the statistical test outputs such as t-values etc.

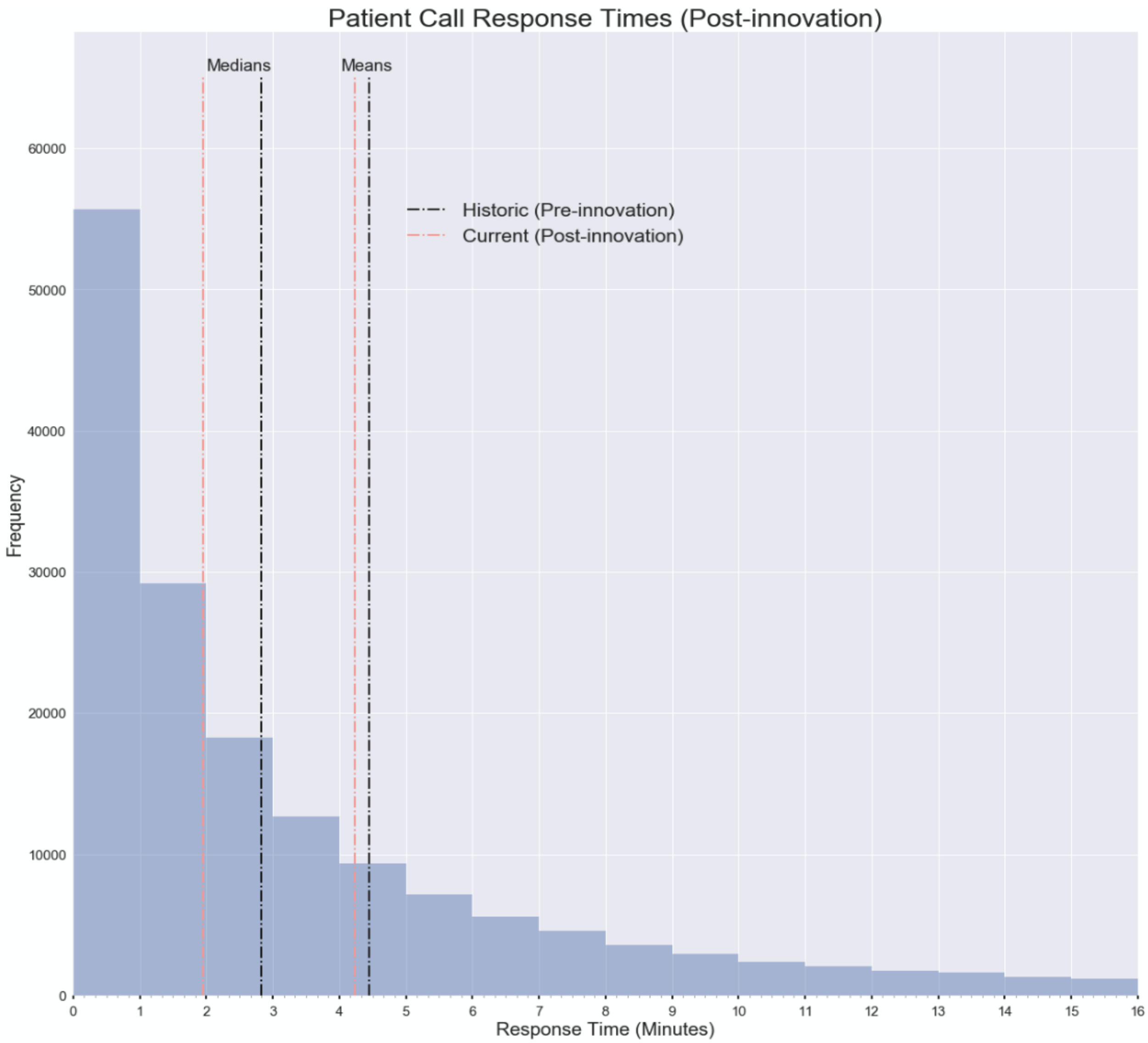


Figure 5.1 - Histogram of Improved Response Times

Additionally, the distribution of response times can be seen to be highly skewed, though due to the large sample size of N=168,059 we can safely relax the normality assumption of the t-test. Though the mean response time is our main metric, in this case it is interesting to consider the median as the distribution is skewed. (Note: these results exclude the bed exit alarms which have even faster response times due to their more urgent nature). Interpreting the median: 50% of calls are now answered in less than 1.95 minutes (1 minute and 57 seconds), just under a minute faster than without the system. It is interesting that the median improved a great deal while the mean only saw a small improvement, this is possible evidence that the system is able to improve response times when nurses are available and can answer quickly, however the system cannot help if all the nurses are preoccupied and unable to answer, hence resulting in the long tail of the distribution.

One-Sample T: Response (dec min)

Descriptive Statistics

N	Mean	StDev	SE Mean	95% Upper Bound for μ
168059	4.2289	5.9884	0.0146	4.2529

μ: mean of Response (dec min)

Test

Null hypothesis H_0: μ = 4.44
Alternative hypothesis H_1: μ < 4.44

T-Value	P-Value
-14.45	0.000

Sign Test for Median: Response (dec min)

Method

η: median of Response (dec min)

Descriptive Statistics

Sample	N	Median
Response (dec min)	168059	1.95

Test

Null hypothesis H_0: η = 2.83
Alternative hypothesis H_1: $\eta \neq$ 2.83

Sample	Number < 2.83	Number = 2.83	Number > 2.83	P-Value
Response (dec min)	100452	0	67607	0.000

Figure 5.2 - Statistical Test Outputs

5.1.2 Direct Care Time

The PDA devices the past time-motion study equipped nurses with periodically alarm and notify them to enter their location and the task they were performing at that moment. From this data they were able to identify which tasks nurses spend their time on and which locations they were in (Figure 5.3). The 2013 study identified that the largest proportion of time is spent on direct care at approximately 46.7% of total shift time. This includes all tasks directly related to caring for a patient (whether inside or outside a patient room). This is followed by documentation at ~17.6% and in-direct care at ~15.5% of total shift time. The past researchers also found that nurses spent approximately 37.5% of shift time at the nursing station, 31.2% in the patient room.

The data collected by the new system does not capture the actual tasks that nurses are performing - only their location, so an exact measure of direct care time is not possible, however the amount of time spent in various areas can be an indicator of certain types work.

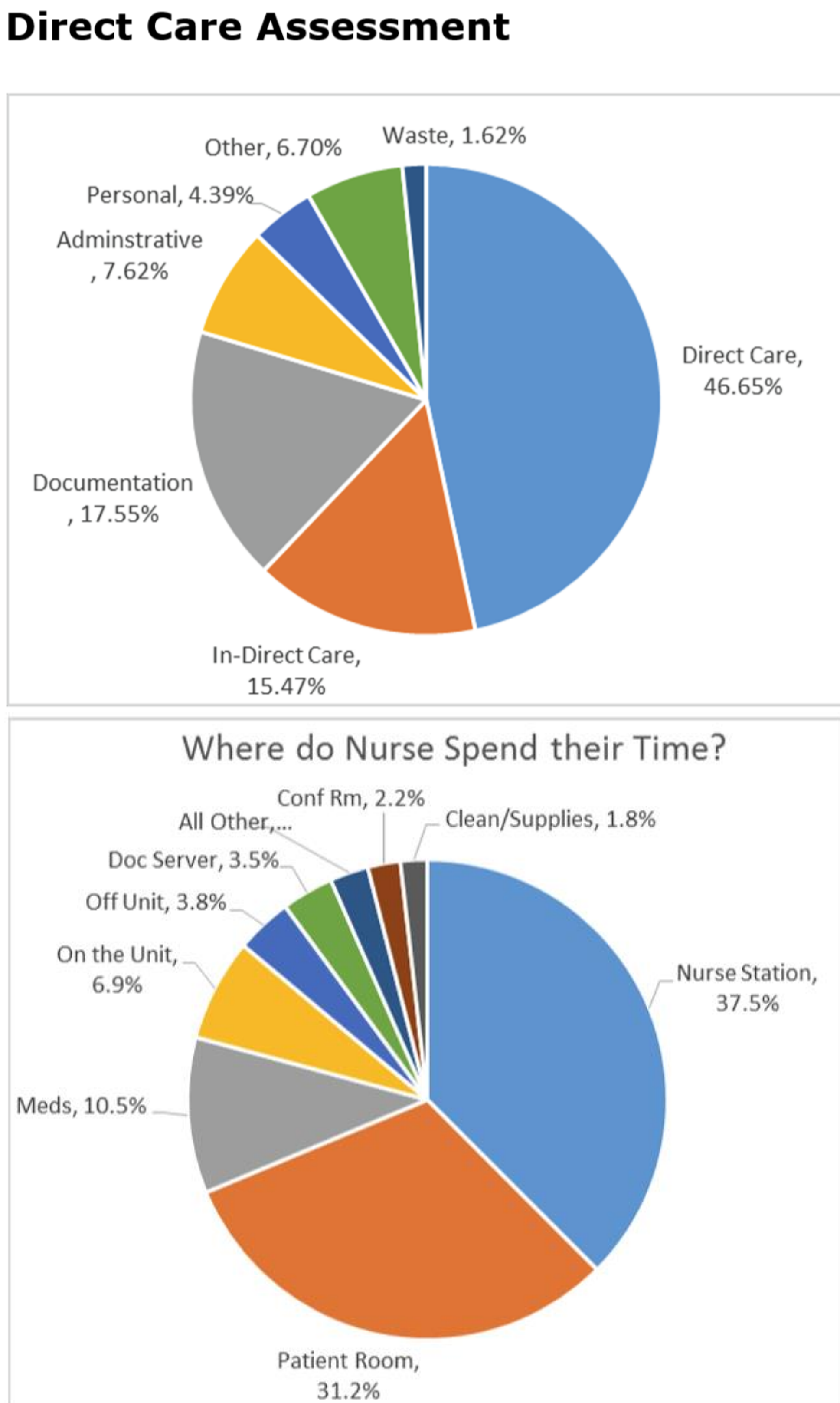


Figure 5.3 - 2013 Nurse Task Breakdowns. Source: Adapted from [31]

Figure 5.4 shows heatmaps with the percentage of visits to a location (left) and percentage of time spent in a location (right). We can see that staff visit the pods and nursing station very frequently and RPNs and RNs in particular spend a great deal of time at the nursing station (~35% & ~44% respectively). This makes sense as the pods are a

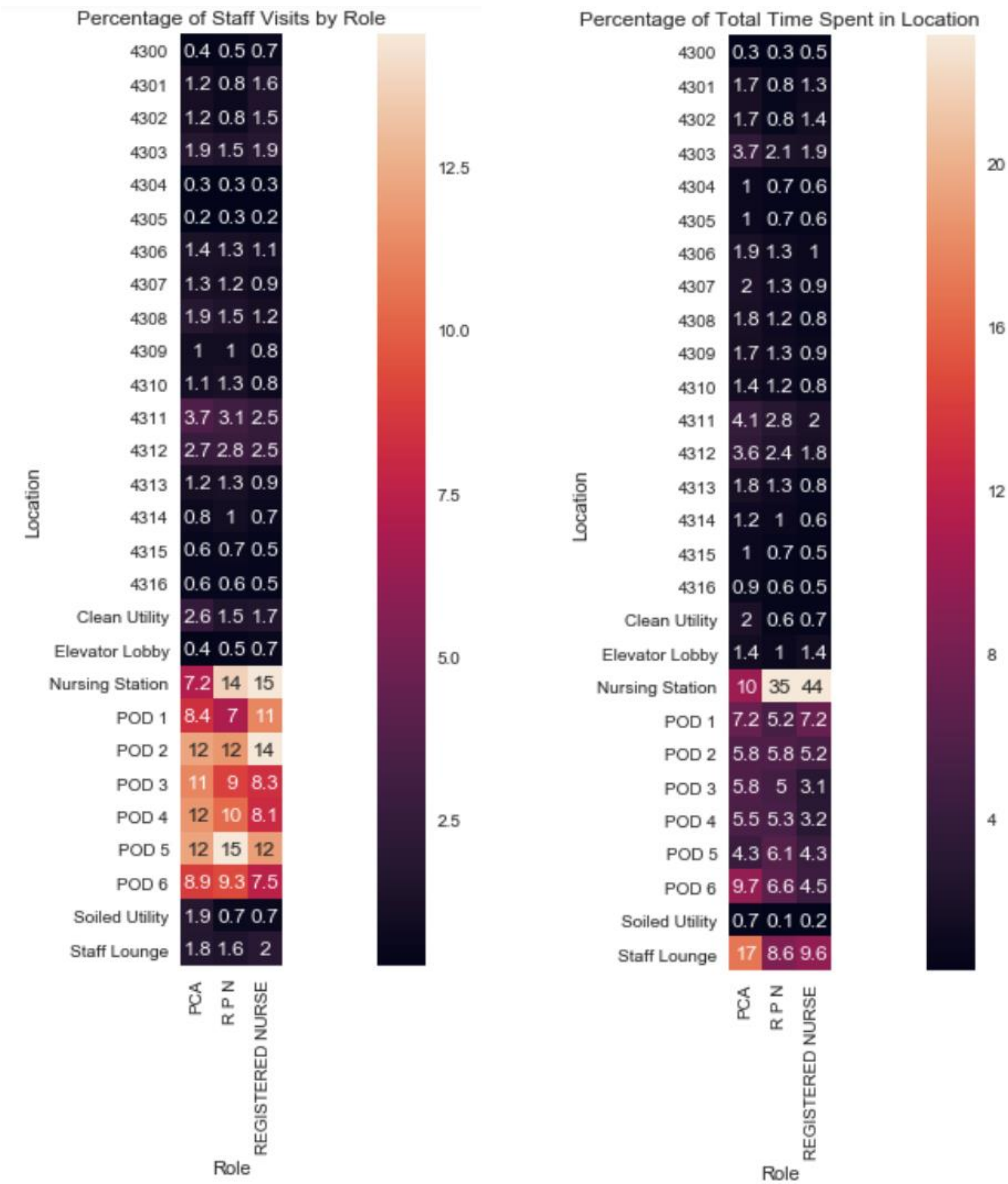


Figure 5.4 - Heatmaps of Nurse Visits and Time Spent in Location

Workstation-On-Wheels (WOW) and contain a computer used for access and documentation with the Electronic Medical Record (EMR) system, as well as a small cache of commonly used supplies and low-dose medications. During the many visits to the unit by the author the nursing station was always abuzz with activity and appeared to serve as the central hub of the unit. The nursing station also contains a few computers and a large TV monitor that displays patient status and the real-time location of all the nursing staff. The medication dispensary is also located at the nursing station, so it is no surprise that the data reflects a high level of activity.

Comparing and contrasting the 2013 data with the new system's location data, it appears that RN's spend more of their time at the nursing station than the 2013 average, although when averaged across all staff it was found that the nurses spend 29.6% of their time there – an approximately 8% decrease. The average amount of time nurses spent in patient rooms made up 21.5% of total shift time; this represents a large decrease from the 2013 level of 31.2% (Figure 5.5 shows the percentage of visits and time spent in patient rooms). It is not clear at this time what has caused these shifts in staff time allocation and the decrease in the time spent by nurses in patient rooms, though a possible contributing factor may be in part due to the implementation of a new EMR system around the time of the older study. Implementation of new EMR systems have been known to increase the time spent in documentation [28]. In this case, it reportedly caused an 8.7% increase in documentation time overall [31]. Checking the time spent by staff at the pods revealed that they spend on average 32.7% of total shift time, which is a large amount although this may be inflated slightly as there are supplies and other reasons to be at the Pods.

It is important to consider the impact that new technologies can have on staff and the operations of the unit; there is great potential for improvement, but also a risk that poorly-designed devices or systems can negatively impact workflow, usability and safety. There is not enough evidence to draw a conclusion either way at this time without being able to measure current direct care times and gather data on specific tasks.

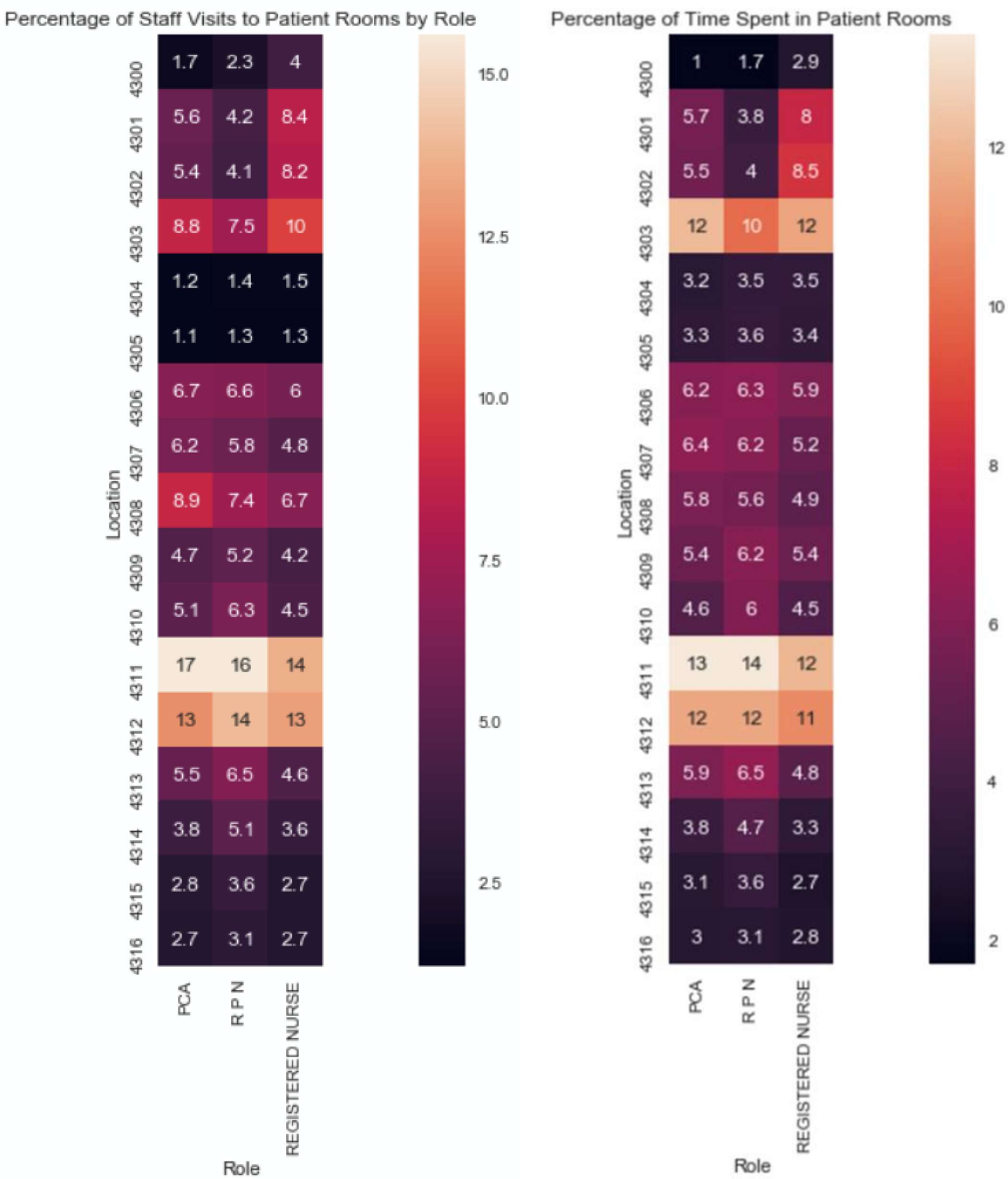


Figure 5.5 – Heatmaps of Visits and Percentage of Time Spent in Patient Rooms

5.1.3 Distance Travelled

The final metric is the distance travelled by nurses during their shifts. As a potentially large benefit to the new system is the ability for nurses to be contacted and respond remotely to patient calls, as well as be located and contacted by other staff for assistance - all of this saving unnecessary travel and time spent searching for people. The past study indicated that each nurse travelled on average 2.55 km per shift.

Post-implementation, nurses were tracked over their shifts from the location data, and in conjunction with measurements from the unit blueprints (evaluated using the aforementioned distance matrix) their travel distances were calculated. As briefly discussed in earlier sections it was found that the average travel distance per shift was 4.26 km. This would appear to be a large change over pre-implementation levels, however it is not the case as the 2013 pre-innovation study mainly considered movements due to patient calls as well as some of the other limitations of the pre-innovation data discussed earlier.

5.2 Simulation Results

Here we will discuss the results gathered from running the alternative call routing scenarios. Each scenario model was run 30 times in a trial and the results used to calculate 95% confidence intervals on the means, allowing us to compare them with some certainty. Figure 5.7 shows the mean hourly response times for all scenarios and the base case to allow for visual comparison.

5.2.1 Scenario 1 – “Proximity”

For the proximity routing scenario, patient calls were routed to the closest nurse. Looking at Figure 5.7 we can see that the hourly response times are slightly less than the base model’s times in most hours, however we cannot say that they are significantly different as the base model’s mean value lies within the confidence limits of the proximity scenario’s results (scenario results confidence intervals can be seen in Appendix G).

This may be because the travel time for nurses makes up only a small part of the total response time for a call, thus strategies aimed at reducing travel will only minimally impact response times. Next considering Figure 5.6, the average nurse travel distance per shift, we can see that there was a large improvement of 20.8% in the amount that nurses had to walk over a shift. Considering both these two results together means that a proximity call routing scenario is potentially a good way to reduce travel distance without while still maintaining the current response time levels. The caveat to this however, is that we know from the validation that the model's travel distances only represent half the potential distance travelled by a nurse, and hence it is likely that any predicted potential improvement of this strategy will not be as great in the real world.

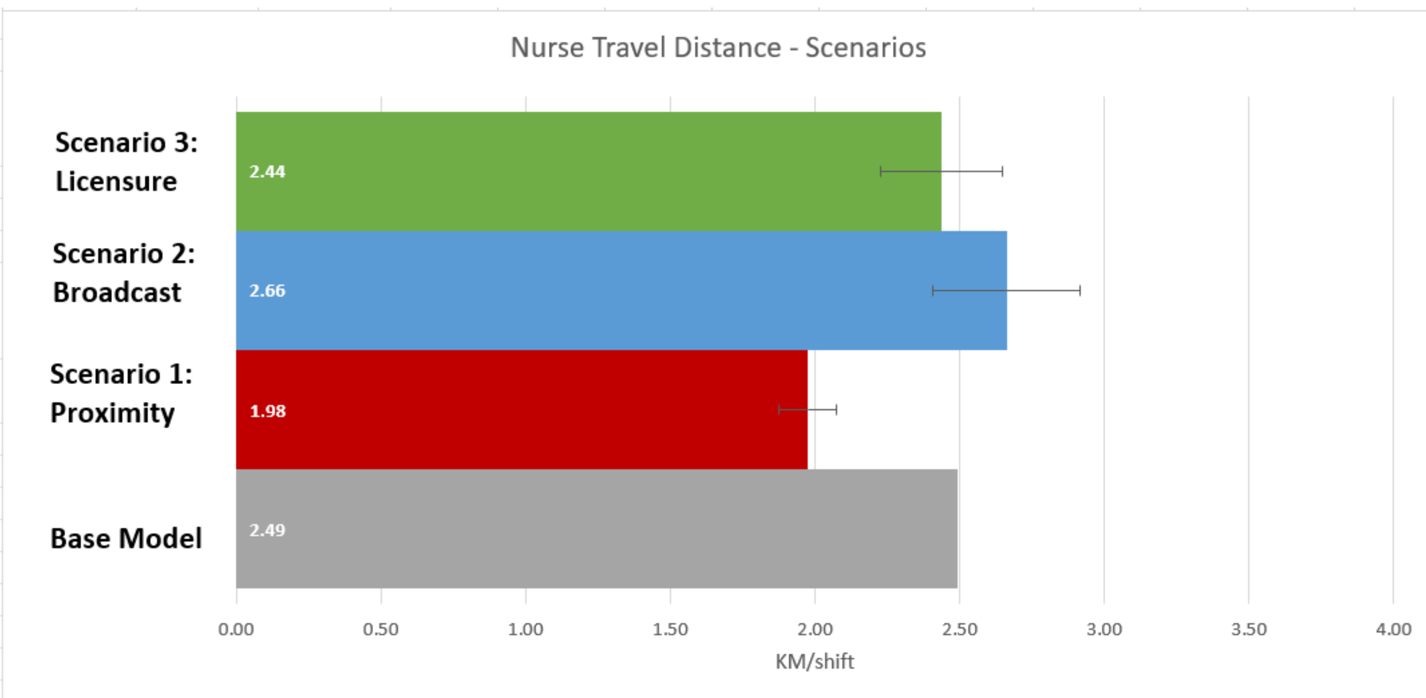


Figure 5.6 - Scenario Nurse Travel Results

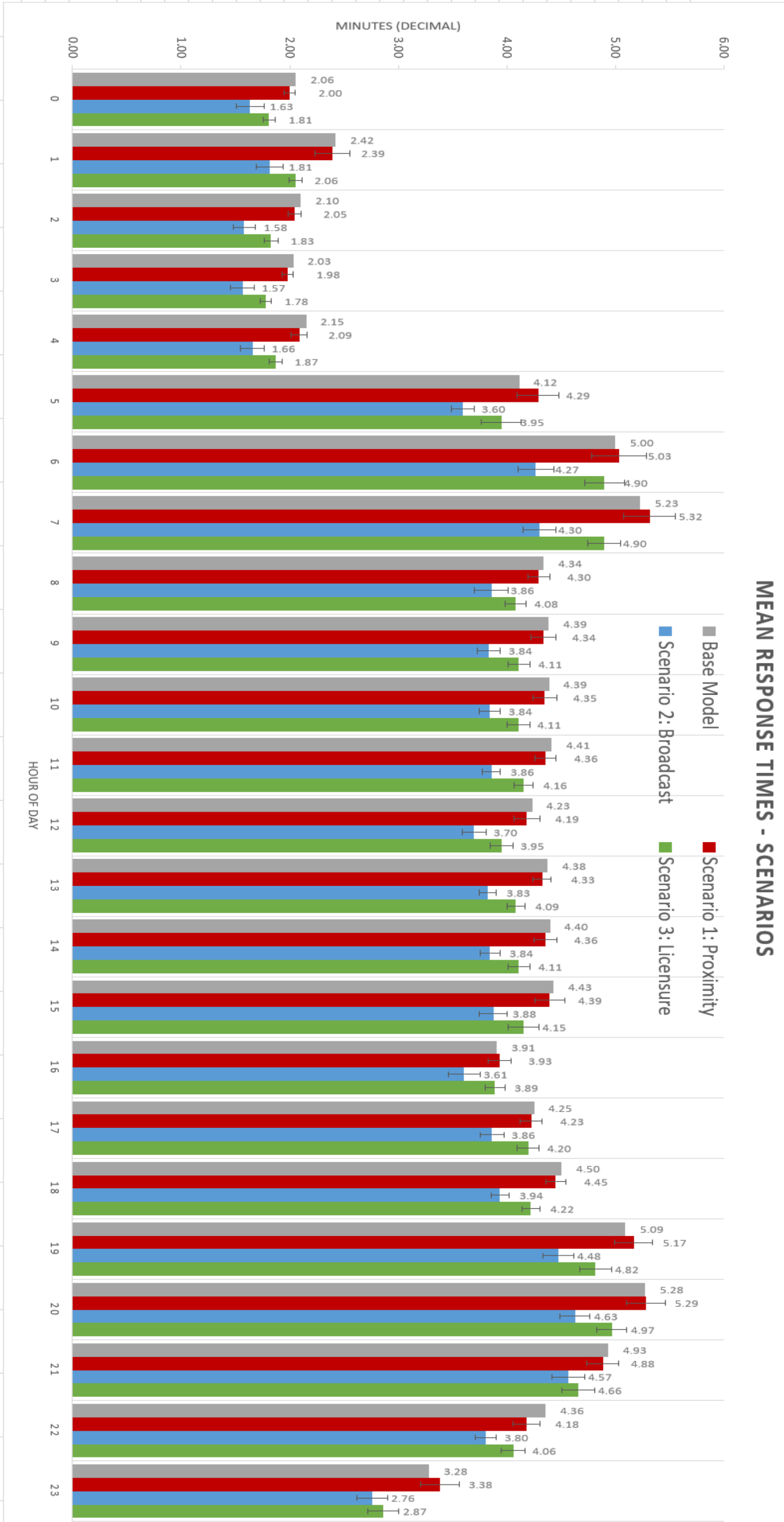


Figure 5.7 - All Scenario Hourly Response Times

5.2.2 Scenario 2 – “CAP”

In this scenario, calls were sent to other available nurses from a different pod and then whichever nurse responded would deal with the call. Figure 5.7 shows that there was a moderate improvement in response times, and interestingly a large improvement during the busy times of the unit, where response times were typically slower in the base model.

The goal of this scenario was to take advantage of additional capacity to answer calls by removing the restriction that nurses only answer their own patient’s calls. This means that in cases where the RN/RPN and the PCA are already busy, a nurse from another pod that is idle can step in and help answer, instead of leaving patients waiting. This strategy is apparently successful as even the upper confidence limits are lower in most hours – delivering an overall reduction of approximately 18.5%.

This improvement comes with a cost in terms of travel distance however, with there being a 6.8% increase over the base model (Figure 5.6). This makes sense, as nurses are being called from further away locations in the unit and are having to travel further to answer each other’s calls. The lower confidence limit is however 2.41 km (compared to the base model’s 2.49 km) so the impact on travel distance may potentially not be that bad, though the upper limit is 2.92 km so this should also be considered. In this case we have two competing metrics – the hospital will have to decide how much they value each as improving one may lead to a negative impact on the other.

5.2.3 Scenario 3 – “Licensure”

This scenario aimed to optimize the use of the nurse’s qualifications and licensing; RNs/RPNs are the only ones allowed to prepare and deliver medications (an RPN with some supervision of an RN). This means that if a PCA answer a pain call the only thing they can do is go find a RN to deal with that call, and if the RN is busy the patient will have to wait. This is inefficient and so the “Licensure” strategy is to have pain calls only get sent to RNs/RPNs and the bathroom calls only sent to PCAs, and normal-type calls can be answered by either.

While Figure 5.6 shows a very similar average distance travelled per shift, Figure 5.7 shows a small (but significant) decrease in response times (11.8% overall), particularly in less busy hours of the day. This is potentially due to the fact that although bathroom calls have similar mean service times to other call types (~8 mins vs ~8.7 mins respectively), they have much greater standard deviations (~20 mins vs. ~13.5 mins respectively) and so can potentially tie up an RN/RPN for a substantial amount of time, preventing them from being able to answer types of calls that only they are licensed to handle.

Chapter 6

6 Conclusion

The goal of this research was to accomplish two things: firstly, determine if implementing this “smart” system had an impact on response times, direct care time, and nurse travel distances and secondly, develop a simulation model and test out alternative call routing strategies to see if the system could be further improved.

Various datasets collected by the new system were analyzed and statistically compared to a previous time-motion study to evaluate changes between the pre-innovation (2013) state of the unit and the current post-innovation state (2014 onwards). From this analysis it was found that the mean and median response times had decreased by approximately 5% and 31% respectively. A limitation of the new system was also exposed; that it cannot measure direct care on its own as it does not collect information about the actual task nurses are completing, only their location. Finally, it was found that the previous study only measured the distances nurses travel while answering calls meaning a full comparison could not be made.

The simulation model was developed based on information gained from discussions with nurses and mangers on how the unit works, as well as the large datasets collected by the new system. The model was then validated against the real-world data to ensure results it produced are representative. A key limitation of the model is that, similarly to the previous time motion study, it only models nurse travel while they are responding to or dealing with patient calls. Once validated, the model was used to test three alternative call routing strategies: “Proximity”, “CAP”, and “Licensure”. Of these it was found that “Proximity” maintained response times while reducing travel distances by ~21%. “CAP” was effective at reducing response times by approximately 19% overall, with good improvements during peak busy times, (but with a ~7% increase in travel). “Licensure” improved response times by ~12% while maintaining current travel levels. This last strategy is more hypothetical as currently the design of the patient call bell prevents nurses from accurately knowing which type of call it is they are receiving (unless they use the system to answer remotely and speak to the patient), though hopefully the potential improvement presented in this study serves as an impetus to redesign the call bell. Based on these results the hospital should consider implementing one of the proposed alternative call routing strategies to further reduce efficiency and improve response times or travel distance. These changes should be made with feedback and buy-in from nursing staff on the unit for maximum impact and chances of success.

In summary, this study lends evidence to the argument that the adoption of ubiquitous smart technology in healthcare can improve operations and reduce inefficiencies and can be further improved with the use of operations research techniques and careful consideration of how new technologies can be used without negatively impacting nurse workflows.

Chapter 7

7 Future Research

Future work should include implementing and running a small pilot study on one of the alternative call routing strategies and use the data from this to inform further iterations or improvements. A pilot study of this nature could be very small, perhaps testing one routing strategy with just a single pod (and its few associated nurses) against the other pods, while evaluating their performance.

Another important possible direction would be to collect some data on the tasks that nurses are performing on the unit and then join that with the location and calls data for a complete picture of the operations of the unit. One way that this could be accomplished without having to resort to traditional observation/shadowing methods (which are both effort and time-intensive as discussed with the pre-innovation data) would be to use similar sensors to the “smart” hand-hygiene (highlighted in Figure 7.1). These sensors have both an RFID and a close-range proximity motion sensor, allowing them to only detect in a small range (in this case only detect those who use the hand-sanitizer). A modified version of these could be strategically placed around the unit (e.g. at the medication dispensing machine, patient bed, supply cabinets etc.) to gather fine-detailed information about not only which room/area the nurses are in, but also about where within the room they are and what they are likely doing. This highly granular information when combined with the current data would allow greater detail to be built into the model and KPIs of interest like direct care time could be measured. A more detailed model would also allow a greater range of scenarios to be tested, aside from just call routing strategies.

Figure 7.1 - Smart Hand Hygiene Sensor

Finally, the combining of the results of this study and a concurrent study being conducted on hand hygiene, falls risk and staff satisfaction in the unit would provide a clearer picture of the overall impact of such smart systems on many different aspects of the hospital unit and its staff.

The results from these two studies will help inform the implementation of wider scale smart systems, not only within the current hospital but at a new Mackenzie Health hospital being constructed for 2020. This new hospital aims to be completely “smart” and utilize many more IOT devices and systems in all units across the hospital. This is an exciting prospect, as we have seen the great disruption, impact and improvement that these mobile and distributed technologies have had on other industries, now it’s time for healthcare’s turn!

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Appendix A

Post-innovation Dataset Samples

The following figures are samples of the three datasets collected by the system.

Calls data:

	Patient ID	Location	Call Placed	Intarrival (dec min)	Total Response Time	Response (dec min)
0	3	4303 - 3	2014-07-15 00:11:39	11.65	00:00:27	0.45
1	3578	4315 - 1	2014-07-15 00:12:38	0.98	00:02:34	2.57
2	721	4305 - 1	2014-07-15 00:23:20	10.70	00:00:47	0.78
3	113	4316 - 1	2014-07-15 00:36:31	13.18	00:01:44	1.73
4	134	4303 - 4	2014-07-15 01:03:52	27.35	00:00:11	0.18
5	2861	4308 - 1	2014-07-15 01:16:37	12.75	00:00:34	0.57
6	204	4306 - 2	2014-07-15 01:19:20	2.72	00:00:17	0.28
7	721	4305 - 1	2014-07-15 01:24:27	5.13	00:03:39	3.65
8	721	4305 - 1	2014-07-15 01:29:27	5.00	00:04:44	4.73
9	2632	4311 - 4	2014-07-15 01:35:24	5.93	00:00:22	0.37
10	391	4314 - 2	2014-07-15 01:43:43	8.33	00:00:46	0.77

Figure A.1 – Sample of Patient Calls Data

Nurse location data:

	Nurse ID	NurseHash	Staff Role	Patient ID	PatientHash	Location	Assigned TimeStamp	Unassigned TimeStamp
0	92	e4ebf6e48c588270652aa...	Primary Caregiver	1703	46a89e2add04af97e3f42...	4300 - 1	2016-11-30 18:57:34	2016-12-01 08:11:38
1	92	e4ebf6e48c588270652aa...	Primary Caregiver	3365	d0f436a5b58f98a2c068b...	4300 - 2	2016-11-30 18:57:34	2016-12-01 08:11:38
2	92	e4ebf6e48c588270652aa...	Primary Caregiver	583	bc16f49fb295651c723e0...	4301 - 1	2016-11-30 18:57:34	2016-12-01 08:11:38
3	92	e4ebf6e48c588270652aa...	Primary Caregiver	2434	5c51d78436797f2ea2f4a...	4301 - 2	2016-11-30 18:57:34	2016-12-01 08:11:38
4	92	e4ebf6e48c588270652aa...	Primary Caregiver	679	8a3ba6e229978baf86b2b...	4302 - 1	2016-11-30 18:57:34	2016-12-01 08:11:38
5	92	e4ebf6e48c588270652aa...	Primary Caregiver	2238	3b215403cd519886f208e...	4302 - 2	2016-11-30 18:57:34	2016-12-01 08:11:38
6	92	e4ebf6e48c588270652aa...	Primary Caregiver	3091	67b568806d6bb6ca1397c...	4303 - 1	2016-11-30 18:57:34	2016-12-01 08:11:38
7	92	e4ebf6e48c588270652aa...	Primary Caregiver	337	1a8f84ca0830c8104e2c3...	4303 - 2	2016-11-30 18:57:34	2016-12-01 08:11:38
8	91	0e7ad129825e6f7c8cd1b...	Primary Caregiver	1438	082c399dfbddae631da34...	4303 - 3	2016-11-30 19:01:01	2016-12-01 08:11:10
9	91	0e7ad129825e6f7c8cd1b...	Primary Caregiver	856	7a4a9ba3f02f4905f2dbd...	4303 - 4	2016-11-30 19:01:01	2016-12-01 08:11:10
10	91	0e7ad129825e6f7c8cd1b...	Primary Caregiver	3443	98a00303bf1190a215ddf...	4304 - 1	2016-11-30 19:01:01	2016-12-01 08:11:10

Figure A.2 - Sample of Nurse Location Data

Nurse Assignment data:

	NurseID	NurseHash	Role	Location	StartTimeStamp	EndTimeStamp	Duration (Dec min)
125930	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	POD 1	2016-12-19 06:56:54	2016-12-19 06:57:17	0.38
125934	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	Staff Lounge	2016-12-19 06:57:17	2016-12-19 07:00:01	2.73
125984	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	Nursing Station	2016-12-19 07:00:01	2016-12-19 07:04:16	4.25
126040	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	POD 5	2016-12-19 07:04:16	2016-12-19 07:04:25	0.15
126041	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	Nursing Station	2016-12-19 07:04:25	2016-12-19 07:04:28	0.05
126042	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	POD 2	2016-12-19 07:04:28	2016-12-19 07:04:43	0.25
126045	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	Nursing Station	2016-12-19 07:04:43	2016-12-19 07:18:04	13.35
126207	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	POD 2	2016-12-19 07:18:04	2016-12-19 07:18:43	0.65
126215	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	4303	2016-12-19 07:18:43	2016-12-19 07:28:04	9.35
126345	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	POD 2	2016-12-19 07:28:04	2016-12-19 07:28:07	0.05
126347	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	Nursing Station	2016-12-19 07:28:07	2016-12-19 07:28:34	0.45
126355	1	dd4f8810ae8285d2ef36e...	REGISTERED NURSE	POD 2	2016-12-19 07:28:34	2016-12-19 07:29:43	1.15

Figure A.3 - Sample of Nurse Assignment Data

Appendix B

Data Joining Scheme

All three datasets were joined on the Unique Nurse and Patient IDs allowing us greater insight into the “big picture” of how nurses on the unit respond to patient needs.

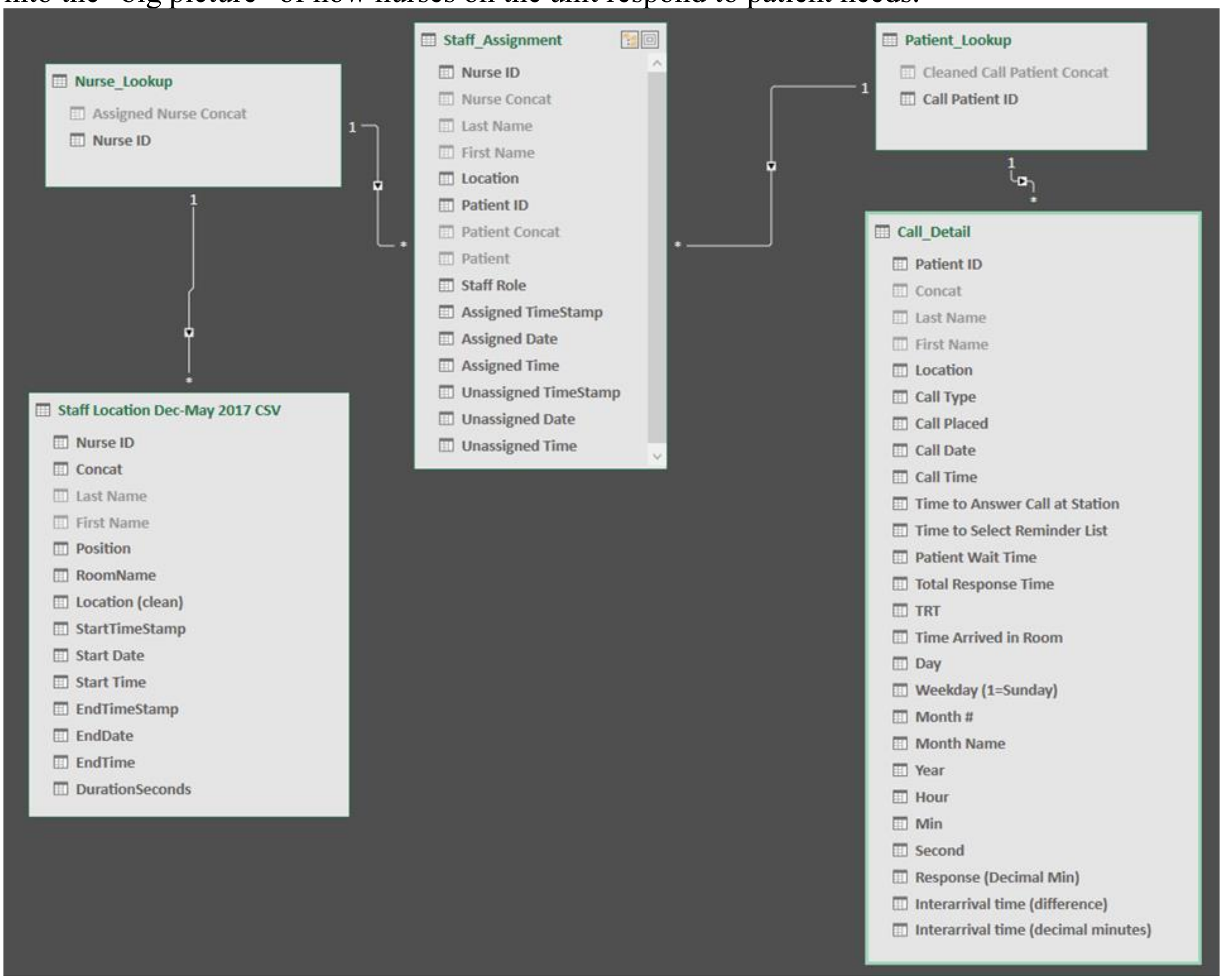

Figure B.1 - The Data Joining Schema

Appendix C

Call Cluster Metrics

The clustering algorithm was run repeatedly with different K values (i.e. number of desired clusters) and at each run the sum of all intra-cluster distances was computed (referred to as “inertia”). The goal was to identify the minimum meaningful number of clusters K that also have a relatively small inertia measure.

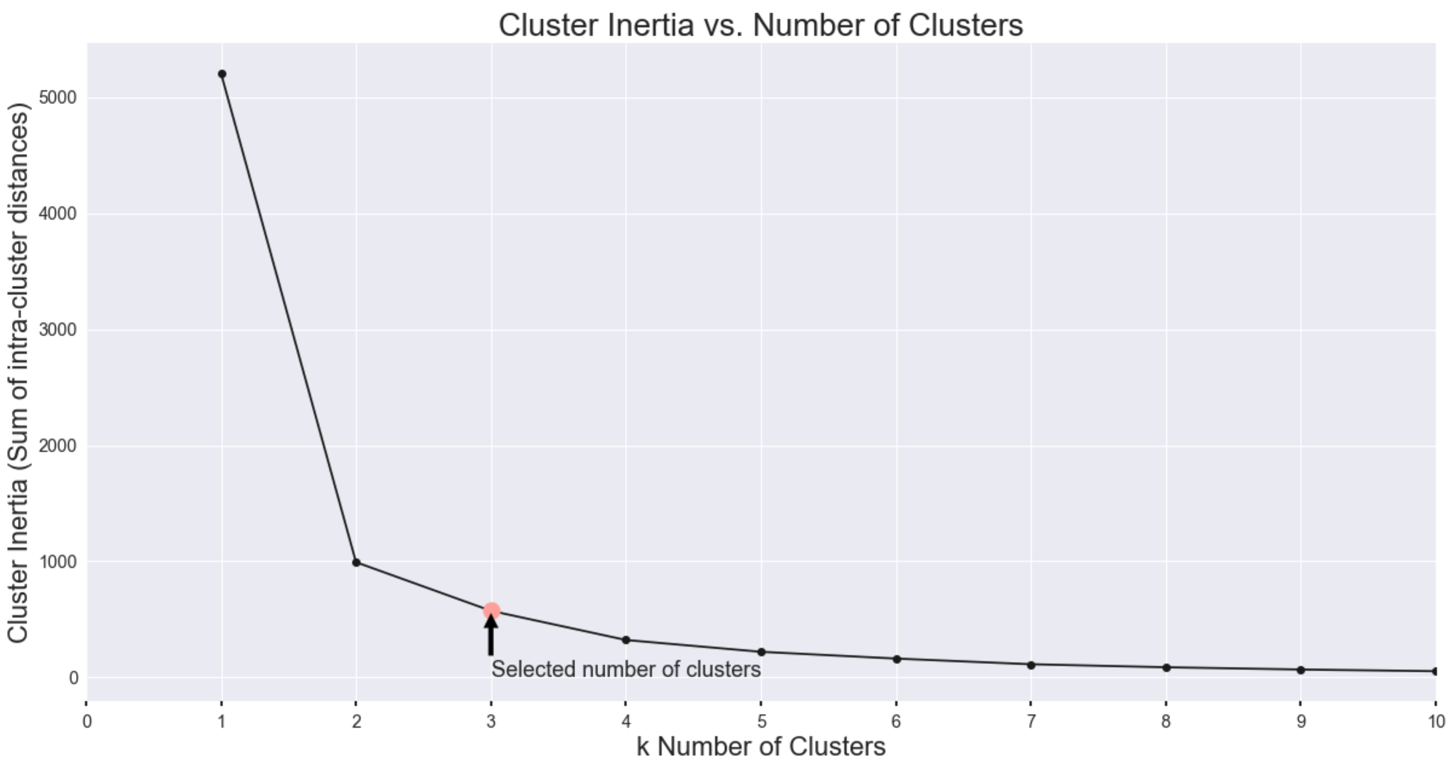

Figure C.1 - Cluster inertia with iterative runs of the K-means algorithm with varying K

A one-way ANOVA was conducted to confirm the differences between clusters (specifically testing for differences in the interarrival times). The results indicated that there are significant differences between clusters ($p<<0.05$ at the 95% confidence level).

One-way ANOVA: C0_Intarrival (dec min), C1_Intarrival ...

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	3	C0_Intarrival (dec min), C1_Intarrival (dec min), C2_Intarrival (dec min)

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	239743	119872	1956.84	0.000
Error	181138	11096086	61		
Total	181140	11335829			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
7.82673	2.11%	2.11%	2.11%

Means

Factor	N	Mean	StDev	95% CI
C0_Intarrival (dec min)	48469	7.9642	10.2826	(7.8945, 8.0338)
C1_Intarrival (dec min)	59663	5.7661	7.0441	(5.7033, 5.8289)
C2_Intarrival (dec min)	73009	5.1588	6.4221	(5.1020, 5.2156)

Pooled StDev = 7.82673

Figure C.2 - Results from One-way ANOVA

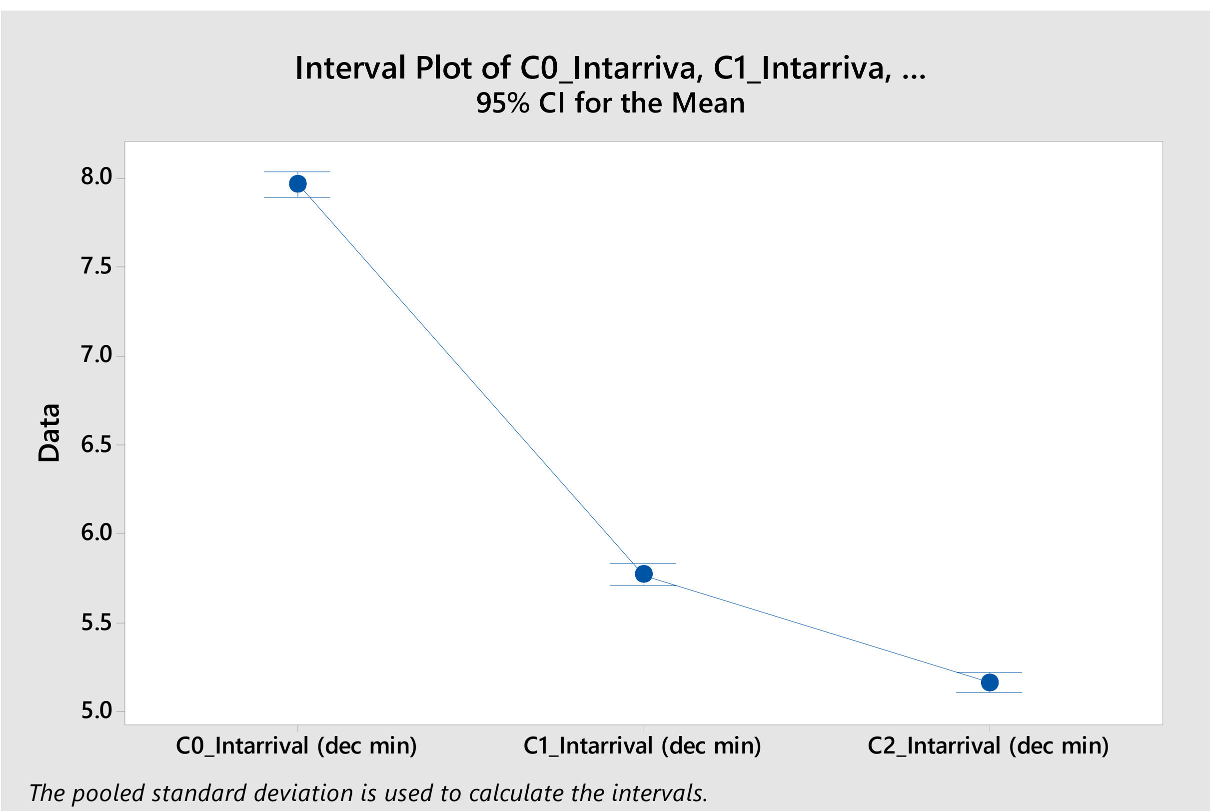

Figure C.3 – Cluster Interarrival Time Interval Plot from ANOVA

Appendix D

Call Inter-arrival Time Distribution Fitting

PP-plots graphically compare the empirical Cumulative Density Function (CDF) of our data against the CDF of our fitted exponential distribution. In a good fit the data will lie straight along the orange line). We can see that the fitted distributions model the data quite well.

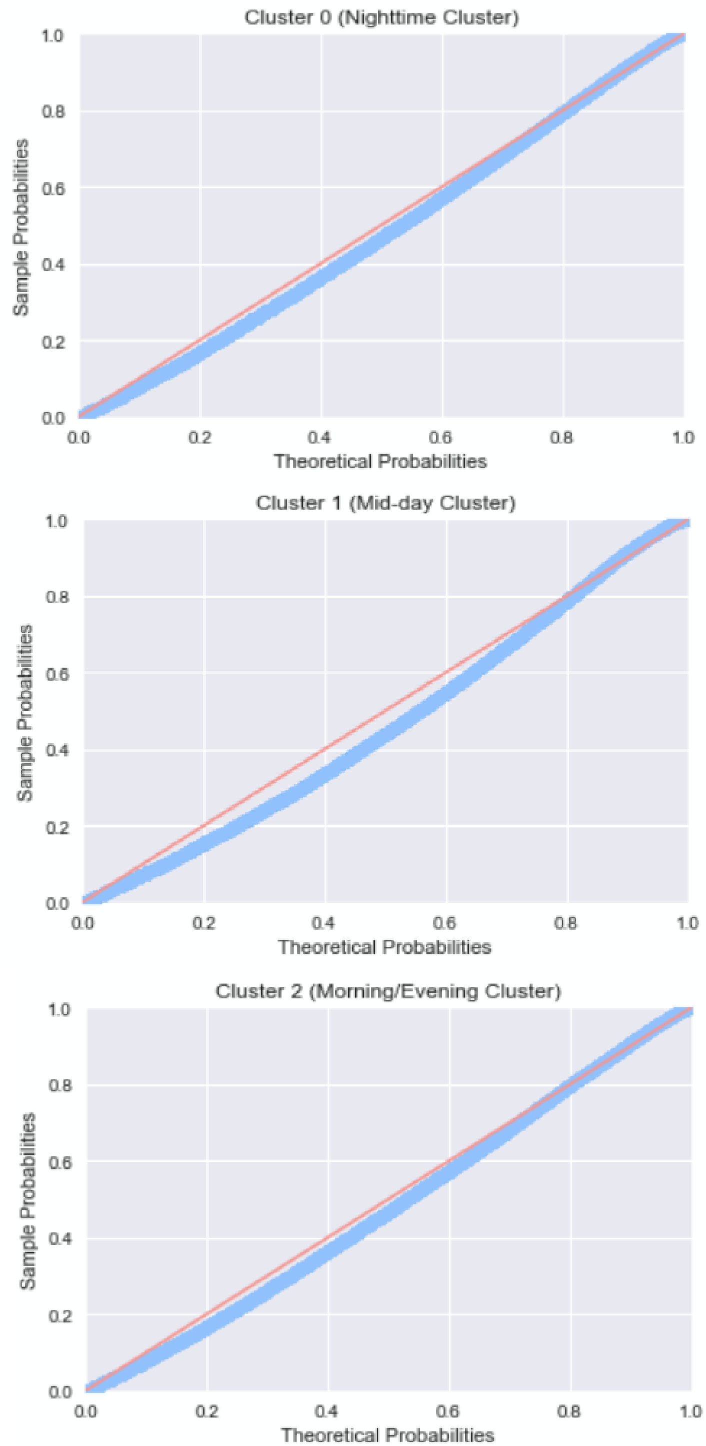

Figure D.1 - PP-plots of Fitted Distributions

Appendix E

The Integrated Patient Call Bell ("Pillow Speaker")

Patient call button and instruction sheet. The "Normal" call button is the largest and most prominent out of the three and results in the majority of patients only using the "Normal being for all types of calls.

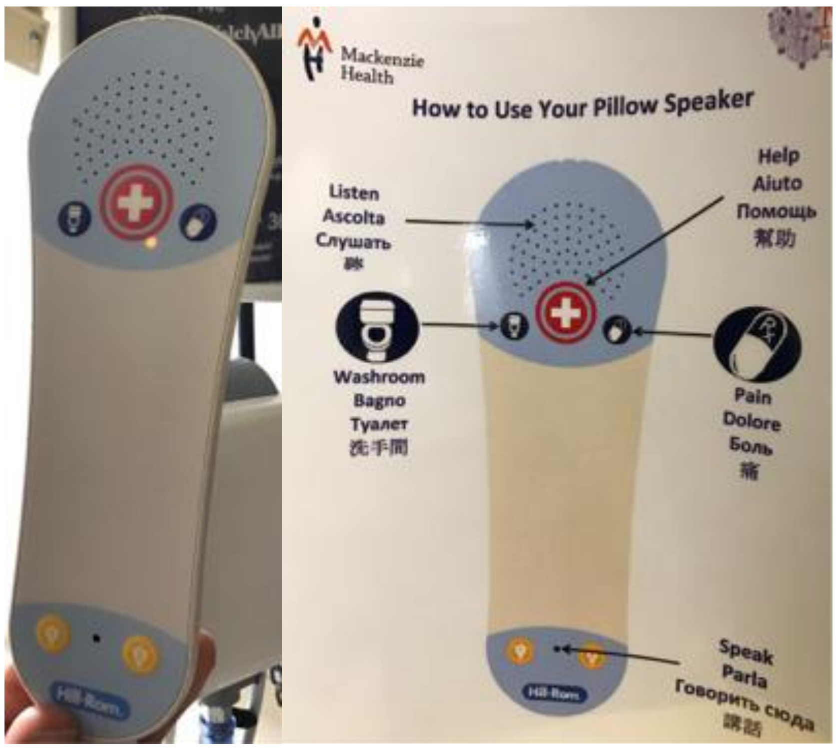

Figure E.1 - Pillow Speaker and Instruction Sheet

Appendix F

Distance Matrix

In order to be able to compute the total distances nurses travelled during shifts, a distance matrix was developed from measurement and blueprints of the hospital unit. The matrix includes the distance from every room or point of interest to every other room or point.

	4300	4301	4302	4303	4304	4305	4306	4307	4308	4309	4310	4311	4312	4313	4314	4315	4316	POD 1	POD 2	POD 3	POD 4	POD 5	POD 6	Nursing Station	Clean Utility	Soiled Utility	Staff Lounge	Elevator Lobby
4300	0.00	11.52	12.78	16.70	23.80	25.47	27.97	28.97	29.48	36.49	35.15	28.64	20.62	22.13	22.96	27.22	26.39	6.51	15.28	22.80	29.81	23.21	25.22	16.03	9.69	20.79	18.37	18.37
4301	11.52	0.00	7.85	12.19	19.46	21.13	23.63	24.63	25.13	32.15	30.81	24.22	16.20	17.70	18.54	24.22	23.38	5.01	10.94	18.45	25.47	18.54	25.89	11.36	8.18	16.45	8.68	20.04
4302	12.78	7.85	0.00	11.02	18.04	19.71	22.21	23.21	23.71	30.73	29.39	23.21	15.28	16.78	17.62	25.47	26.30	6.26	9.52	17.03	24.05	17.62	21.13	10.44	9.44	15.03	10.19	21.54
4303	16.70	12.19	11.02	0.00	12.36	14.03	16.53	17.54	18.04	25.05	23.71	21.88	13.86	15.36	16.20	24.05	24.88	10.19	3.84	11.36	18.37	16.20	19.71	9.02	22.13	9.35	15.03	26.39
4304	23.80	19.46	18.04	12.36	0.00	8.68	14.03	15.03	15.53	22.55	21.21	21.46	20.37	21.88	22.71	30.56	31.40	17.28	8.52	8.85	15.87	22.71	26.22	15.53	20.46	8.85	21.54	32.90
4305	25.47	21.13	19.71	14.03	8.68	0.00	12.36	13.36	13.86	20.88	19.54	19.79	22.04	23.55	24.38	32.23	33.07	18.95	10.19	7.18	14.20	20.21	27.89	17.20	22.13	10.52	23.21	34.57
4306	27.97	23.63	22.21	16.53	14.03	12.36	0.00	7.85	8.18	18.87	17.54	17.79	24.55	26.05	26.89	34.74	35.57	21.46	12.69	5.18	12.19	18.20	30.39	19.71	24.63	13.03	25.55	36.91
4307	28.97	24.63	23.21	17.54	15.03	13.36	7.85	0.00	7.35	19.87	18.54	18.79	25.55	27.05	27.89	35.74	36.57	22.46	13.69	6.18	13.19	19.21	31.40	20.71	25.63	14.03	26.55	37.91
4308	29.48	25.13	23.71	18.04	15.53	13.86	8.18	7.35	0.00	14.86	13.53	13.78	19.21	24.88	25.72	30.06	30.90	22.96	14.20	6.68	8.18	14.20	25.72	21.21	26.14	14.53	26.39	37.74
4309	36.49	32.15	30.73	25.05	22.55	20.88	18.87	19.87	14.86	0.00	7.85	12.27	17.70	23.38	24.22	28.56	29.39	29.98	21.21	13.69	6.68	12.69	24.22	19.87	35.24	14.36	26.55	37.91
4310	35.15	30.81	29.39	23.71	21.21	19.54	17.54	18.54	13.53	7.85	0.00	10.94	16.37	22.04	22.88	27.22	28.06	28.64	19.87	12.36	5.34	11.36	22.88	18.54	24.80	13.03	25.55	36.91
4311	28.64	24.22	23.21	21.88	21.46	19.79	17.79	18.79	13.78	12.27	10.94	0.00	10.69	16.37	17.20	21.54	22.38	22.38	19.87	12.61	5.59	5.68	17.20	12.86	15.03	7.52	20.71	32.06
4312	20.62	16.20	15.28	13.86	20.37	22.04	24.55	25.55	19.21	17.70	16.37	10.69	0.00	11.19	12.02	16.53	17.37	14.36	11.86	18.04	11.02	5.01	12.19	4.84	15.53	9.02	15.03	26.39
4313	22.13	17.70	16.78	15.36	21.88	23.55	26.05	27.05	24.88	23.38	22.04	16.37	11.19	0.00	7.85	12.19	13.03	15.87	13.36	20.88	16.70	10.69	7.85	6.35	11.19	14.70	10.19	21.54
4314	22.96	18.54	17.62	16.20	22.71	24.38	26.89	27.89	25.72	24.22	22.88	17.20	12.02	7.85	0.00	11.02	11.86	16.70	14.20	21.71	17.54	11.52	6.68	7.18	10.02	15.53	8.68	20.04
4315	27.22	24.22	25.47	24.05	30.56	32.23	34.74	35.74	30.06	28.56	27.22	21.54	16.53	12.19	11.02	0.00	7.85	19.21	22.04	28.89	21.88	15.87	4.34	15.03	7.68	19.87	7.52	16.20
4316	26.39	23.38	26.30	24.88	31.40	33.07	35.57	36.57	30.90	29.39	28.06	22.38	17.37	13.03	11.86	7.85	0.00	18.37	22.88	29.73	22.71	16.70	5.18	15.87	8.52	20.71	8.85	15.03
POD 1	6.51	5.01	6.26	10.19	17.28	18.95	21.46	22.46	22.96	29.98	28.64	22.38	14.36	15.87	16.70	19.21	18.37	0.00	8.77	16.28	22.71	16.70	20.88	9.52	3.17	14.28	4.51	15.87
POD 2	15.28	10.94	9.52	3.84	8.52	10.19	12.69	13.69	14.20	21.21	19.87	19.87	11.86	13.36	14.20	22.04	22.88	8.77	0.00	7.52	14.53	14.20	17.70	7.01	11.94	5.51	13.69	25.05
POD 3	22.80	18.45	17.03	11.36	8.85	7.18	5.18	6.18	6.68	13.69	12.36	12.61	18.04	20.88	21.71	28.89	29.73	16.28	7.52	0.00	7.01	13.03	25.22	14.53	19.46	7.85	20.71	32.06
POD 4	29.81	25.47	24.05	18.37	15.87	14.20	12.19	13.19	8.18	6.68	5.34	5.59	11.02	16.70	17.54	21.88	22.71	22.71	14.53	7.01	0.00	6.01	17.54	13.19	28.56	7.68	20.71	32.06
POD 5	23.21	18.54	17.62	16.20	22.71	20.21	18.20	19.21	14.20	12.69	11.36	5.68	5.01	10.69	11.52	15.87	16.70	16.70	14.20	13.03	6.01	0.00	11.52	7.18	9.35	4.01	13.69	25.05
POD 6	25.22	25.89	21.13	19.71	26.22	27.89	30.39	31.40	25.72	24.22	22.88	17.20	12.19	7.85	6.68	4.34	5.18	20.88	17.70	25.22	17.54	11.52	0.00	10.69	3.34	15.53	4.51	15.87
Nursing Station	16.03	11.36	10.44	9.02	15.53	17.20	19.71	20.71	21.21	19.87	18.54	12.86	4.84	6.35	7.18	15.03	15.87	9.52	7.01	14.53	13.19	7.18	10.69	0.00	14.03	5.51	14.86	26.22
Clean Utility	9.69	8.18	9.44	22.13	20.46	22.13	24.63	25.63	26.14	35.24	24.80	15.03	15.53	11.19	10.02	7.68	8.52	3.17	11.94	19.46	28.56	9.35	3.34	14.03	0.00	18.70	8.18	19.54
Soiled Utility	20.79	16.45	15.03	9.35	8.85	10.52	13.03	14.03	14.53	14.36	13.03	7.52	9.02	14.70	15.53	19.87	20.71	14.28	5.51	7.85	7.68	4.01	15.53	5.51	18.70	0.00	19.21	30.56
Staff Lounge	18.37	8.68	10.19	15.03	21.54	23.21	25.55	26.55	26.39	26.55	25.55	20.71	15.03	10.19	8.68	7.52	8.85	4.51	13.69	20.71	20.71	13.69	4.51	14.86	8.18	19.21	0.00	17.87
Elevator Lobby	18.37	20.04	21.54	26.39	32.90	34.57	36.91	37.91	37.74	37.91	36.91	32.06	26.39	21.54	20.04	16.20	15.03	15.87	25.05	32.06	32.06	25.05	15.87	26.22	19.54	30.56	17.87	0.00

Figure F.1 - Nurse Travel Distance Matrix

Appendix G

Simulation Results

Simulation scenario mean response time results and 95% confidence intervals.

Response Time (decimal minutes)							
Hour of Day	**Base Model**	**Scenario 1: Proximity**	**95% Confidence Interval**	**Scenario 2: Broadcast**	**95% Confidence Interval**	**Scenario 3: Licensure**	**95% Confidence Interval**
0	2.06	2.00	0.05	1.63	0.13	1.81	0.05
1	2.42	2.39	0.16	1.81	0.12	2.06	0.06
2	2.10	2.05	0.06	1.58	0.10	1.83	0.06
3	2.03	1.98	0.05	1.57	0.11	1.78	0.05
4	2.15	2.09	0.07	1.66	0.11	1.87	0.06
5	4.12	4.29	0.19	3.60	0.11	3.95	0.18
6	5.00	5.03	0.25	4.27	0.16	4.90	0.19
7	5.23	5.32	0.24	4.30	0.15	4.90	0.15
8	4.34	4.30	0.10	3.86	0.16	4.08	0.10
9	4.39	4.34	0.11	3.84	0.10	4.11	0.10
10	4.39	4.35	0.11	3.84	0.10	4.11	0.10
11	4.41	4.36	0.10	3.86	0.08	4.16	0.09
12	4.23	4.19	0.12	3.70	0.11	3.95	0.11
13	4.38	4.33	0.08	3.83	0.08	4.09	0.08
14	4.40	4.36	0.10	3.84	0.09	4.11	0.10
15	4.43	4.39	0.14	3.88	0.13	4.15	0.14
16	3.91	3.93	0.10	3.61	0.15	3.89	0.09
17	4.25	4.23	0.10	3.86	0.11	4.20	0.10
18	4.50	4.45	0.09	3.94	0.08	4.22	0.08
19	5.09	5.17	0.17	4.48	0.14	4.82	0.15
20	5.28	5.29	0.18	4.63	0.14	4.97	0.14
21	4.93	4.88	0.15	4.57	0.15	4.66	0.15
22	4.36	4.18	0.12	3.80	0.10	4.06	0.11
23	3.28	3.38	0.18	2.76	0.14	2.87	0.14
Overall Mean:	**4.23**	**3.97**		**3.45**		**3.73**	

Figure G.1 - Scenario Results with Confidence Intervals