8-2023

Visibility based hospital inpatient unit design.

Uttam Karki
University of Louisville

VISIBILITY BASED HOSPITAL INPATIENT UNIT DESIGN

By

Uttam Karki
B.E., Tribhuvan University, 2017
M.S., Wright State University, 2019

A Dissertation
Submitted to the Faculty of the
J. B. Speed School of Engineering of the University of Louisville
in Partial Fulfillment of the Requirements
for the Degree of

Doctor of Philosophy in Industrial Engineering

Department of Industrial Engineering
University of Louisville
Louisville, Kentucky

August 2023

VISIBILITY BASED HOSPITAL INPATIENT UNIT DESIGN

By

Uttam Karki

B.E., Tribhuvan University, 2017

M.S., Wright State University, 2019

A Dissertation Approved on

July 21, 2023

By the following Dissertation Committee:

____

Dissertation Director, Pratik J. Parikh, Ph.D.

____

Jason J. Saleem, Ph.D.

____

Monica Gentili, Ph.D.

____

Corinne H. Mowrey, Ph.D.

ACKNOWLEDGMENTS

I would like to express my deepest appreciation and gratitude to all those who have guided, encouraged, and supported me throughout this challenging yet rewarding journey.

First and foremost, my sincere gratitude goes to my advisor, Dr. Pratik J. Parikh, for his outstanding guidance, unwavering support, and immense knowledge over the past five years. His wisdom and mentorship have shaped me not only as a researcher, but also as an individual. I am genuinely grateful for his belief in my potential and for setting the standards that inspired me to strive for excellence in my work. I am grateful to Dr. Monica Gentili for her invaluable insights, motivation, and consistent encouragement. Your suggestions and guidance have significantly enriched my research experience. To Dr. Jason Saleem and Dr. Corinne Mowrey, thank you for your expertise, patience, and constructive feedback, which played an integral role in this research process.

I would also like to extend my heartfelt thanks to my family for their unwavering faith in me and their constant love and support. This journey would not have been possible without you. To my friends, thank you for your understanding and constant encouragement and for being my source of strength during challenging times. This dissertation is a testament to the collective efforts of all these individuals and the roles they played in my academic journey. Thank you, all.

ABSTRACT

VISIBILITY BASED HOSPITAL INPATIENT UNIT DESIGN

Uttam Karki

July 21, 2023

Patient fall is one of the adverse events in an inpatient unit of a hospital that can lead to disability and/or mortality. Healthcare literature suggests that increased visibility of patients by unit nurses is essential to improve patient monitoring and, in turn, reduce falls. However, such research has been descriptive in nature and does not provide an understanding of the characteristics of an optimal inpatient unit layout from a visibility-standpoint.

This dissertation fills significant voids in this domain and adds much-needed realism to develop insights that hospital decision-makers can use to design their inpatient unit layout. Our first contribution (Chapter 2) adopts an interdisciplinary approach that combines the human field of regard with facility layout design approaches. Specifically, we propose a bi-objective optimization model that jointly determines the optimal (i) location of a nurse in a nursing station and (ii) orientation of a patient's bed in a room for a given layout. The two objectives are maximizing the total visibility of all patients across patient rooms and minimizing inequity in visibility among those patients. We consider three different layout types, L-, I-, and R-shaped; these shapes exhibit the section of an inpatient unit that a nurse oversees. To estimate visibility, we employ the ray casting

algorithm to quantify the visibility of a target in a room when viewed by the nurse from the nursing station. This algorithm considers nurses' horizontal visual field and their depth of vision. We also propose a Multi-Objective Particle Swarm Optimization (MOPSO) heuristic to find (near) optimal solutions to the bi-objective optimization model. Our findings suggest that the R-shaped layout outperforms the other two layouts on these visibility-based objectives. Further, the position of the patient's bed plays a role in maximizing the visibility of the patient's room.

In our second contribution, we extend the model in the first contribution to now include position of the bed in patient rooms as a decision variable and consider various door positions. We consider four distinct layout types, L–shaped, U-shaped, R-shaped, and I-shaped, with eight patient rooms and a nurse-to-patient ratio of 1:4. We propose an ε-constrained approach to convert the corresponding bi-objective optimization model into a single objective optimization model, prioritizing equity as an objective function. We propose a progressive refinement algorithm to solve this optimization model within a reasonable time. Our findings suggest that a significant improvement in the equity score of a layout can be obtained through the joint determination of patient beds and nurse positions. We also perform a comparative analysis of equity offered by various layout types and observed that angular layout types are a promising output. We also observed that higher spatial distance between nurses is beneficial in achieving higher equity measures when obstruction is high in the case of angular layouts.

There are several implications of our findings to practice. The insights from our study related to the impact of layout shapes, bed locations, and obstruction levels on patient visibility can help decision-makers in both greenfield and retrofitting of existing inpatient unit layout designs. Our models can quickly identify highly visible layouts, avoiding costly trial and error in layout changes. Improved decision-making in inpatient unit design will facilitate better patient experiences through equitable visibility distribution and enhanced quality of care.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Hospital-based adverse events pose significant harm to patients and serve as an indicator of poor patient care quality (Walshe, 2000; DHHS, 2012). These events are considered one of the top ten global causes of death and disability, affecting over 250,000 patients annually in the U.S. alone (WHO, 2019; Skelly, Cassagnol & Munakomi, 2021). Furthermore, the aftermath of these adverse events, such as increased hospital stays, mortality rates, and unexpected patient readmissions, are unpleasant and result in poor patient outcomes (Wang et al., 2020). The above-mentioned adverse effects are not only limited to the patient's quality of life, but also create a significant economic strain on the healthcare system; e.g., $4.4 billion in additional healthcare costs carried by U.S. Medicare in 2012 (DHHS, 2012).

This begs the question: what factors result in these hospital adverse events? Among the commonly studied factors, such as human error, inadequate training or incompetence, poor communication, and similar, the physical environment and the inpatient unit layout design have been identified as critical in helping reduce the occurrence of these events. For instance, an optimized inpatient unit layout design can potentially reduce blind spots between a nurse and their patient, in turn improving patient visibility and care quality. This increased visibility helps mitigate adverse events by allowing nurses to constantly monitor patients/layouts during adverse events (Ulrich et al., 2004). However, poor and compromised layout design can lead to inefficient patient monitoring, triggering adverse events (e.g., patient falls) and exacerbating quality of patient life (Joseph & Rashid, 2007; Harvey & Pati, 2012).

Hospital management, therefore, owns a crucial responsibility in designing inpatient unit layouts that optimize visual connectivity between nurses and patients and reduce response times—fundamental prerequisites for delivering high-quality care. This interplay between patient visibility affected by an inpatient unit layout and patient safety is the focus of this research.

1.1 Patient Visibility

Poor patient visibility is a key factor contributing to hospital adverse events, with nurses failing to monitor patients during adverse events such as patient falls (Hitcho et al., 2004; Lu et al., 2014; Gella, 2018). In U.S. hospitals, the rate of patient falls per 1,000 patient days varies between 3.3 to 11.5, with a rate of 1.08 for severe injuries occurring from these falls (Rensburg et al., 2020). This translates into a staggering annual estimate of 700,000 to 1,000,000 falls. However, enhanced visibility aids nurses in monitoring their patients reportedly decreasing patient falls, thus elevating the quality of patient care and reducing hospital mortality rates by 33% (Gulwadi & Calkins, 2008; Lu, 2010; Lu et al., 2014; Fierce Healthcare, 2016). On the contrary, rooms with inadequate visibility carry an increased risk of patient mortality, as continuous patient monitoring by nurses is hampered (Choi, 2011; Sundberg et al., 2020). This illustrates the importance of keeping high visual connectivity between nurses and their patients, more importantly during the patient's initial movement from their bed.

Considering patient visibility from layout design, visibility directly correlates with the arrangement of design elements of inpatient unit layout such as nursing station, patient room, layout shape, door positions, and obstructions caused by solid walls and column locations. Suboptimal design of these elements can impede nurses' line of sight to the patient resulting in inefficient patient monitoring. Therefore, it is critical for hospital management and decision makers to prioritize the design of an inpatient unit layout.

1.2 Design Elements of an Inpatient Unit Layout

As previously mentioned, various design elements of an inpatient unit layout (e.g., layout shapes and dimensions, obstructions, placement or orientation of the patient bed) directly influence patient visibility. The design and dimensions of inpatient units influence both the ease of navigation and wayfinding within healthcare facilities and nurses' ability to monitor their patients visually (Devlin, 2014; Hadi & Zimring, 2016). The inpatient unit layouts are often complex; however, they can often be decomposed into smaller sections (see Figure 1), considered as standard layouts in our study. Hence, it is crucial to analyze these standard layouts to understand their impact on the visual connection between nurses and patients, a critical factor for high-quality care.

We consider three key design elements of inpatient unit layout in our study to expose the relations between these elements in efficient patient monitoring. *First*, 'layout shape' serves as a foundational aspect of planning and organizing the physical spaces within an inpatient unit as it provides easy access to essential hospital services, and facilitates patient visibility and care. To account for the effect of layout shapes on patient visibility, we consider multiple standard layouts (see Figure 1) and study the effects of these on nurse-patient visibility.

Second, research has established a correlation between the 'patient room' design within a layout and patient visibility. The strategic alterations or redesigns to the patient room—such as the positioning of windows, doors, obstructions, and patient beds—can significantly enhance visual connectivity. For instance, patient visibility may be compromised if a patient's bed is located around a room's corner and isn't directly visible from the nursing station. In such instances, repositioning the patient bed towards the direct line of sight from a nursing station or away from obstructions can maximize and maintain optimal patient visibility.

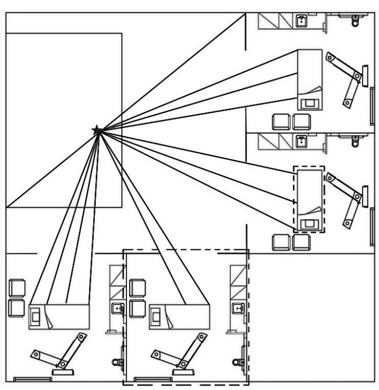

Figure 1a: L-shaped layout

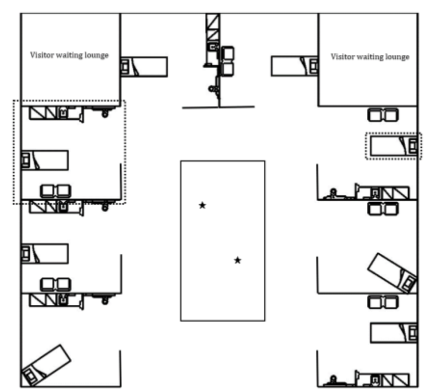

Figure 1b: U-shaped layout

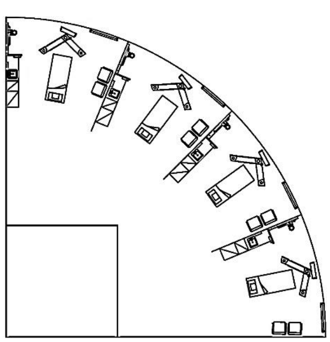

Figure 1c: R-shaped layout

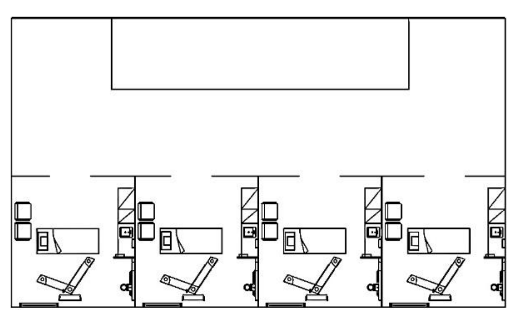

Figure 1d: I-shaped layout

Figure 1 Decomposed standard layout shape

Finally, the last design elements, the 'nurse position', is considered a significant factor in patient visibility. Changes in a nurse's position (e.g., top corner, bottom corner, or center in the designated nursing station) and minimum distance between two nurses can disrupt or enhance the line of sight between nurses and patients, impacting patient visibility.

1.3 State-of-the-Art in Inpatient Unit Layout Design

One common approach hospital designers adopt to enhance nurse-to-patient visibility is exploring various layout shapes. Besides I-shaped layouts featuring a single corridor (see Figure 1d), L-shaped, U-shaped, and R-shaped layouts have been explored. Such layout designs may better align with a nurse's inherent scanning pattern, enhance patient visibility, and present an appealing aesthetic. While some of the prior research has proposed qualitative studies to analyze an existing layout in terms of visibility, none have been able to propose an optimal layout to benchmark existing layouts. Moreover, these studies are limited to the specific layout being evaluated, and findings are unique to that particular layout.

It is worth mentioning that recent research in retail design has proposed an optimization-based approach to improve shoppers' visibility of products on the shelf (Mowrey, Parikh, & Gue, 2018; Guthrie & Parikh, 2019; Karki, Guthrie, and Parikh, 2021). However, the findings are specific to that domain and cannot be directly applied to resolve the challenges of inpatient unit layout design. Furthermore, unlike other domains, ensuring equitable target visibility is vital within an inpatient unit, which is another shortcoming of the model proposed by retail literature. Hence, a quantitative optimization model is needed to find the optimal layout among different layout options presented in the inpatient unit layout design literature.

Our research concentrates on quantifying a patient's visibility inside a room, considering various candidate bed locations, levels of obstruction, and door positions. For a given layout, we aim to quantify the patient visibility across all rooms in a layout from a given nurse position using equity and effectiveness-based measures. We also consider scenarios involving single and multiple nurses within a nursing station and the impact on the equity provided by different layout shapes.

1.4 Research Questions

We now summarize the research questions, followed by our research contributions.

Q1. For a given layout section, how does the position of a nurse in a nursing station affect the visibility of their patients?

Q2. How does the patient room configuration (e.g., bed orientation in the room and obstruction to the room) affect visibility affordance?

Q3. How does the patient visibility change as the layout section of the inpatient unit changes?

Q4. What effect does the level of obstruction have on patient visibility?

Q5. How does the joint determination of bed location and nurse location affect total patient visibility and equity offered by the layout?

Q6. Which layout shape offers the best equity in patient visibility in multi-nurse settings?

Q7. How does the minimum distance between two nurses in a nursing station affect equity offered by various angular layout sections?

We address research Q1-Q4 through Contribution 1 and Q5-Q7 through Contribution 2. These are both described below.

1.5 Research Contributions

1.5.1 Contribution 1 – Visibility-Based Layout Of A Hospital Unit – An Optimization Approach

Our first contribution provides a first-of-its-kind optimization-based model to the limited literature on inpatient unit layout design. To address *Q1*, we consider a nurse's field of regard (FoR) as the extent of horizontal head and eye movements in a 2D inpatient unit layout. To calculate the nurse's entire FoR, we also factor in the yaw movement of the nurse's chair, along with the nurse's head and eye movements. The FoR refers to the total area captured by the continuous movement of human head and body during viewing. It is essential to distinguish it from the field of view, which refers explicitly to the angular cone perceived at a particular moment and is much smaller than the FoR. Furthermore, we develop a ray-casting algorithm to quantify the visibility between a nurse and a patient within a given layout. We introduce three layout types (e.g., R-, L-, and I-shaped) representing a common sub-section of typically complex layouts. Finally, we propose a non-linear multi-objective optimization model with equity and effectiveness as two objectives, and apply it across all proposed layout types. We evaluate the equity using the Gini index, which measures the statistical dispersion in visibility values across all patient beds. Effectiveness refers to the sum of visibility of the target across all rooms.

Due to the non-closed form of the visibility estimation function and non-linearities in the objective terms, our proposed problem is challenging to solve with a commercial solver. Hence, we propose a multi-objective particle swarm optimization (MOPSO) solution technique that simultaneously maximizes each targets' total visibility and minimizes the Gini index measure. MOPSO has been shown in the literature to have rapid convergence, high efficacy, and ability to balance between exploration and exploitation.

To address *Q2*, we examine four patient rooms, each containing a single bed, for all layout types. We also consider four different bed orientations along with two levels of obstruction impacting the visibility of the patient bed from the nurse's position in the nursing station. We also explore the relative impact of bed orientation and obstruction level. For *Q3*, we compare the proposed layout types concerning patient visibility and equity levels. Finally, we conduct a comparative study between optimal nurse position during different obstruction levels for all layout types and address *Q4*.

Our study revealed several insights, which are summarized below:

- R-shaped layouts are more promising than the other two layout shapes; it offers up to 10.78% additional equity and 16.68% additional effectiveness measures.
- In case of high obstruction, the target region of the bed (head or foot) should always be faced toward the opening side of the room. This ensures visual connectivity between nurses and patients while maximizing equity.
- As the obstruction level in a patient room increases, a nurse in the nursing station should be positioned away from that patient room (with target), allowing for better visual connection between nurse and the targets. For example, we observed higher

patient visibility when the nurse shift away from patient beds inside a nursing station as obstruction level increase.

1.5.2 Contribution 2 – Multi Nurse and Room Configuration Design

To address Q5-Q7, in our second contribution, we focus on both the position of the nurses and beds, again considering both equity and effectiveness (i.e., total visibility) measures. However, unlike Contribution 1, we consider an ε-constrained method, which allows for the conversion of a bi-objective model into a single objective model. This technique is appropriate for solving non-convex problems (aligning with our problem characteristics) and it does not require scaling objective functions unlike the weighted sum approach. In our case, equity is retained in the objective function, while effectiveness is considered in the ε-constraint. This is because, although effectiveness is essential, if available to a small portion of the population, then it may not be considered equitable; i.e., there is a tradeoff between the two measures.

We consider four distinct layout types, L–shaped, U-shaped, R-shaped, and I-shaped, to answer the proposed research questions in Contribution 2. We evaluate patient visibility using the ray casting algorithm developed as part of Contribution 1. Based on feedback from a nurse at the University of Louisville's College of Nursing and existing literature, we consider layouts with eight patient rooms and a nurse-to-patient ratio of 1:4. Subsequently, we propose a non-linear optimization model that determines the optimal nurse's position in each layout to maximize equity for the same selected layout. We propose a progressive refinement algorithm to solve our optimization model within a reasonable time. This approach uses a coarse and fine approach, which helps tradeoff computation time and solution quality. In progressive refinement approach several high-quality solutions are first generated using a coarse approximation of visibility (via large ray interval size of 3°). These solutions are refined using a finer approximation of visibility (via smaller ray interval size of 0.1°), ultimately producing the best solution for the chosen layout problem. This approach provides several advantages compared to other solution approaches, such as requiring less memory and quickly producing initial results.

Specifically for *Q5,* we first consider a baseline layout for all four layout types wherein the patient bed position is prespecified. For each baseline configuration (one per layout type) where we fix the bed position in each room to a prespecified position, we use the above optimization model to identify positions of both nurses to maximize equity in patient visibility. This is followed by relaxing the bed position and jointly determining the positions of both nurses and beds in each room for the same layout type considering various patient room door positions and obstruction levels.

To address *Q6*, we consider each layout separately and determine the equity value of at various effectiveness measure values from lower to upper bound. While solving the model, we consider different combinations of door position and obstruction levels.

Lastly, to address *Q7*, we systematically vary the minimum distance between two nurses (closer to away), and observe the equity offered by all angular layout types.

Collective findings from addressing Q5-Q7 revealed several insights, key among them are summarized below.

- Joint determination of patient bed and nurse position in a nursing station improves the equity offered by any given layout compared to optimizing only nurse position with fixed bed location; on average, 45.2% improvement in low and 26.5% in high obstruction settings, respectively, was observed.

- Angular layouts (i.e., R-, U-, and L-shaped) yielded the best equity values compared to the linear (I-shaped) layout; improvements were up to 29% in low and 53% in high obstruction settings, respectively.
- An increase in obstruction levels generally lowers the equity offered by a layout (on average, by 31.7%). In case of high obstruction, there exists a case where some of the beds are often less visible from the nurse position resulting in a high variance in visibility values across beds, in turn, lowering the equity.
- In high obstruction settings, the spatial distance between two nurses increases in an angular layout, the equity measure tends to increase.

1.6 Research Implications

The potential implications of our research are worth mentioning. *Firstly*, the decision-makers can acquire insights into how layout elements such as layout shapes, door locations, and obstruction levels impact patient visibility (especially, equity and effectiveness). *Secondly*, our models can help decision-makers identify optimal and sub-optimal areas within a nursing station, enabling more effective positioning of nursing staff based on available open areas. *Thirdly*, our models can facilitate the quick identification of highly visible layouts, which can aid in avoiding costly trial-and-errors in layout changes. *Lastly*, improved decision-making in inpatient unit design will facilitate better patient experiences through equitable visibility distribution and enhanced quality of care.

Our research will also offer numerous benefits to the academic community. *Firstly*, our study can be a foundation for developing more nuanced models in inpatient unit layout design and patient room reconfiguration, including additional decision variables such as multiple beds in a room and medical equipment location. *Secondly*, researchers interested in examining larger and more intricate layout shapes - incorporating additional nurses and patient beds or accounting for the effects of corridor design - can adapt elements from our models to understand how these designs influence patient visibility and equity. *Finally*, in other domains, our model for estimating patient visibility can serve as a reference for analyzing layouts in other sectors, such as retail, airports, libraries, residential facilities, nursing homes, and museums, where understanding the relationship between human visibility and layout design is valuable.

1.7 Dissertation Outline

The organization of the remainder of this dissertation is as follows. Chapter 2 investigates the specifics of Contribution 1, whereas Chapter 3 presents Contribution 2. Finally, Chapter 4 concludes by summarizing the key findings from this research and proposing directions for future research.

CHAPTER 2

VISIBILITY-BASED LAYOUT OF A HOSPITAL UNIT – AN OPTIMIZATION APPROACH

2.1 Introduction

An adverse event is an injurious and undesirable clinical outcome that happens to a patient's health because of medical care. Adverse events in a hospital can cause harm to the patient and are an indication of poor quality of patient care (Walshe, 2000; DHHS, 2012). These events are considered one of the 10 leading causes of mortality and disability globally; in the U.S. alone, more than 250,000 patients annually experience these events (WHO, 2019; Skelly, Cassagnol & Munakomi, 2021). These events are associated with a long hospital stay, high mortality rate, unplanned patient readmission, and poor patient health status (Wang et al., 2020). Along with harming patient's quality of life, these events equally create an economic burden to the healthcare system. For instance, in 2012, U.S. Medicare had to carry a $4.4 billion worth of financial overload due to these adverse events (DHHS, 2012).

A comprehensive review of 600 articles by Ulrich et al. (2004) links the physical environment of a unit to patient care quality (e.g., fewer adverse events and better health care quality) and staff outcomes (e.g., effective patient care, reduced stress, and fatigue). Specifically, failure in hospital layout design can result in poor patient monitoring triggering adverse events and affecting patient safety (Joseph & Rashid, 2007; Harvey & Pati, 2012). An inpatient unit's shape and size not only affect navigation and wayfinding in healthcare facilities but also affect nurses' visibility of their patients (Devlin, 2014; Hadi & Zimring, 2016).

Poor patient visibility is one of the contributing factors of adverse events in a hospital as nurses fail to keep an eye on the patient during the fall (Hitcho et al., 2004; Lu et al., 2014; Gella, 2018). For every 1,000 patient days in U.S. hospitals, the patient falls rate ranges from 3.3 to 11.5, with a rate of 1.08 of severe injuries during a fall (Rensburg et al., 2020). This number sums up to 700,000 - 1,000,000 falls annually, of which 30%-35% sustain an injury adding more than six days to a patient's hospital stay (MarketScale, 2020). Further, there is a high mortality rate of the patient assigned to a low visibility room as nurses cannot monitor their patients all the time (Choi, 2011; Sundberg et al., 2020). An increase in patient visibility can reduce patient falls by 41%, improving patient care quality and reducing mortality in the hospital (Gulwadi & Calkins, 2008; Lu, 2010; Lu et al., 2014, Fierce Healthcare, 2016). These findings indicate that the high visual connectivity of nurses to their patients is critical.

Figure 2 shows examples of inpatient unit layouts; Figure 2a shows an L-shaped layout where rooms are arranged around a corner, while Figure 2b represents a R-shaped layout where rooms are arranged in a circular manner around the nursing station. We also noticed that some hospitals have complex unit layouts. While these layouts varied considerably, these layouts can typically be decomposed into smaller sections such as L-shaped, I-shaped, and R-shaped, as shown in Figure 17a and 17b.

So which layout is the best? While research exists that evaluates the relationship between hospital inpatient unit layout and patient visibility, they are retrospective, and descriptive in nature, where researchers analyze existing layouts using a variety of visibility metrics (Seo, Choi, & Zimring 2010; Lee, Ostwald, & Lee 2017; Fay et al. 2017; Wei & Li 2021). However, none provide any guidelines for an effective layout with respect to visibility or propose a method to design one such layout.

Our study fills this important void by proposing an optimization-based approach to *generate a layout of an inpatient unit that maximizes a nurse's visibility of their patients*. We use an interdisciplinary approach that combines the human field of regard with facility layout design approaches. Our approach can not only serve as a benchmark to evaluate existing inpatient unit layouts, but also develop a much-needed understanding of design principles for overall unit design. In addition, our study aims to develop an approach that is flexible enough for designers to use in any setting under the requirement that the input parameters must be adjusted to reflect the adopted setting. The specific questions our study addresses include the following:

1. How does the position of the nurse in a nursing station in a given layout section affect the visibility of their patients?
2. How does the patient room configuration (e.g., bed orientation in the room and obstruction to the room) affect visibility affordance?
3. How does the patient visibility change as the section of a unit's layout changes?

Our contributions are as follows. *First*, we propose a multi-objective optimization model to jointly determine the optimal location of a nurse in a nursing station and orientation of patient's bed (located in the center as shown in Figure 3) in a room for a given layout. The objective of this model is to simultaneously maximize the total visibility of all targets across patient rooms and minimize inequity in visibility among those targets; a target refers to patient's bed, head- or foot-area, or any specific focal point in a patient's room. To measure inequity in visibility values, we adopt the Gini index that measures statistical dispersion within the groups as a unit-less value that ranges from 0 (perfect equality) to 1 (extreme inequality). We consider three different layout types, L-shaped layout, I-shaped and R-shaped layout; these shapes can represent the nurse's viewpoint of the section.

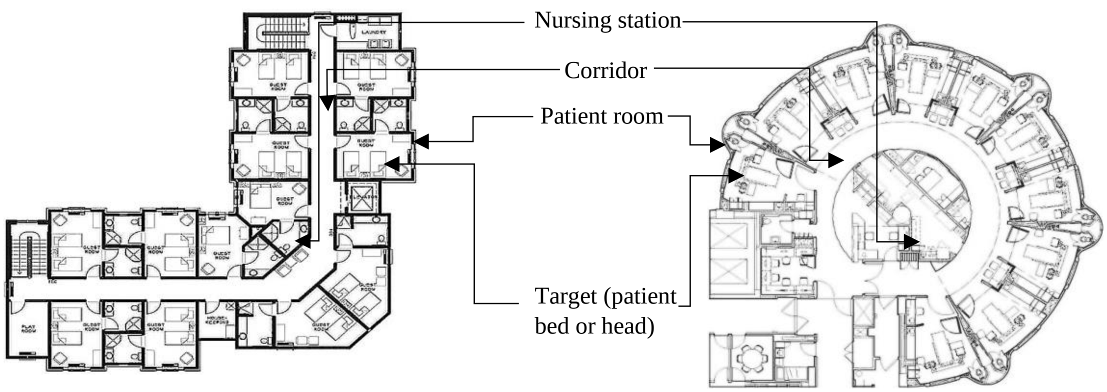

Figure 2a: L-shaped hospital inpatient layout (Shipley, 2022)

Figure 2b: R-shaped hospital inpatient unit layout (Lê, 2022)

Figure 2 Example of various inpatient unit layouts in the U.S.

Second, to estimate visibility, we employ the ray casting algorithm to quantify the exposed area of a target in a room from a nursing station considering nurse's horizontal visual field and their depth of vision, layout type, and obstruction along the front end of the room. Because of the high computational burden to run this algorithm, we use a bilinear interpolation technique that uses a priori estimates from the Ray casting algorithm. *Third*, because the visibility estimate is not in closed form, we propose a heuristic based on Multi-

Objective Particle Swarm Optimization (MOPSO) to find (near) optimal solutions. *Finally*, through our experimental study, we identify critical insights of practical relevance to designers of inpatient unit layouts.

Figure 3 Patient bed in a patient room (Rashid, 2006)

Our experiments suggest that the visibility value changes as we change the layout types. We noticed that a R-shaped layout offers the maximum visibility value, while maximizing the equity in the visibility value among patients. We also found that when a specific portion of a bed is considered a target in each layout type, bed orientation with a target facing front is always favored. Further, the optimal location of the nurse changes considerably based on the type of layout and obstruction level.

With this background, we now present details of our study organized as follows. Section 2.2 reviews the most relevant literature on hospital layout and analyzes patients' layout visibility. Our proposed multi-objective optimization model is presented in Section 2.3. Section 2.4 presents the MOPSO approach to solve this multi-objective problem, with details on our proposed method to estimate visibility. We present our experimental design in Section 2.5, summarize our key findings, and discuss potential future research in Section 2.6.

2.2 Literature Review

A hospital inpatient unit layout problem falls within the broader healthcare facility layout planning problem. A variety of measures have been proposed in the healthcare facility layout literature; e.g., distance traveled (Tongur et al., 2020), adjacency of departments (Lorenz et al., 2015; Hassanain et al., 2022), provider interruptions (Joshi et al., 2022), care quality (Parsia and Tamyez, 2018; Bernhardt et al., 2021), and exposure/visibility (Fay et al., 2017; Wei and Li, 2021).

The literature on hospital inpatient unit design has traditionally focused on minimizing the rate of adverse events and providing quality patient care. One way to provide quality care is through appropriate inpatient unit configuration design, improving patient-nurse surveillance, and reducing adverse events like patient falls in high-acuity inpatient units (Michael et al., 2000; Wolf et al., 2013).

Increasing patient-nurse surveillance has been discussed widely, at least since Florence Nightingale's proposal on hospital design problems. For instance, Lu et al. (2009) studied patient-nurse visibility and found that nurses prefer observation points (in a nursing station) that directly maximize their target's (patient head) visibility. Leaf, Homel & Factor (2010) also observed the correlation between the patient's room visibility and patient mortality in the layout of the medical ICU ward. They found that low-visibility rooms are more prone to patient mortality than high-visibility rooms. Similarly, Choi (2011) states that patient falls are prominent if the patient is not visible from the nursing station or hallways. That is, improving the target's visibility (patient bed or patient head) reduces patient falls and improves patient outcomes (Pati et al., 2009; Choi, 2011; Lu et al., 2014).

In addition, redesigning the inpatient unit shapes improves patient observation and aids in efficient patient monitoring (Hadi & Zimring, 2016). This nurse-patient visibility also plays a significant role in healthcare servicescapes, promoting a sense of safety, trust, and comfort to patients, and can significantly improve patient satisfaction and well-being.

However, the literature on visibility-based hospital layout design is primarily descriptive in nature; i.e., it analyzes patient's or layout's visibility in an existing unit layout. For example, Lu (2010) compared visibility between three different layout types using the ArcGIS platform. In the layouts, they analyzed the structure of visual fields from a nursing station on targets, which in their case were patient beds. They found that the radial unit layout offers the highest number of visible patient beds from nursing stations, followed by double-corridor and single corridor layout types. Seo et al. (2010) compared two different double corridor layouts of different sizes and found that unit size also affects patient visibility. Smaller units can offer more visible beds from the nursing station than the larger ones. For larger unit sizes, additional observation points (i.e., substations) were required to increase the patient's visibility. Lu et al. (2014) extended the work by Leaf, Homel & Factor (2010) using a conceptual replication methodology. Through this retrospective study, they found that the room directly facing the nursing station has the maximum visibility compared to a room at the corner of the unit. This improved visibility influences patient survival in a unit, also resulting in nurses' shorter walking distance.

Johanes and Atmodiwirjo (2015) developed an analytical tool and analyzed the visual acuity from the nursing station and during nurses' walking behavior in the corridor. They found that the layout's spatial arrangement – corridor design and patient room positions – affect the overall visual access from the nursing station in an inpatient ward.

Bosch et al. (2016) employed quasi-experimental, pre- and post-intervention analysis with fixed nurse position and room obstruction level to study nurse-to-patient visibility. They altered the position of the patient bed in a radial nursing unit layout and found that moving the patient bed away from the nurses' line of sight increased the adverse event count as the bed was not visible from the nursing station.

Besides the layout's shape and formation, corridor design and position of the layout's components also affect the layout's visibility measures (Rashid, 2006; Cadenhead and Anderson, 2010). Researchers have been using dedicated space syntax software to quantify these visibility measures. Hadi and Zimring (2016) used Depthmap (a visibility analysis software package) to study the effect of corridor design and layout shape geometry on patient visibility. They found that a layout with a higher corridor width increases the chances of seeing a patient. However, this probability decreases if the layout configuration can be broken down into smaller convex spaces. Lee et al. (2017) also used Depthmap and performed a case study on the effect of different hospital departments' positions on their visibility profile using three different single and double corridor layout types. They found that the setup of the layout's components – nursing station, corridor, and lobby – can affect the visible area by creating more occlusivity to a specified target.

Focusing on the arrangement of the nursing station itself, Fay et al. (2017) evaluated the impact of centralized and decentralized stations on patient visibility and peer line of sight. They found that a centralized nursing station can achieve 100% of nurses'-to-nurses' visibility, but a higher number of visible beds can only be achieved in a decentralized nursing station. Wei and Li (2021) found that patient room configuration also plays a role in patient privacy, visibility, and accessibility, thus affecting patient outcomes. They

Table 1 Summary of the collected research papers

Reference	*Facility layout type**	*Adopted layout configuration*					*Methodologies used to study target visibility*					
		Radial	*Linear/Single corridor*	*Racetrack/Double corridor*	*Residential house*	*Patient room*	*Optimization/Mathematical model*	*Surveys and questionnaires*	*Observation*	*Visibility analysis tool*	*Pre and post study*	*Quantitative measures*
Lu, 2010	NU	✓	✓	✓						✓		
Seo et al., 2010	ICU			✓					✓			
Lu et al., 2014	ICU			✓					✓			✓
el Ansary & Shalaby, 2014	SL				✓		✓					
Johanes & Atmodiwirjo, 2015	AC			✓						✓		
Bosch et al., 2016	OU	✓	✓					✓	✓		✓	
Hadi & Zimring, 2016	ICU			✓						✓		✓
Lee et al., 2017	RAC		✓	✓						✓		
Fay et al., 2017	AC/ICU		✓	✓				✓	✓		✓	
Wei & Li, 2021	NH					✓						✓
Mowrey, Parikh, & Gue, 2018	R		✓				✓					
Guthrie & Parikh, 2019	R		✓				✓					

*Abbreviations: AC: Acute care units; ICU: Intensive care unit; NH: Nursing homes; NU: Nursing unit; OU: Orthopedic unit; R: Retail; RAC: Residential aged care; SL: Site layout

suggest that access to patient beds from all three sides, positioning bathroom doors to improve patient visibility and privacy, and redesigning the room to provide more leisure space are some critical considerations in the patient room to improve patient outcomes.

However, all previous research in visibility-based layout in inpatient unit design focused on descriptive analysis; no optimization-based approaches have been proposed that can help a designer identify an optimal layout of the unit and/or benchmark existing layouts.

Outside of healthcare, visibility-based layout design has received increasing attention. For instance, in architectural floor plan design, Schneider and Koenig (2011) proposed an optimization approach to solve a layout problem with visibility as a decision variable. They generated the unit layout based on the visibility (isovist) properties. First, an evolutionary algorithm was adopted to produce different floor plans, and then the average visible area of the layout was evaluated using an evaluation mechanism. In a construction site layout planning, el Ansary & Shalaby (2014) proposed a multi-objective problem to minimize the visibility between neighboring apartments, while maximizing the visibility towards a target location by altering the building's position and orientation. However, they assumed all the buildings had the same shape and size. In retail, Mowrey, Parikh, & Gue (2018) solved a store rack layout problem to maximize the exposure of the rack to the customer. They proposed a mixed-integer nonlinear optimization model and solved the model using a PSO-based heuristic approach. Guthrie & Parikh (2019) proposed a mixed-integer nonlinear optimization model and generated several insights that help improve exposure over a traditional orthogonal rack layout system. However, the above research is tailored to their specific domains and cannot simply be adopted to solve our proposed inpatient unit layout problem. For instance, the retail research ignores possible obstruction between the observer (shopper) and target (products on the rack), which frequently occurs in the inpatient unit layout due to walls separating the rooms and the corridor. Further, equity in visibility among patients is critical in an inpatient unit unlike other domains.

A clear gap exists in solving the inpatient unit layout problems by accounting for unit-specific constraints like obstruction level and nurses' position in the nursing station. While literature suggests that patient visibility is improved during nurse surveillance during walking, literature also suggests that nurses spend maximum time in their nursing station. The latter is yet to be explored and that is a void we intend to fill in our proposed work. Further, traditional analysis-based approaches are insightful, but limited as they cannot prescribe an optimal layout. In addition, these approaches are limited to the layout that has been studied and the findings are specific to that layout. Further, there is no way to analyze the impact of changes in layout features on the outcome measure. Another significant limitation is not knowing how this layout performs against an optimal layout for that setting. Optimization-based approaches mitigate most of these issues by generating an optimal layout for a specific context and helping develop generalizable insights through evaluating various layouts and via sensitivity analysis.

Our study fills this gap by proposing a novel optimization-based approach and using an interdisciplinary approach that combines the human field of regard with facility layout design approaches to construct a visibility-based inpatient unit. The eventual goal is to improve nurse-patient visual connectivity and reduce adverse events. Table 1 summarizes all relevant literature we found during the literature review process. The ‘Facility layout type’ column explains the adopted layout type where the study was performed. The ‘Adopted layout configuration’ column represents the arrangement of the layout components, such as patient beds, nursing stations, corridors, or open spaces within a facility. Further, the column ‘Methodologies used to study target visibility’ refers to the tool or method of study applied to study patient/layout visibility in the cited research paper. We now present our proposed model for this problem.

2.3 An Optimization Model for Visibility-Based Layout

We propose an optimization approach to jointly determine the position of a nurse in the nursing station and the orientation of the target in the room. The target refers to a bed in the room or a specific portion of the bed (e.g., head-area or foot-area).

The two objectives in this multi-objective model are maximizing *equity* (fairness in visibility values between targets) and maximizing *effectiveness* (sum of visibility across all targets). While equity is a well-known objective, it suffers from certain limitations (and produces unacceptable solutions) if used as a standalone objective (Burkey et al., 2012; Smith et al., 2013; Enayati et al., 2019). This is because the highest level of equity may be achieved even though the total visibility across all rooms is low. For instance, consider 3 rooms where the maximum visibility in each room is 0.5. For a solution with visibility value of 0.2, 0.2, and 0.2 for each room, although we have maximized equity (inequity=0), the sum of these three is 0.6 (maximum being 3x0.5=1.5). Such solutions are possible with equity as a standalone objective. However, decision-makers might entertain another solution with a higher sum of visibilities among the target, but at a slight expense of the equity measures (say, 0.4, 0.45, and 0.5). Due to these limitations of equity as a standalone objective, it is critical to consider effectiveness (sum of room-specific metric, visibility in our case) as a supporting term in the objective function (Burkey et al., 2012; Smith et al., 2013; Enayati et al., 2019).

Our model is set up to consider three layout types, with a single nursing station, and four patient rooms (one bed per room) as key layout components. The typical number of rooms in such layouts range from 2 to 6 with 1 nurse; i.e., nurse-to-patient ratio ranges from 1:2 to 1:6 in such a unit (Boston Medical Center, 2016; Lasater et.al., 2020; Wolters, 2020). We chose 1:4 nurse-to-patient ratio for this paper as it is the most frequently cited ratio in previous literature and confirmed by a registered nurse from a local hospital.

Figure 4a shows an example L-shaped inpatient unit with four beds and a single nursing station. The targets (beds in this case) are aligned along the right (i.e., "R") in each room. It should be noted that the dimensions of the layout and nursing station were adjusted to effectively accommodate layout type changes, thereby avoiding encroachment of one layout component into another (e.g., corridor and nursing station).

We make the following assumptions in developing our model:

- The nursing station is in a rectangular space.
- The nurses' horizontal angular vision is limited to 180° (Parker & West, 1972); this includes 90° attributed to combined head and eye movement and 90° attributed to yaw (left and right movement) of the chair the nurse is seated in.
- The nurses' height is assumed to be enough to allow clear visual contact with the patients in a room.
- There are no physical obstructions, except occlusion to the room (created by walls or opaque glass along the room's outside wall) that blocks nurses' vision from their location in the nursing station.
- All targets have identical orientation in patient rooms. These targets are positioned in the middle of the patient room with easy access to the medical equipment.

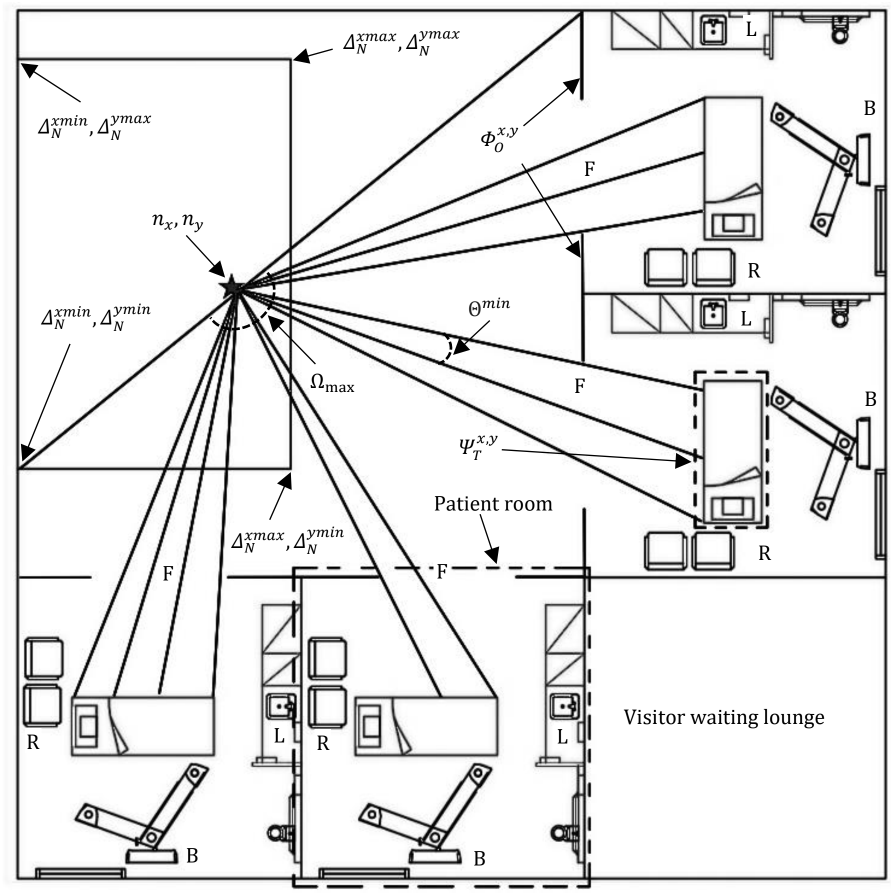

Figure 4a: L-shaped inpatient unit with parameters and decision variables (note: when observed from the corridor, L=left, R=right, B=back, and F=front)

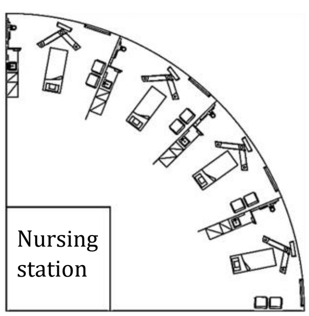

Figure 4b: R-shaped inpatient unit

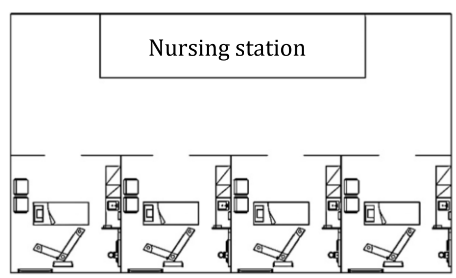

Figure 4c: I-shaped inpatient unit

Figure 4 Representative inpatient unit layouts

Table 2 and 3 shows the parameters and decision variables (illustrated in Figure 4a) used in the optimization model.

Table 2 Parameters used in the model

Notation	*Definition*
T	Set of targets; $t \in T$
I	Set of permitted orientations of the target; $i \in I$
P^t	Set of perimeters of the selected target t
$\Gamma^{x,y}$	Set of all coordinates that define a selected layout
$\Psi_T^{x,y}$	Set of all coordinates that define the boundary of target t
$\Pi_O^{x,y}$	Set of all coordinates that define the boundary of occlusion to target t
$\Delta_N^{xmin}, \Delta_N^{xmax}$	Minimum and maximum *x*-coordinate of the nursing station ***N***
$\Delta_N^{ymin}, \Delta_N^{ymax}$	Minimum and maximum *y*-coordinate of the nursing station ***N***
$\Omega_{\max}$	Maximum angular limit of visual scanning of a nurse (°)
DOV	Nurse's depth of focused vision (ft)

Table 3 Decision variables used in the model

Notation	*Definition*
n_x, n_y	Position of nurse in the nursing station in the layout
θ_i	1, if target orientation *i* is selected; 0, otherwise
v_t	Fraction of target *t* visible to the nurse; $\bar{v}_t$ is average visibility equaling $\frac{\sum_t v_t}{\lvert T \rvert}$

We now propose the following optimization model to solve the visibility-based inpatient unit layout problem.

$$Z_1 : \text{maximize} \qquad 1 - \frac{\sum_{i,j \in T} \lvert v_i - v_j \rvert}{2\lvert T \rvert^2 \bar{v}_t}$$

$$Z_2 : \text{maximize} \qquad \sum_t v_t$$

subject to

$$v_t = f(\Omega_{\max}, \mathrm{DOV}, \Gamma^{x,y}, \Psi_T^{x,y}, \Pi_O^{x,y}, \mathrm{P}^t, \theta_i, (n_x, n_y)) \quad \forall t \tag{1}$$

$$\sum_i \theta_i = 1 \tag{2}$$

$$\Delta_N^{xmin} \leq n_x \leq \Delta_N^{xmax} \tag{3}$$

$$\Delta_N^{ymin} \leq n_y \leq \Delta_N^{ymax} \tag{4}$$

$$0 \leq v_t \leq 0.5 \quad \forall t \tag{5}$$

$$\theta_i \in \{0,1\} \quad \forall i \tag{6}$$

Given an inpatient unit layout, the objective of our proposed model is to minimize inequity in visibility among patients, while maximizing the sum of visibilities of targets across all rooms. We minimize inequity by maximizing Z_1, i.e., subtracting the Gini Index from 1; Gini index measures inequity among the targets and is estimated as a ratio of area between perfect equality and the Lorenz curve (distribution generated by different target's visibility values) to the total area under perfect equality (Hörcher & Graham, 2020; Sitthiyot & Holasut, 2020).

Constraints (1) estimate the fraction of target t visible to the nurse. This is done through function f, which incorporates nurses' visibility parameters and position, layout and room's configuration, and target's perimeter and orientation. Constraints (2) guarantee that only one bed orientation is selected, while Constraints (3) and (4) establish bounds for the nurse's position. Constraints (5) indicates bounds on the visible fraction of target t from the nursing station, and Constraints (6) indicate bounds on the target orientation.

Note that it is difficult to express function f (that estimates v_t) in a closed analytical form. Prior research has estimated such visibility through commercially available visual and spatial network analysis software such as Depthmap and ArcGIS (Hadi & Zimring, 2016; Poerwoningsih et al., 2016; Lee, Ostwald, & Lee, 2017). The non-closed form of function f, along with non-linearities in the objective function, render our proposed model difficult to be solved using state-of-the-art mathematical programming solvers (e.g., CPLEX or Gurobi). Consequently, we propose a metaheuristic approach based on the multi-objective particle swarm optimization (MOPSO) framework to efficiently solve the problem.

2.4 Proposed Solution Approach

Our proposed solution approach is based on the MOPSO framework. MOPSO is a nature-inspired metaheuristic algorithm that mimics the social cooperative and competitive behavior of bird flocking and fish schooling (Kennedy & Eberhart, 1995). MOPSO has advantages over gradient-based approaches because of its ability to handle multiple objectives, discrete variables, non-linearities, multimodality, discontinuity, non-sensitive to initial starting conditions, and can better explore the search space to find high-quality solutions in a reasonable time (Baldi, 1995; Jones et al., 2002; Ruder, 2016; Kohler et al., 2016; Ünal & Kayakutlu, 2020). Furthermore, when solving multi-objective problems, the finite size of Pareto solutions is generated uniformly along with the Pareto frontier, which supports the decision-maker in selecting appropriate solutions for different practical cases (Zhang and Li, 2007; Lin & Chen, 2013). Due to its fast convergence speed, easy implementation, and high effectiveness, many successful applications of MOPSO have been reported; e.g., flow shop and job scheduling problems (Moslehi & Mahnam, 2011; Tavakkoli-Moghaddam et al., 2011), vehicle routing problem (Castro, Landa-Silva & Pérez, 2009; Norouzi et al., 2011; Rabbani et al., 2022), and data mining (Carvalho & Pozo 2009; Zahiri & Seyedin 2009; Zhang & Chau, 2009).

In our proposed MOPSO approach, each particle is represented as a vector of decision variables ordered as (i) nurse's position in (x, y) coordinate, and (ii) bed orientation (θ) with respect to the vertical axis. An example of such a vector is as followss: $\{x, y, \theta\}$, where positions #1 and #2 represent the x and y coordinate of the nurse's position in a nursing station, and position #3 represents the bed orientation across all patient rooms.

The key features of our implementation include a novel way to estimate function *f* (Evaluation subroutine) and balancing exploration-exploitation (Update subroutine). The various subroutines implemented in the MOPSO are summarized below.

2.4.1 Candidate Solution Subroutine

This subroutine generates random numbers between [Δ_N^{xmin}, Δ_N^{xmax}] and [Δ_N^{ymin}, Δ_N^{ymax}] to represent a feasible *x* and *y* coordinate of the nurse position in a nursing station. Furthermore, this subroutine also selects the bed orientation (θ) such that $\Phi \in [0,4]$. The Φ value is then transformed to the four possible physical orientations considered in our model:

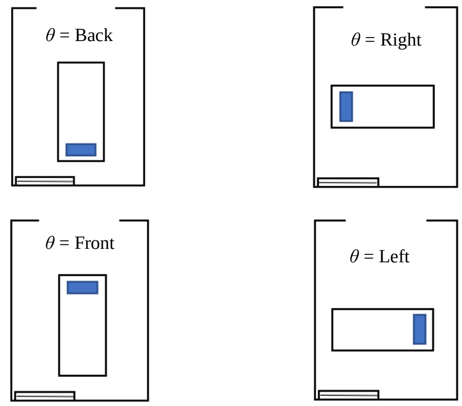

Figure 5 Possible bed orientations in a room

$$\theta \begin{cases} = \text{Back, if } \Phi \leq 1 \\ = \text{Left, if } 1 < \Phi \leq 2 \\ = \text{Front, if } 2 < \Phi \leq 3 \\ = \text{Right, if } \Phi > 3 \end{cases}$$

An example of a particle's vector of decision variable after this subroutine may look like {120, 110, Left}, where (120,110) is the coordinate of the nurse position and the bed orientation is towards the 'left' of the room.

2.4.2 Evaluation Subroutine

Given the room's layout type and obstruction level, this subroutine evaluates function f and returns visibility values for selected $\{x, y, \theta\}$, which is used to calculate effectiveness and equity objective terms. Because of the difficulty in modeling nurse's visibility of a patient in a closed form (i.e., function f), we first implement the ray casting algorithm that simulates a nurse's field of regard (FoR) – the total space potentially available for viewing and Ω_{max} from a nursing station to the target patient's bed or head. Ray casting is a rendering technique that emits rays from a point (e.g., candidate nurse position) within a virtual space (e.g., a given layout type) until they hit a target (e.g., patient bed or head) within the virtual scene (Techopedia, 2017). This algorithm has been widely adopted in the literature; e.g., for visualizations and rendering of irregular grids (Silva & Mitchell, 1997; Mora et al., 2002; Chatwani et al., 2020), in proton therapy and medical imaging (Nelson & Elvins, 1993), and in layout planning to examine the visibility from a candidate location.

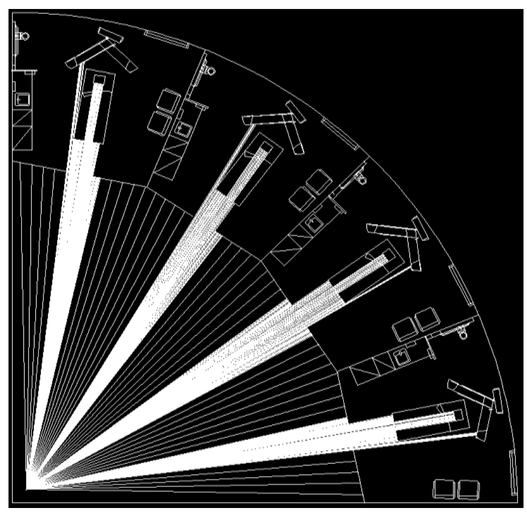

Figure 6 Ray casting algorithm

We employ a 2D version of the ray casting algorithm that casts rays across the horizontal axis, covering the entire range of angular limit (Ω_{max}). Literature has used commercial software like ArcGIS to estimate patient/layout visibility. However, these commercial software need prior knowledge and hands-on experience to generate visibility values effectively; they are also inflexible as the layout changes. So, we built a generic approach based on ray casting algorithm, which has the same underlying working principle of ArcGIS but is more agile to implement new layout types, easier to use and integrates with Python or similar programming languages used to implement our heuristic. Figure 6 shows an example of the output produced by this algorithm for a R-shaped layout with a high obstruction level. Notice that, as we are modeling a 2D environment, the nurse can see a maximum of 50% of the target at any time (also shown in Figure 7). As ray casting is a time-consuming algorithm, scanning the entire layout with 0.1° interval would increase total computation time by 400% compared to running with a 5° interval. However, running the algorithm with 5° interval would result in a poor estimation of the visible proportion of the target. Hence, to speed up the algorithm, while keeping the high accuracy of estimation, we run the ray casting algorithm over two steps. Initially, these rays are separated at an interval of 5° degrees (first step) as they scan the space. The target location is pre-calculated and stored as an (x, y) coordinate in a data frame, which is used by ray casting as a reference to identify targets during the search process. As soon as the target falls between two 5° degrees rays, the ray's interval is further reduced to 0.1° degrees (second step) within the target's periphery, thus improving the visibility estimation from the algorithm. We record the intersection points between 0.1° rays and the target perimeter and calculate the Euclidean distance between intersected points to estimate the target's total visible length. During the simulation, ray casting scans the entire FoR, including the obstruction created by the walls and doors. The visible portion of the prespecified target is measured by taking a ratio of the total visible length of the target to its perimeter (see Figure 7). In Figure 7, bed or head visibility is the percent of the target's total perimeter visible to the nurse.

There is, however, a tradeoff between accuracy and computation time when using the ray casting algorithm. It takes about 25 seconds to calculate the visible portion of all targets from a candidate location of a nurse given the intervals specified above (5° and 0.1°). This becomes computationally prohibitive in the optimization model where a large number of such candidate locations are evaluated; the time required often exceeds 65 hours. In fact, more than 95% of the time to solve the optimization model is spent on the ray casting algorithm. Given this limitation, we implement a bilinear interpolation technique to reduce the computational time by 92.08% compared to the ray casting algorithm; see Appendix A. Considering that the average error from the bilinear interpolation technique is 0.8% for effectiveness and 0.7% for equity measures, we use this in the MOPSO heuristic described below.

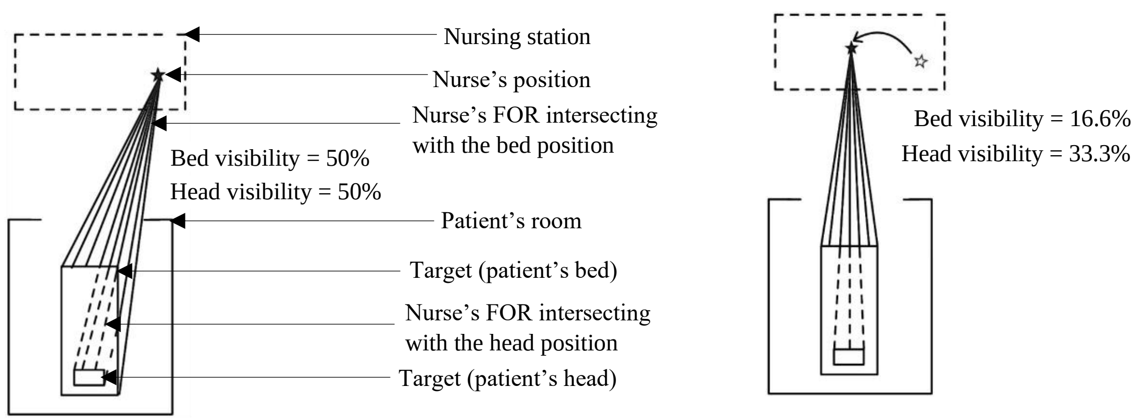

Figure 7a: Visible area from nurse positions (star) at the corner

Figure 7b: Visible area from nurse positions (star) moved to a location in the center

Figure 7 Visible area of targets from two different nurse positions (star) within the nursing station; (a) at the corner and (b) moved to a location in the center

To continue with the above example {120, 100, Left}, assuming we consider the patient bed as a target in R-shaped layout with low obstruction, this subroutine first passes this vector to the interpolation function, and then outputs equity and effectiveness measure value as 0.95 and 1.25, respectively, for this case.

2.4.3 Non-dominated Solution Subroutine

This subroutine generates non-dominated solutions from the list of feasible solutions identified by the particles during the search process. The solution is considered non-dominated if no better solution is found; i.e., neither of the objectives can be improved without sacrificing the other. The particle best objective functions (from different particles) are compared, and the worst solution is considered dominated and subsequently rejected. An infinite number of possible solutions exist as our solution space is continuous. Hence, we discretized the effectiveness measures by 0.1 to generate a finite number of Pareto solutions.

2.4.4 Update Subroutine

This subroutine updates the non-dominated solutions in the repository (a collection of non-dominated solutions) along with the particle's position and velocity. Besides, a leader is also selected randomly from the pool of non-dominated solutions to update each particle's position. Then, the particles' new position is updated based on equations (7) and (8). The randomization of the leader selection process increases the chances of diversity and exploration in the solution space, preventing particles from getting stuck in a local optimum.

$$V_{ij}^{t} = W(V_{ij}^{t-1} + C_1 r_1\left(Pbest_{ij}^{t-1} - X_{ij}^{t-1}\right) + C_2 r_2\left(leader_{ij}^{t-1} - X_{ij}^{t-1}\right)) \quad (7)$$

$$X_{ij}^{t} = X_{ij}^{t-1} + V_{ij}^{t} \quad (8)$$

At each iteration i, the position of the particle is represented by X_{ij}^{t} and velocity by V_{ij}^{t}. In equation (7), r_1 and r_2 follow Uniform(0, 1) that control particle movement towards the particle's best or selected leader. Coefficients C_1 and C_2, known as acceleration constants, control particle movement in the search space. To ensure that exploration is favored during the initial stage of the search process, and exploitation in the later stage, we set C_1= 2.05 per Clerc and Kennedy (2002); we also set C_2 = 0.6 and increase it by 0.2 after the first 700 iterations and 1,000 iterations per preliminary runs. We also let the initial inertia weight (W) to be 0.7282 per Clerc and Kennedy (2002) and linearly reduce W to balance exploration and exploitation. After the particle's position is updated, it goes back to the evaluation subroutine and continues the process until it meets the termination criteria.

2.4.5 Termination Subroutine

This subroutine controls the iteration-based termination of the search process of the MOPSO algorithm. We tested with different iterations (from 500 to 30,000 iterations) and found that 1,500 iterations are suitable for finding the Pareto frontier within a reasonable computation time. The particles in the MOPSO converged to the final solution, with minimal changes after 1500 iterations across many different settings. That is, the final Pareto frontier is output by our approach after 1,500 iterations.

2.5 Experimental Study

We conducted an experimental study using datasets from literature and our observation of hospital settings to generate insights that could aid an inpatient unit designer in designing such units. These are discussed in detailed below.

2.5.1 Data Collection and Experimental Factors

We assumed that the nurse is sitting on a chair that has yaw movement (left and right). Accordingly, we used a nurse's easy head (H_E) and eye (E_E) movement to be 90° (Parker and West, 1972) and the chair's yaw (Y_c) movement to be 90°; collectively, this made the nurse's FoR to be 180°. The nurse's depth of view, which is the distance nurse can clearly see, was assumed to be 50 ft (Guthrie & Parikh, 2019).

We considered two different targets (patient's bed and head/foot area), as these are critical areas while tracking the patient in a room. We adopted three different layout types, L-shaped, I-shaped, and R-shaped (as shown in Sections 2.3), representing commonly found sections of a hospital's inpatient unit. Table 4 summarizes the dimensions of the layout (Critical Care Medicine, 1995; CADdetails, 2021; Healthcare Facilities Today, 2021; AvaCare Medical, 2022).

Table 4 Dimension of layout component

Layout components	*Dimension*
Layout Size	32 ft × 32 ft
Nursing Station	13 ft × 12 ft
Patient Room	12 ft × 10 ft
Patient Bed	6ft × 3ft
Patient Head	2ft × 1.5 ft
Corridor width	7 ft

To mimic obstructions caused by solid walls and wooden doors to the patient room, we considered two levels of obstruction, low and high. The low obstruction represents that 50% of the room is obstructed and with high obstruction, the obstruction is 80%. Table 5 summarizes the parameters and values used in the experimental design. Table 4 shows the data on hospital settings we have used in our study. We estimated the visibility of the target in the patient room using the approach discussed in Sections 2.3 and 2.4.

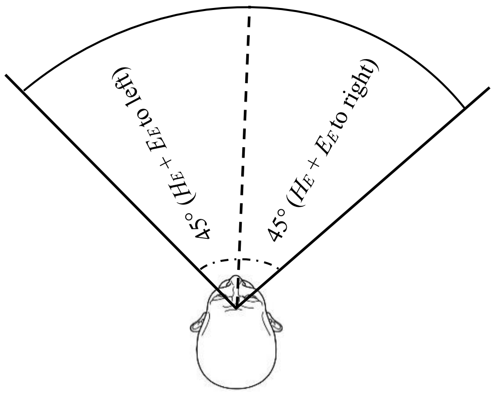

Figure 8a: Nurse's horizontal angular head and eye movement

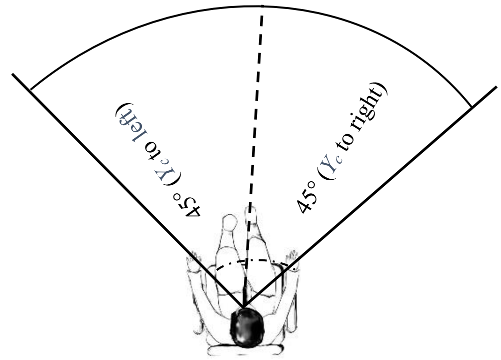

Figure 8b: Nurse's chair yaw movement during a seated position

Figure 8 Nurse's visual parameters used in our experimental study

2.5.2 Results and Insights

We present our results in two categories, one with bed as target and another with head/foot as target. These experiments took 5.1 hours on average to obtain the reasonable solution quality. Note that the results and insights presented here are based on the assumptions outlined in Section 2.3.

Table 5 Parameters values used in the experimental study

Parameters	*Levels*	*Values*
Target	2	Patient bed, Patient head
Layout types	3	L-shaped, I-shaped, and R-shaped
Obstruction	2	Low, High

2.5.2.1 Bed as the target

Table 6 Summary of results for patient's bed as target

Obstruction	*Layout*	*Orientation (θ)*
Low	I-shaped	Front or Left
	L-shaped	Right or Back
	R-shaped	Front
High	I-shaped	Front or Left
	L-shaped	Right or Front
	R-shaped	Right or Back

Table 6 summarizes the target orientation from our optimization model for all layout types and obstruction levels with a patient bed as the target (see Appendix B for detailed results). Remember that because of the bi-objective nature of this problem, there is no single optimal solution. Instead, we get a Pareto frontier of non-dominated solutions which are combination of nurse position and bed orientations. The designer can select any of these solutions based on their relative preference between equity and effectiveness. Figure 10 and 13 show bed orientations areas in the nursing station that belong to the Pareto frontier.

Insight 1: R-shaped layout appears to be the most promising layout type.

Our results suggest that R-shaped layout offers maximum visibility among all the three layout types; L-shaped is the second-best, while I-shaped is the least preferred. The visibility in the R-shaped layout was, on average, 10.78% higher for equity and 16.68% higher for effectiveness measures than in the L-shaped layout.

As we know, the visual angles between the nurse and the target affect the target's visibility. As this visual angle gets obtuse, it limits the target's visible area reducing the effectiveness measure in an objective function. To understand this further, consider Figure

9, which compares the target's visibility in two different layout types. In the R-shaped layout, there is a natural synchrony between the FoR and the layout itself. This results in a high degree of visual connectivity between the nurse and target. For example, refer to target #5 in Figure 9; a very small portion of target #5 is visible from a nursing station in an I-shaped configuration. However, as the layout configuration changes to R-shaped, an additional portion of this target is visible from the nursing station, favoring the effectiveness-based objective function. Notice that this increase in effectiveness value also aids in increasing equity among targets; such dynamics existed for all levels of obstruction. Consequently, R-shaped layout stood out as the preferred layout from both equity and effectiveness standpoint. Note that when identifying the optimal layout, our optimization model searches all potential nurse locations within the nursing station, selecting the one that best balances equity and effectiveness. An example of decision-making process in our optimization model based on how shifting the nurse's position yields different effectiveness values can be seen in Figure 13. A similar trend exists between L-shaped and I-shaped layouts.

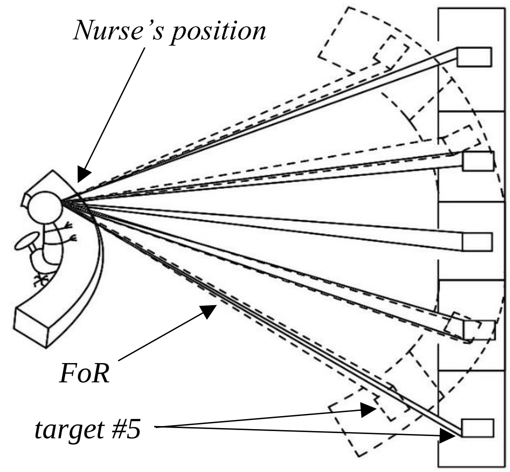

Figure 9 Target's exposure in R-shaped vs. I-shaped layout type

Insight 2: There exists a trade-off between equity and effectiveness measures.

As suspected earlier, for a given obstruction level, we observed that as the effectiveness measure increases, the value of the equity measure drops (see Figure 9). Note that equity-based objective tends to position nurses in a way that ensures that all targets have nearly the same visibility value; i.e., reducing variance increases equity. However, the effectiveness-based measure tends to position nurses to increase the overall layout's visibility ($\sum_t v_t$ in Section 2.3), even if that means some targets have a very high visibility value, while others have relatively low. Clearly, this increases variance and reduces equity. This is why we see a set of non-dominated Pareto solutions which suggest that to gain benefits on one measure, we may have to give up on the other measure. Notice that, as we consider bed orientation as a decision variable, multiple bed orientations can contribute to a Pareto frontier (see Figure 10).

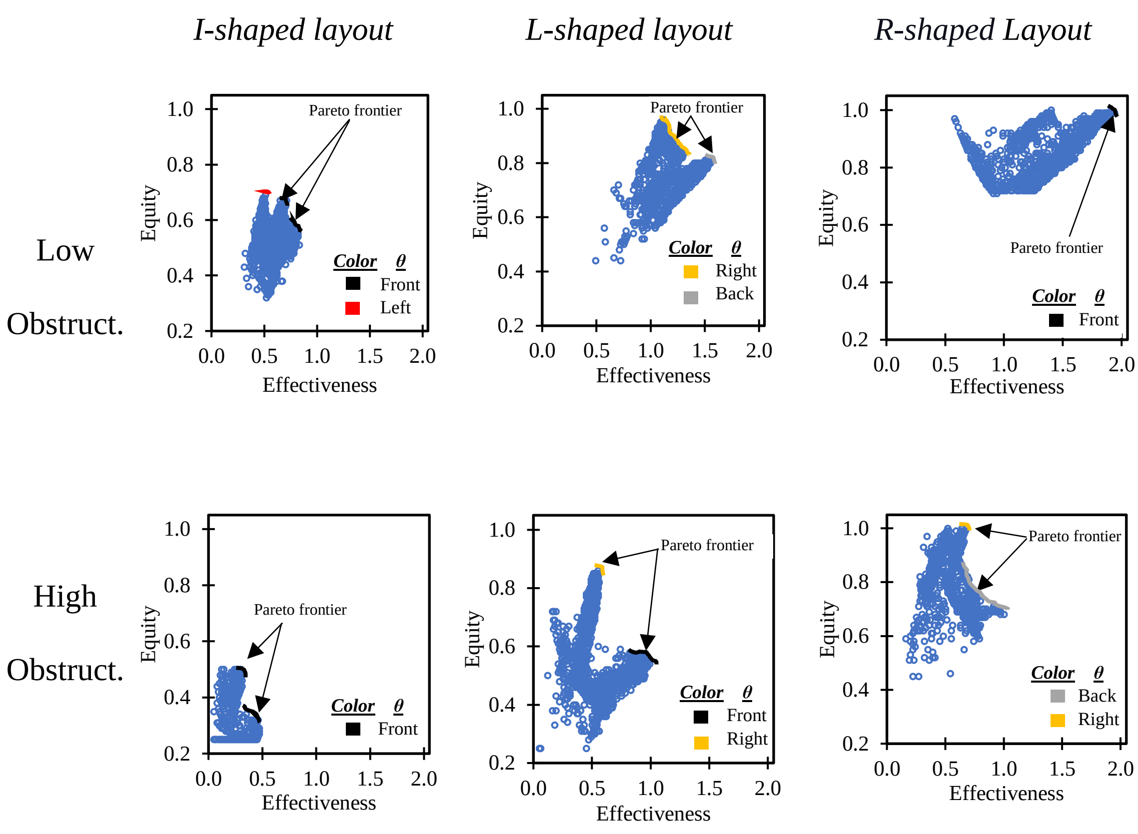

Figure 10 Feasible solutions with patient's bed as a target for all configuration

Furthermore, we observed that the Pareto curve for high obstruction is below than that for low obstruction compared to L-shaped high and low obstruction in Figure 11). For example, in the case of low obstruction, as the opening gap in the patient room is high, all targets are visible from the majority of positions in the nursing station. Therefore, the model can increase the equity and effectiveness measures simultaneously. However, higher obstruction levels result in low visual acuity from a nursing station, with a limited number of candidate positions exhibiting high equity and effectiveness measures. Due to this, a target visible from one location might not be visible from another, preventing an increase in both objective functions simultaneously. Consequently, the Pareto frontier from a high obstruction setting will have a reduced effectiveness value compared to a low obstruction setting.

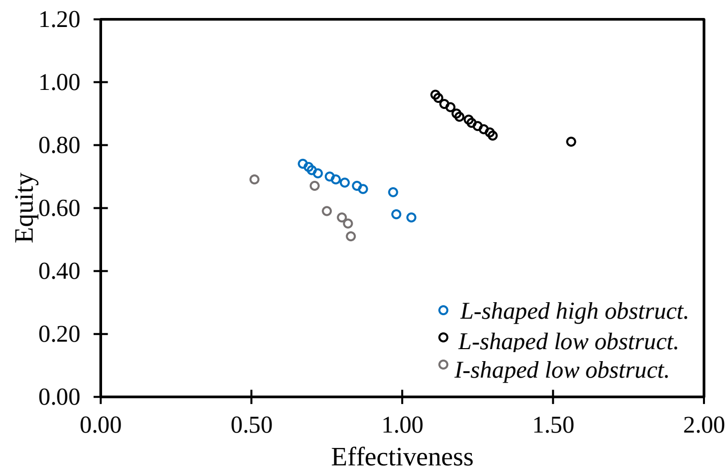

Figure 11 Pareto solutions from experimental study

Insight 3: At high obstruction levels, regions further away from the patient's room are promising.

Figure 12 depicts this phenomenon under the assumption that the nurse's depth of view allows for viewing from such further locations. Intuitively, the nurse's effective FoR (region of FoR within which a target falls) gets reduced when the nurse is closer to the patient's room.

As seen in the Figure 12a, when the nurse is positioned near the patient's room in a high obstruction setting, some targets (e.g., the patient's heads #1 and #2) are not fully visible. However, the same target becomes visible as the position is adjusted to a new location in a nursing station (see heads #1 and #2 in Figure 12b). Clearly, this is beneficial for both objective functions; equity and effectiveness. Additionally, notice that there is reduced effort in the nurse's angular movement to see all targets from the position away from the patient room (Figure 12b) compared to the position near to the patient room (Figure 12a). However, a nurse's position further away from the patient room requires higher walking distances and a longer time to reach the patient.

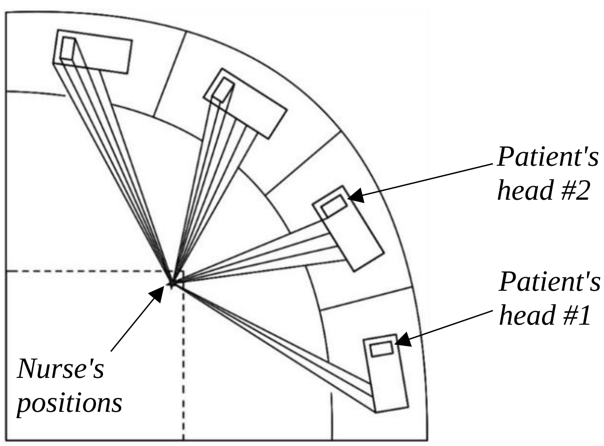

Figure 12a: Nurse position closer to the patient room

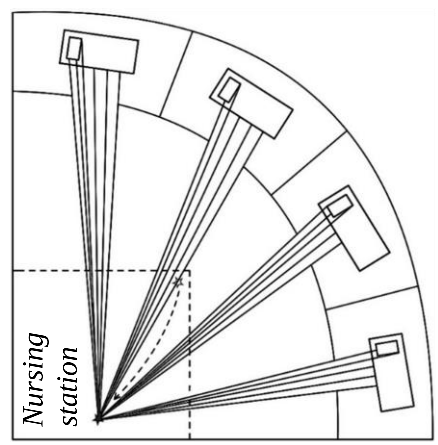

Figure 12b: Nurse position away from the patient room

Figure 12 Target's visibility from two different positions in a nursing station

Figure 13 also shows a switch in the nurse's position when the obstruction level increases from low (shape '+') to high (shape '×'). For instance, in Figure 13a, for the L-shaped layout, the dominant region contributing to the Pareto frontier is towards the far-right side from the center region of a nursing station. However, as the obstruction level increases, these dominant regions shift towards the top side from the center region of the nursing station. This is because of the increased occlusion caused due to higher obstruction, which moves the nurse's position further back and towards the top in the station. Detailed results with pareto solutions are shown Appendix C. A similar trend is observed in Figure 13b for the R-shaped layout, where positions are shifted to the bottom left of the nursing station (again, further away) when obstruction shifts from low to high; for the I-shaped layout, the positions are shifted to back of the nursing station (see Figure 13c). Figure 14 illustrates the increase in visibility as the nurse moves away from the patient room in all three layouts at higher obstruction levels.

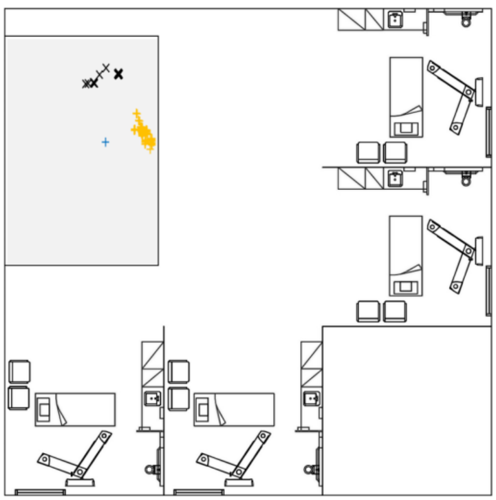

Figure 13a: L-shaped layout

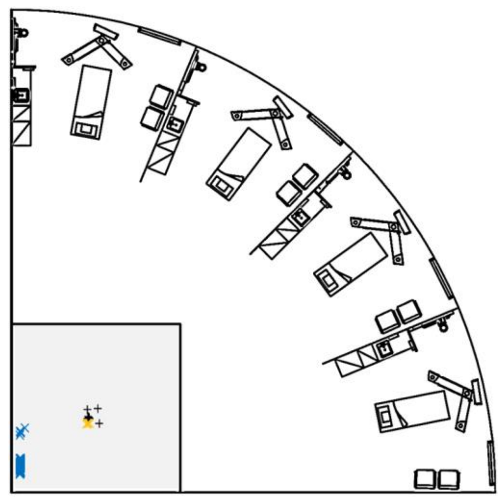

Figure 13b: R-shaped layout

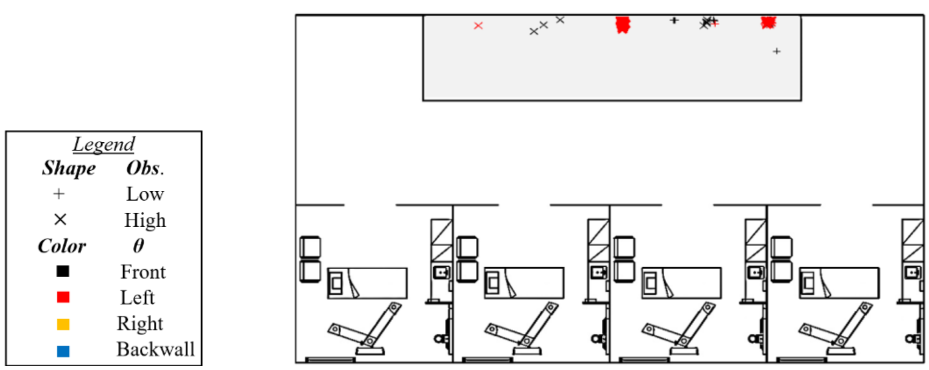

Figure 13c: I-shaped layout

Figure 13 Pareto solutions for the nurse position in the nursing station (shaded) with bed as target

2.5.2.2 Head/Foot area as the target

We discuss the findings below with head area as the focus, but the findings remain unchanged if it were the foot area. Table 7 summarizes the patient's head orientation from our experiments for all layout types and obstruction levels. The Pareto solutions obtained from the model with head/foot area as the target is shown in Figure 15.

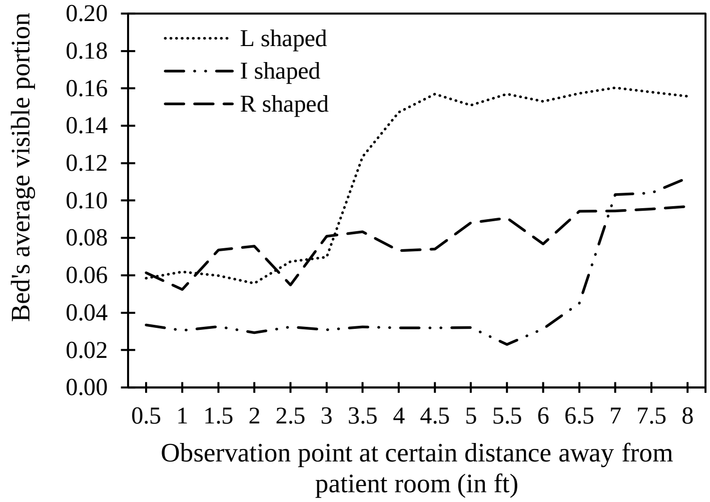

Figure 14 Average bed's visibility in three layouts as the nurse moves away from the patient room

Table 7 Summary of results for patient's head as target

Obstruction	*Layout*	*Orientation (θ)*
Low	I-shaped	Right
	L-shaped	Front
	R-shaped	Front
High	I-shaped	Right
	L-shaped	Front
	R-shaped	Front

Insight 4: A change in target (bed to head) can change the preferred bed orientation in the R-shaped layout.

When the patient's head was selected as a target, we observed that front was the preferred bed orientation compared to back in the R-shaped layout (see Table 7). Recall that our effectiveness-based objective function is highly dependent on the visibility of the selected target across all patient rooms. The open space between the nursing station and the patient rooms (from which nurses can see the patient) plays a vital role in the target's visibility. As these open areas in a high obstruction setting are limited, the patient's head in front orientation increases the target's visibility and maximizes the objective function. Figure 16 shows two scenarios with patients' heads at front and back orientations in high obstruction settings.

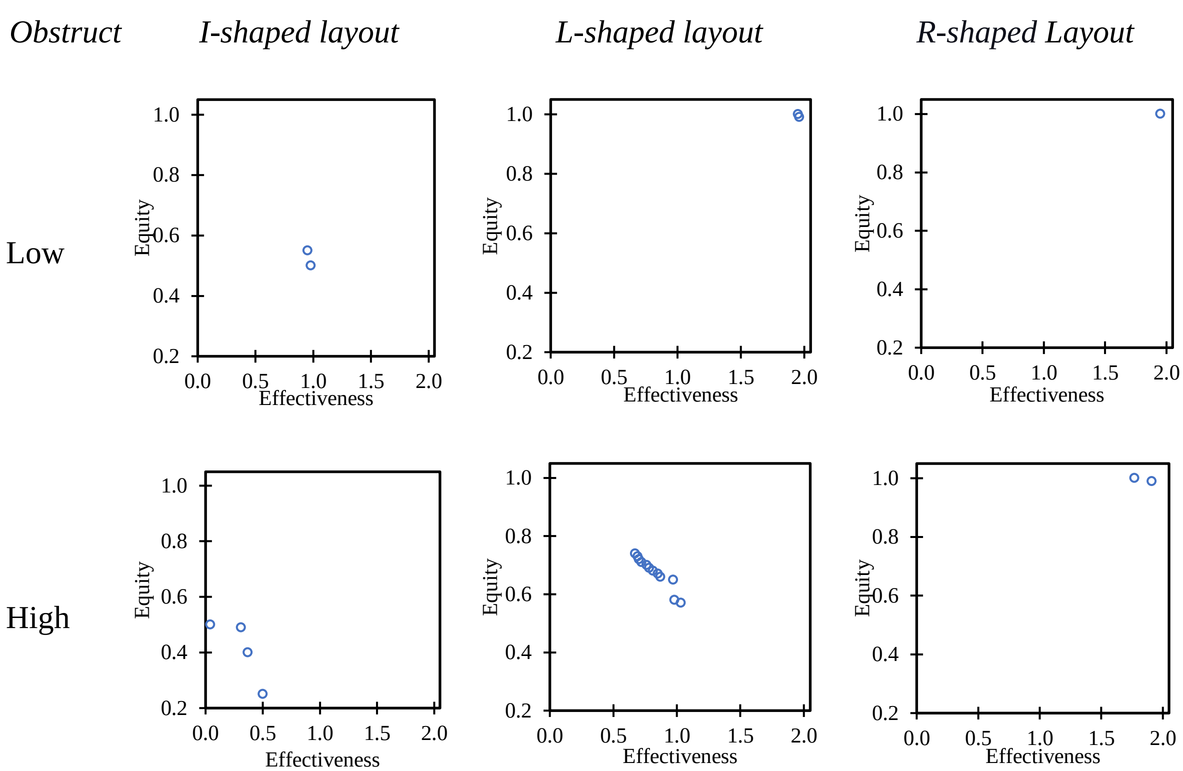

Figure 15 Pareto solutions with patient's head as a target for all configurations

Table 8 shows visibility values generated through our optimization model in support of this insight. The position of the nurses was fixed for a given layout in both R-shaped and L-shaped layouts. Observe that for both layouts, *front* orientation maximizes the equity measure (Z_1) compared to the other two orientations (see Table 8), while also improving the effectiveness measure (Z_2).

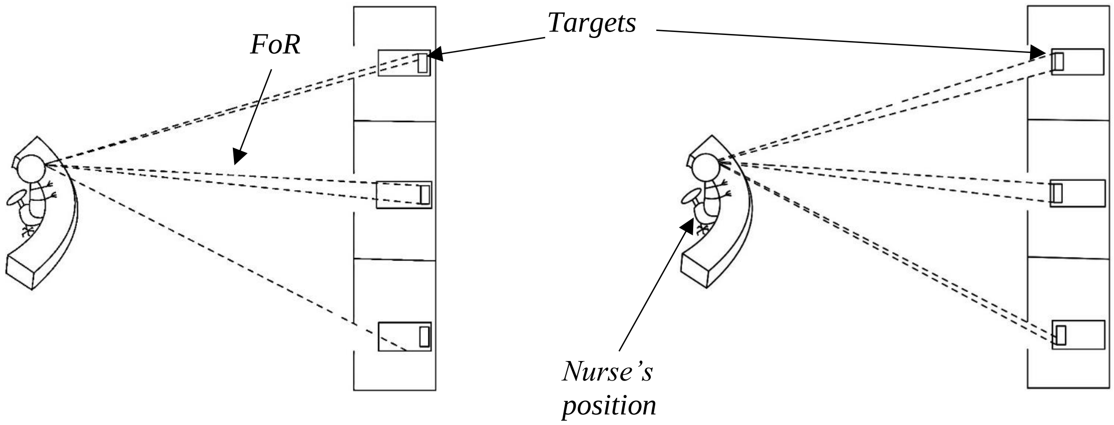

Figure 16a: Patient's head visibility in back orientation

Figure 16a: Patient's head visibility in front orientation

Figure 16 Patient's head visibility at two different orientations

Table 8 Comparison between R-shaped and L-shaped layouts over different orientations (head as target)

Layout	*Nurse's position*	*Obstruction*	*Orientation*	v_1	v_2	v_3	v_4	Z_1	Z_2
R-shaped	(120, 120)	Low	Back	0.48	0.36	0.44	0.38	0.94	1.66
			Front	0.42	0.41	0.43	0.48	0.97	1.74
			Right	0.47	0.42	0.22	0.00	0.88	1.56
			Left	0.00	0.22	0.45	0.45	0.65	1.12
L-shaped	(100, 450)	Low	Back	0.28	0.00	0.45	0.46	0.67	1.19
			Front	0.48	0.00	0.46	0.41	0.72	1.35
			Right	0.38	0.28	0.05	0.48	0.70	1.19
			Left	0.44	0.00	0.48	0.00	0.49	0.92

2.6 Conclusion and Future Research

Improving patient monitoring and, in turn, their experience during their hospital stay can improve patient outcomes. One way to accomplish this is via increased visibility of patients by their nurses during a patient's stay in an inpatient unit. The importance of unit layout in achieving greater visibility has been alluded in prior research. However, such research has been descriptive in nature and does not provide a way to identify designs that can help benchmark existing and other novel designs. Realizing this gap, we proposed an optimization model for the visibility-based inpatient unit design problem. Our optimization model can serve two purposes; first, it generates an optimal layout for a given objective and system constraints; second, it allows for generating generalizable insights. This will enable layout designers in either retrofitting existing layouts or in greenfield design of new layouts. To solve this model, we designed a MOPSO-based heuristic.

Our experiments that considered I-shaped, L-shaped, and Radial layouts, along with two obstruction levels, suggested the following:

- The inpatient unit layout's configuration significantly affects visibility. For instance, the R-shaped layout offers 10.78% higher visibility (effectiveness measure) compared to the L-shaped layout.
- While redesigning the patient room with a patient head as the target, orientation towards the front of the room increases visual access to the target from the nursing station. More than 80% of the results from the experimental study supported this insight.
- A Pareto solution set exists for each layout to allow the designer to trade off equity with effectiveness. This set can help hospital administration select or reconfigure an existing layout based on their preference for equity vs. effectiveness.

There are many implications of our findings for an inpatient unit designer and hospital administration. For example, in high-priority critical care units, the targeted region of the beds can be orientated towards the door so that nurses can constantly monitor the patient from the nursing station and minimize walking. With the Pareto solution from our results, decision-makers can select a variety of solutions (equity vs. effectiveness) to retrofit their existing layout. Further, hospital management can use our research as a supporting tool to propose a new inpatient unit layout or remodel it accordingly. The need to trade off economic aspects of layout design and/or changes, along with the crowdedness in an inpatient unit, is another possible extension of this paper.

Our study has some limitations. For instance, our model assumes that no obstructions exist between the patients and nurses in the nursing station other than the occlusion considered in our study. However, we realize that other objects (e.g., cabinets, medical equipment) may exist in the corridor in a real-world scenario, further impeding the line of sight from the nursing station. Moreover, our model was designed assuming the patient bed is in the center of the room. This implies that medical devices within the room are flexible and can be moved to accommodate the patient's need instead of being fixed to specific corners of the room. We also consider that all patient rooms have a same bed orientation. This is an important aspect that hospital designers should take into consideration while analyzing the insights from our study.

This research can be extended in many ways. First, it would be worthwhile to extend our model to a layout with additional rooms, each allowed to have its own optimal bed orientation. While changing the bed orientation, considering the impact on other aspects of the room design, for instance, the position of medical equipment, space available for family members, could be considered. Additionally, extending our model to a multi-nurse setting, common in large inpatient units, would be interesting. Doing this will, however, increase the problem complexity and the proposed MOPSO must be enhanced, or another algorithm may need to be designed. Further, while we considered a nurse's movement only inside the nursing station, incorporating the nurse's walking behavior around the corridor and accounting for the visibility of patients would be a worthwhile endeavor.

CHAPTER 3

MULTI NURSE AND ROOM CONFIGURATION DESIGN

3.1 Introduction

Hospital layout design is the process of planning and organizing the physical spaces within a hospital to optimize patient care, staff efficiency, and overall functionality. This layout design is considered a crucial aspect of healthcare architecture, and its goal is to allow easy access to essential hospital services and effective patient care. Literature suggests that inpatient layouts in a modern hospital can be complex in design. For example, Figures 17a and 17b show two inpatient unit layouts of different overall shapes and different arrangement of layout components (e.g., patient rooms, nursing station, door position).

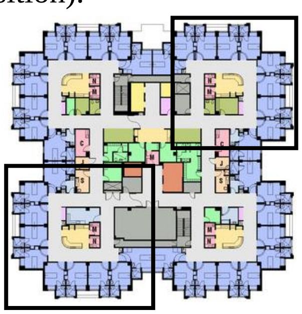

Figure 17a: Complex hospital inpatient unit layout

Figure 17b: Hospital inpatient unit layout with a racetrack corridor

Figure 17 Different inpatient unit layout design

However, these complex appearing layouts are often creative arrangements of simple, standard layout shapes. For instance, Figure 17a consists of four standard L-shaped layouts (black border), while Figure 17b is a combination of I-shaped (red border) and angled L-shaped layouts (black border). Hence, studying these standard layouts is crucial to understanding its impact on nurse's visual connectivity with the patient, a measure touted as a critical factor in achieving high-quality care.

Improved patient visibility helps reduce the risk of accidents and injuries, and minimizes emergency response times. For example, clear sightlines from the nursing station to the patient bed may allow nurses to be proactive and predict the likelihood of an adverse event (e.g., a patient fall) before they occur. These adverse events are considered as one of the 10 leading causes of mortality and disability globally (WHO, 2019; Skelly, Cassagnol & Munakomi, 2021). In addition, they are associated with a more extended hospital stay, high mortality rate, unplanned patient readmission, poor patient health status, and a high economic burden on the healthcare system. Improved visual connection between nurses and patients has been shown to reduce patient falls by 41% (Fierce Healthcare, 2016) and reduce mortality by 33.5% in the hospital (Lu, 2010; Lu et al., 2014).

So how can we improve the visual connection between nurses and patients? Research conducted in the past explains the correlation of the above-mentioned standard layouts in patient visibility. They suggest that modifying or redesigning the inpatient unit layout is one of the ways to maximize patient visibility in an inpatient layout. This includes strategic placement of layout components, such as windows, doors, and other openings, nursing station design, and reconfiguration of patient rooms to achieve high visual connectivity. For example, if a patient's bed is situated around the corner of a room and is not directly visible from the door, it may result in reduced patient visibility. In such situations, adjusting the position of the patient bed, door, or any obstructions can help to enhance and maintain optimal patient visibility. Prior work has focused on changes in patient visibility based on nursing station (Cai & Zimring, 2012; Hua et al., 2012), layout sizes (Pati et al., 2008; Seo et al., 2010), patient room configuration (Lee et al., 2020; Wei and Li, 2021) etc., but has been descriptive in nature. A prescriptive approach based on optimization techniques to simultaneously evaluate the effect of key layout elements on patient visibility and identify optimal layouts has not been fully explored (see Section 3.2 for details).

In this work, we proposed an optimization-based approach to jointly determine the location of multiple nurses and the location of patient beds across multiple rooms within a single optimization model. The specific questions our study addresses include the following:

1. How does the joint determination of bed location and nurse location affect patient visibility and equity offered by the layout?
2. Which layout shape tends to offer the best visibility in a multi-nurse setting in an inpatient layout?
3. How does the minimum distance between two nurses in a nursing station affect equity offered by various angular layout sections ?

Our contributions are as follows. *First*, we propose an optimization model to jointly determine the optimal locations of nurses in a nursing station and the location of multiple patient beds for a given layout. This model aims to minimize the inequity among total visibility of all patient beds (we refer to them as targets) across patient rooms while satisfying minimum effectiveness. We adopt the Gini index to measure inequity in visibility values; Gini index measures statistical dispersion within the groups. Effectiveness is calculated as the sum of visibility values across all targets. We consider four layout types: L-shaped, I-shaped, R-shaped, and U-shaped, with two nurses and eight single-bed patient rooms. We also consider factors such as nurses' line of sight, patient room configuration arrangement, and nursing station design. *Second*, to estimate visibility, we employ an improved, efficient version of the popular ray casting algorithm (Freud et al., 2006; Decherchi & Rocchia, 2013) to quantify the exposed area of a target in a room from a nursing station, considering the nurse's horizontal visual field and their depth of vision, layout type, and obstruction along the front end of the room. Our improvements include parallelization and skipping the project of rays over unwanted areas of interest in the patient room. *Third*, because the visibility estimate is not available in closed mathematical form rendering commercial solvers ineffective, we propose a heuristic based on Particle Swarm Optimization (PSO) to find (near) optimal solutions. *Finally*, through our experimental study, we identify critical insights of practical relevance to designers of inpatient unit layouts. Our approach could act as a benchmark tool and provide a valuable resource for hospitals looking to improve the design of their inpatient units and enhance the experience for both patients and healthcare providers.

Our experiments suggest that although optimizing the position of nurses with a fixed bed position in each room was beneficial to equity score, a substantial enhancement in equity measure was observed with a joint determination of nurse and patient bed positions. On average, this joint determination of patient bed and nurse locations can yield benefits up to 45% in low and 26.5% in high obstruction settings across all layout types.

Similarly, we found that the visibility value changes as we change the layout types. For example, we noticed that angular layouts (such as R-shaped, U-shaped, and L-shaped) maximize equity compared to an I-shaped layout; average increase is about 29%. Additionally, we observed that an increase in spatial distance between two nurses enhances the layout's equity in angular layouts, allowing better nurse repositioning to maximize the visibility of their assigned patients. Finally, when shifting from a low to high obstruction setting, we observed an increase in variability in the distribution of patient visibility, resulting in a reduced equity measure.

We now provide an outline of our paper. Section 3.2 provides an overview of the most relevant literature on inpatient hospital layouts and patient visibility. Section 3.3 introduces our proposed optimization model, a nonlinear mixed-integer programming model. Section 3.4 describes our proposed *Progressive Refinement* approach, which we implement using a Particle Swam Optimization framework to efficiently solve the model. In Section 3.5, we discuss our experimental design, and in Section 3.6, we highlight our main conclusions and explore possible directions for future research.

3.2 Literature Review

In recent years, the focus on hospital layout design has grown. Despite numerous studies examining various aspects of healthcare, such as communication and patient satisfaction (Chaudhury et al., 2009; Rathert, Wyrwich, and Boren, 2013; Reader, Gillespie, and Roberts, 2014), layout design and patient-nurse visibility continue to be a highly emphasized topic in the healthcare domain. Below we review key literature on the impact of layout design on visibility.

Much research has been conducted in the past, primarily focusing on patient visibility in a hospital in an effort to improve patient safety. The objective of these studies is to examine various aspects of hospital layout configurations, including nursing stations, patient rooms, and overall layout types. They investigate patient visibility from designated areas, such as nursing stations, by employing visibility measurement tools, surveys, or interviews. For example, Rashid (2007) conducted a retrospective, correlational study using a multiple linear regression model and identified that direct patient visibility could be improved by changing the layout design features; e.g., centralized nursing stations and glass partitions.

Pati et al. (2008) conducted a discussion and surveys with experts from leading healthcare design firms who participated in the symposium to rate six layouts. They found that configurations with outboard toilet locations were suitable, and that room configurations and design choices significantly enhanced patient visibility, patient safety, and overall healthcare outcomes. While keeping patient safety in focus, Ulrich et al. (2008) reviewed evidence-based healthcare design literature and found that well-designed nurse stations can lead to improved patient-nurse visibility and better patient outcomes, along with enhanced staff communication, coordination, and monitoring of patients. In a study comparing the impact of unit layout size on patient visibility, Seo et al. (2010) conducted observations and exploratory analysis of nurse trips between the two unit sizes and discovered that smaller units provide a higher number of visible beds from the nursing station compared to larger units. They noted that increasing patient visibility in larger units requires additional observation points, such as substations. Likewise, Lu (2010) utilized the ArcGIS platform to examine various layout types to assess visibility from nursing stations to patient beds. Their findings indicated that the shape of the layout influences the number of beds that can be seen. Among the different layout types, the radial unit layout showed the most potential for maximizing the visibility of patient beds from nursing stations.

In terms of nursing stations, Chaudhury et al. (2009) observed conducted an extensive literature review and focus groups to determine the effect of the physical environment, such as nursing unit layout and patient room design, on nursing efficiency and quality of care. They found that a radial nursing station was preferred in a unit with high-acuity patients as this design provides high patient visibility. On the contrary, decentralized nursing stations were also identified as preferred as in such a design, nurses are closer to the patient room reducing fatigue, enhancing nursing efficiency. Similarly, Cai & Zimring (2012), based on a case study using space syntax analysis, found that a centralized nursing station also promotes nurses' communication, which ultimately aids in a better understanding of patient needs and quality of care. Hua et al. (2012) conducted a multi-method, cross-sectional, and pre/post study to identify the relationship between clinical spatial environment and its impact on patient safety and satisfaction. They found that a new multi-hub nursing unit design successfully improved patient experience and quality of care, as evidenced by increased patient satisfaction. However, the multi-hub design had a lower nurse satisfaction rate than the original decentralized nursing station.

In another study, Lu & Zimring (2012) assessed patient visibility in ICUs using improved Visibility Graph Analysis (VGA) methodology. They found that hospital managers should consider layout design with nursing stations and substations to allow nurses to interact with others while closely observing their patients. Similarly, Lee et al.

(2017) used Depthmap software to study the impact of various positions of hospital departments on their visibility profile. They found that the arrangement of the layout components can affect visibility by creating more occlusion. Fay et al. (2017) collected data using the observation and time-motion studies of nurses in a unit and presented that a decentralized layout offers higher visible beds than a centralized nursing station. However, in the case of nurse-nurse visibility, the centralized nursing station was favored over the other.

Similarly, obstruction created around the inpatient unit or in the patient room lowers the ability to see a patient from the nursing station. For instance, Chaudhury et al. (2009) suggested that an unobstructed nursing station design with clear glass was beneficial for high patient visibility and quality of care. Trzpuc and Martin (2010) studied three medical surgical units using space syntax theory and found that design characteristics such as extending solid walls, curved corridors, and opaque booth/support cores obstruct direct visibility influencing the patient visibility in a layout. Lu & Zimring (2012) also identified that obstruction created by doors in ICU design directly affects patient visibility. In a space syntax analysis of the U.S. hospital's emergency department, MohammadiGorji et al. (2023) also suggested that obstruction in the layout is an important design consideration. Obstruction created by columns and solid walls in the layout can lower the mean visual depth of the layout and the ability to maintain direct visibility between a nurse station and a target.

In another stream of literature, researchers have continued exploring the impact of patient room arrangement/reconfiguration on visibility in hospital layouts. For instance, Lee et al. (2020) suggested that moving the multi-bed patient rooms closer to the nurse station would increase the number of patients seen and improve care quality. Similarly, Wei and Li (2021) suggested that patient beds be accessible from all three sides, bathroom doors should be positioned to improve patient visibility, and rooms should be redesigned to provide more leisure space. Piatkowski et al. (2021) also suggested that direct visibility from the patient bed to the bathroom door would consider safer, inducing less risk of patient falls.

In summary, prior literature underscores the importance of patient visibility and layout design elements in improving patient outcomes, safety, and staff efficiency in hospital settings. However, existing research has been descriptive in nature; i.e., approaches are proposed to analyze existing layouts. An optimization-based approach to solving these unit layouts and patient visibility problems would help a designer to improve decision-making by objectively evaluating myriad possible solutions in an effort to find a layout that optimizes a certain objective; e.g., maximizing visibility of patients.

Outside healthcare, an optimization-based approach in visibility-based layout design have been explored, such as in architectural floor plan design (Schneider and Koenig, 2011), construction site layout planning (el Ansary & Shalaby, 2014), and retail (Mowrey, Parikh, & Gue, 2018; Guthrie & Parikh, 2019; Karki, Guthrie, and Parikh, 2021). These optimization-based studies provide enhanced data-driven decision-making for the proposed problem. However, these studies are tailored to their specific domains and cannot be easily adapted to solve the inpatient unit layout problem. While our prior work did introduce an optimization model for an inpatient unit, it was limited to a single nurse with a fixed patient bed across all rooms and fixed door locations.

Table 9 Summary of the collected research papers

Reference	*Facility layout type**	*Adopted layout configuration*					*Methodologies used to study target visibility*					
		Radial	*Linear/Single corridor*	*Racetrack/Double corridor*	*Residential house*	*Patient room*	*Optimization/ Mathematical model*	*Surveys / questionnaires*	*Observation*	*Simulation/Visibility analysis tool*	*Quantitative measures*	*Literature review*
Rashid, 2007	ICU	✓	✓	✓		✓						✓
Pati et al., 2008	ICU		✓	✓				✓			✓	
Ulrich et al., 2008	HF	✓	✓	✓								✓
Chaudhury et al., 2009	AC	✓	✓	✓								✓
Trzpuc and Martin, 2010	SU			✓				✓		✓		
Seo et al., 2010	ICU			✓					✓			
Lu, 2010	HF	✓		✓						✓		
Cai & Zimring, 2012	ICU			✓		✓		✓	✓	✓		
Hua et al., 2012	NU			✓				✓			✓	
Lu & Zimring, 2012	ICU		✓	✓						✓		
el Ansary & Shalaby, 2014	SL				✓		✓					
Lee et al., 2017	RAC		✓	✓						✓		
Fay et al., 2017	AC		✓	✓				✓	✓			
Mowrey, Parikh, & Gue, 2018	R		✓				✓					
Guthrie & Parikh, 2019	R		✓				✓					
Lee et al., 2020	SU		✓	✓						✓		
MohammadiGorji et al., 2023	ED	✓		✓						✓		
Wei & Li, 2021	NH					✓					✓	
Piatkowski et al., 2021	PR					✓		✓				

*Abbreviations: AC: Acute care units; ICU: Intensive care unit; ED: Emergency department; HF: Healthcare facilities; NH: Nursing homes; NU: Nursing unit; OU: Orthopedic unit; PR: Patient room; R: Retail; RAC: Residential aged care; SL: Site layout; SU: Surgical unit

Table 9 summarizes all the papers in the literature review section regarding methodology and layout types analyzed in their study.

Realizing the gaps in visibility-based healthcare facility layout literature, we propose a novel optimization-based approach for a multi-nurse layout, with a focus on jointly determining the positions of two nurses and location of beds in each room while considering the effect of obstruction, door position, and layout shape. We now present our proposed model for this problem.

3.3 Optimization Model

Our optimization model aims to jointly determine the optimal positions of (i) two nurses in the nursing station and (ii) patient bed in multiple rooms. The model has two main objectives: maximizing *equity* in visibility (among targets across the rooms) and maximizing *effectiveness* (sum of visibility across all targets). However, solving multi-objective optimization problems can be challenging, especially in the presence of large number of decision variables (as shown in Table 11).

When solving complex multi-objective healthcare problems, decision-makers often prioritize equity to ensure that healthcare services are fairly accessible to all individuals (Bor et al., 2017; Gaffney & McCormick, 2017). In contrast, effectiveness is essential, but if available to a small portion of the population, then it may not be considered equitable. While the weighted sum approach is sometimes used for multi-objective problems, it is only practical for convex problems. It can also result in different solutions depending on the weightings, which lack an objective basis for selection. On the other hand, the ε-constrained approach is appropriate for non-convex and non-linear optimization problems, that aligns with our problem's characteristics and permits sensitivity analysis by adjusting ε (effectiveness) values while achieving maximum level of equity (Rong et al., 2015; Dou et al., 2020).

In our implementation of the ε-constrained approach, we prioritize equity over effectiveness by setting a limit (ε) on the maximum allowable deviation on the effectiveness measure. In so doing, we convert the original bi-objective model to a single-objective optimization model, which, in turn, may enhance the comparison of solutions and informed decision-making when the priority of the objectives is pre-determined (Savic, 2002; Alhammadi & Romagnoli, 2004).

We consider four different layout types, each with two nurses in a single nursing station and eight patient rooms with one bed each. Typically, these layouts have a nurse-to-patient ratio ranging from 1:2 to 1:6 in units with one nurse, depending on the type of the unit (e.g., ICU will have a higher ratio compared to a medical unit) (Welton, et. al.; 2006; Massachusetts Hospital Association; 2006; Wolters Kluwer, 2020). After reviewing existing literature and consulting a registered nurse from a local hospital, we chose a nurse-to-patient ratio of 1:4 for this study, which is the most cited ratio in the literature (Welton, et. al.; 2006; Lasater et al., 2020; Wolters Kluwer, 2020); however, our optimization-based approach is generic enough for any nurse-to-patient ratio.

We make the following assumptions in developing our model:

- The nursing station is situated within a rectangular area.
- The nurses are assumed to have sufficient height to see the patients in a room clearly.

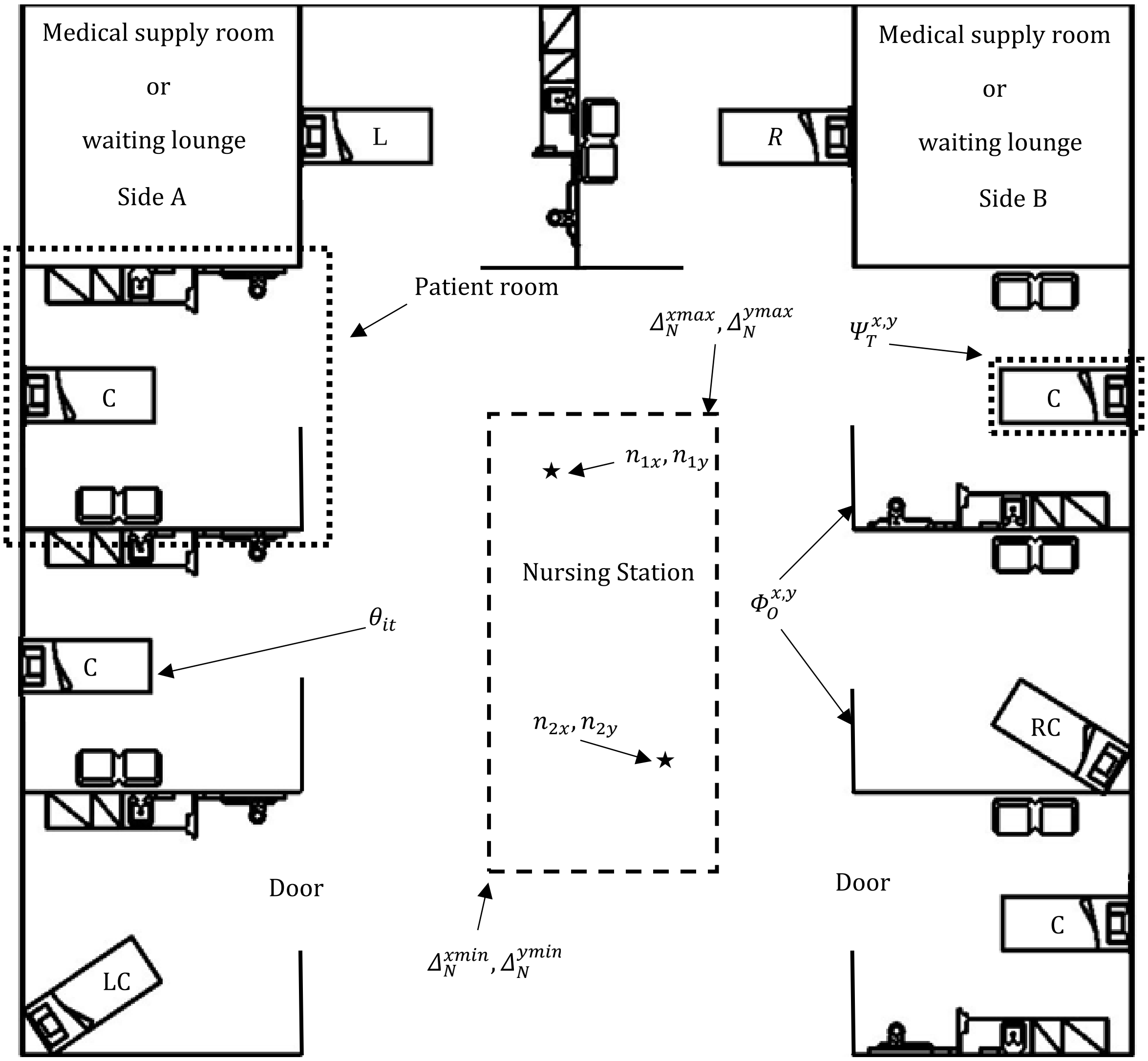

Figure 18 Representative inpatient unit with parameters and decision variables

- Nurses' visual range is restricted to 180° horizontally, which comprises a 90° field of regard from the combined movement of their head and eyes and an additional 90° range due to the chair's yaw movement (Parker & West, 1972).
- There are no physical obstructions, except for the occlusion caused by walls or opaque glass along the room's exterior wall, which would hinder nurses' visibility from their position in the nursing station.

Figure 18 shows an example U-shaped inpatient unit with eight beds and a single nursing station. The targets (beds) are aligned to 5 unique different possible positions in each room from the nurse's viewpoint; C = center, R= right, L = left, RC = right center, and LC = left center (see Figure 18).

The door positions for the layout are represented by the door position of the first four rooms, referred to as side A (left side of the nursing station), while the door positions on the other side, side B, are mirrored. Figure 18 shows one such example where side A's door position is '*RRRR*' from the nurse's viewpoint, with side B mirrored. In the figure upper and lower stars represent example positions of the two nurses inside the nursing station with their targets (beds) on side A and side B, respectively.

Table 10 Parameters used in the model

Notation	Definition
T	Set of targets; $t \in T$
R	Set of patient room; $r \in R$
I	Set of permitted positions of the target t; $i \in I$
J	Set of nurses in a given nursing station; $j \in J$
S_j	Set of target t assigned to nurse j; $s_j \in T$
A_r	Door position of room r
P^t	Set of perimeters of the selected target t
$\Gamma^{x,y}$	Set of all coordinates that define a selected layout
$\Psi_T^{x,y}$	Set of all coordinates that define the boundary of target t
$\Phi_O^{x,y}$	Set of all coordinates that define the boundary of occlusion to target t
$\Delta_N^{xmin}, \Delta_N^{xmax}$	Minimum and maximum x-coordinate of the nursing station
$\Delta_N^{ymin}, \Delta_N^{ymax}$	Minimum and maximum y-coordinate of the nursing station
$\Omega_{\max}$	Maximum angular limit of visual scanning of a nurse (°)
$\mathrm{D}_{\min}$	Minimum Euclidean distance between any two nurses (ft)
ε	Minimum effectiveness measure for a given setting
DOV	Nurse's depth of vision (ft)

Table 11 Decision variables used in the model

Notation	Definition
n_{jx}, n_{jy}	Position of nurse *j* in a nursing station
θ_{it}	1, if target position *i* is selected for given target *t*; 0, otherwise
v_t	Sum of fraction of target t visible to the nurse *j*; $\sum_j v_{jt}\ \forall t$, where $\bar{v}_t$ is average visibility and equals to $\frac{\sum_t v_t}{\lvert T\rvert}$

We propose the following optimization model to solve the visibility-based inpatient unit layout problem.

maximize:

$$\sum_t \left(1 - \frac{\sum_{i,j \in T} \lvert x_i - x_j \rvert}{2\lvert T\rvert^2 \bar{v}_t}\right)$$

subject to

$$v_{jt} = f\left(\Omega_{\max}, \mathrm{DOV}, A_r, \Gamma^{x,y}, \Psi_T^{x,y}, \Phi_O^{x,y}, \mathrm{P}^t, \theta_i, (n_x, n_y)\right) \forall j, t \in S_j \tag{1}$$

$$v_t \geq \varepsilon \ \forall t \tag{2}$$

$$\sum_i \theta_{it} = 1 \ \forall t \tag{3}$$

$$\sqrt{\left(n_{jx} - n_{j'x}\right)^2 + \left(n_{jy} - n_{j'y}\right)^2} \geq \mathrm{D}_{\min} \ \forall\, j, j' \in J;\ j \neq j' \tag{4}$$

$$\Delta_N^{xmin} \leq n_{jx} \leq \Delta_N^{xmax} \quad \forall j \tag{5}$$

$$\Delta_N^{ymin} \leq n_{jy} \leq \Delta_N^{ymax} \quad \forall j \tag{6}$$

$$0 \leq v_{jt} \leq 0.5 \quad \forall j, t \tag{7}$$

$$\theta_{it} \in \{0,1\} \quad \forall i, t \tag{8}$$

Our proposed model aims to maximize the equity in the visibility of targets among patient rooms within an inpatient unit layout. The equity is measured by subtracting the Gini Index from 1. Note that, Gini index is a commonly used statistical measure that quantifies the level of inequality of a specific objective within a given population. To convert this measure into an equity measure, we subtract it from 1, similar to Contribution 1 (Chapter 2).

Constraints (1) utilize function $f(\cdot)$ to estimate the portion of target t that can be seen by the nurse, considering factors such as the nurse's position and visibility parameters, room configuration, and patient bed position. Constraints (2) implement the ε-constrained approach, where we establish a minimum effectiveness level for a given layout setting. Constraints (3) ensures that only one bed position is selected for each room, while Constraints (4) guarantees a minimum distance between nurses in a nursing station. Constraints (5) and (6) define limits on the nurse's position along the X- and Y-coordinates. Constraints (7) set boundaries on the visible fraction of target t from the nursing station and Constraints (8) specify bounds on the position of target t in a room.

It is important to note that expressing function $f(\cdot)$, which is used to estimate the visibility of target t, in a closed analytical form is challenging because of the complex relationship between the nurse's field of regard ($\Omega_{\max}, \mathrm{DOV}$) and the layout parameters ($\Gamma^{x,y}, \Psi_T^{x,y}, \Phi_O^{x,y}$). Therefore, we estimate visibility using the ray casting algorithm, as per Contribution 1 (Chapter 2). Due to the non-closed form of function f and the non-linearities in the objective function, our proposed model cannot be solved efficiently using state-of-the-art mathematical programming solvers, such as CPLEX or Gurobi. Therefore, we suggest a metaheuristic approach based on the Particle Swarm Optimization (PSO) framework to solve this problem.

3.4 Methodology

Recall that the optimization model we propose relies on determining the visibility of each patient's bed according to a specific layout configuration. The visibility values for all patient beds are then utilized to compute two essential measures in our optimization model - equity and effectiveness. It is evident that there are two stages of calculation: 1) estimating the visibility values for patient beds and 2) solving the optimization model to identify optimal positions for nurses and beds. Consequently, as detailed below, we have structured our methodology in this paper based on how these two stages are determined.

3.4.1 Visibility Estimator

This estimator determines the visibility of patient beds within a room using the decision variable vector as an input. Ray casting involves emitting rays from a specific point in a virtual space and determining the visibility of a target (i.e., patient beds in our case) based on the intersection of the rays with the target. We employ a 2D version of the ray casting algorithm, which casts rays horizontally across the full range of angular limits (Ωmax).

Figure 19 illustrates the utilization of the ray casting algorithm in two distinct layout configurations examined in our research. First, based on input parameters such as layout types, bed positions, door locations, nurse placement, and ray intervals, the algorithm projects rays throughout the layout, scanning for visible segments of patient beds. The identified sections are aggregated to determine the total visible proportion of the bed's perimeter. It is important to note that there is a tradeoff between computation time and accuracy when determine an appropriate ray interval; small intervals improve accuracy but can be time consuming.

Our implementation utilizes two distinct ray intervals: 3° for the coarse search and 0.1° for the progressive refinement algorithm (see Section 3.4.2). The bed position from the optimizer is first converted to an (x, y) coordinate in a data frame. The ray-casting algorithm then uses this information as a reference to identify targets during the search process. The visible portion of the pre-specified target is determined by calculating the ratio of the total visible length of the target to its perimeter.

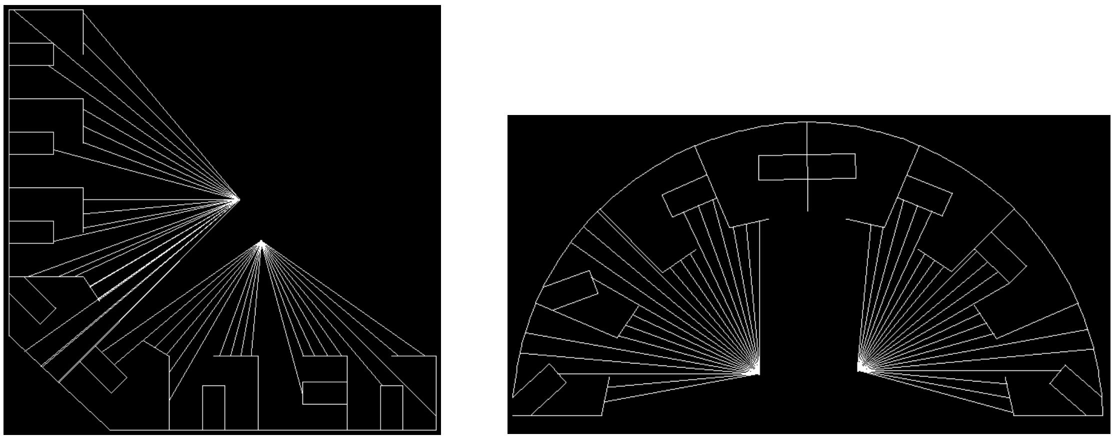

Figure 19a: L-shaped layout *Figure 19b: R-shaped shaped layout*

Figure 19 Ray casting algorithm implementation on two different layout types

3.4.2 Proposed Progressive Refinement Algorithm

We propose a Progressive Refinement algorithm to efficiently solve our optimization model. It begins by generating a rough estimate of the solution, which is then refined with increased precision. This method provides several advantages compared to other optimization methods, including increased speed, better accuracy, and stability.

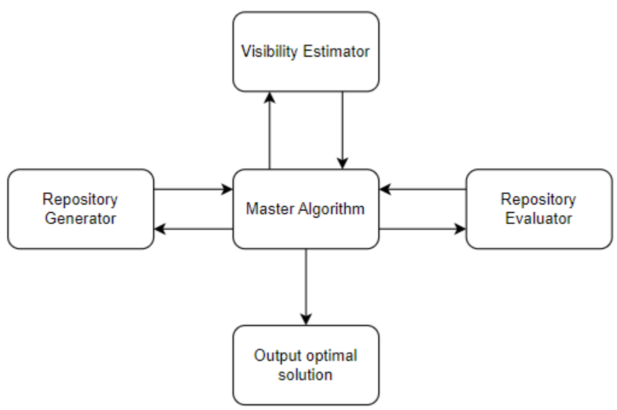

Figure 20 Interaction between master algorithm, visibility estimator and progressive refinement algorithm

Our proposed approach consists of two primary routines involved by a Master Algorithm: (i) a Repository Generator and (ii) a Repository Evaluator, as shown in Figure 20. A Master Algorithm governs both of these processes. During (i), the Master Algorithm employs a Particle Swarm Optimization (PSO) technique to solve the optimization model, which produces *n* potential solutions (stored in a repository). Because the visibility estimator is called repeatedly during this process, we use 3° ray interval to reduce the computation time. In (ii), the Master Algorithm reevaluates these repository solutions, this time using the visibility estimator with a finer 0.1° ray interval to get accurate estimates. Lastly, the Master Algorithm determines the optimal solution of the problem by selecting the solution with the highest equity. In case, we have alternate optimal solutions, we select a solution with highest effectiveness measure. A thorough explanation of each component is presented in the following sections.

3.4.3 Repository Generator Routine

The Repository Generator routine monitored by the master algorithm is based on the PSO framework. The concept of PSO evolves from the social dynamics of bird flocking and fish schooling, as described by Kennedy and Eberhart (1995). In the context of PSO, a set of particles is initialized within a search space, where each particle's position represents a potential solution to a given problem. Then, over multiple iterations, the particles travel the solution space finding the most favorable solutions, ultimately converging to the optimal solution. PSO has proven to be particularly adept at addressing optimization problems characterized by non-linearity and non-convexity (Chen et al., 2014). Additionally, PSO is advantageous for problems involving continuous decision variables, as it can efficiently explore and exploit the continuous solution space using an initialized swarm of particles (Bratton and Kennedy, 2007).

PSO is well-suited for this problem given that our problem involves non-linearity (e.g., function $f(.)$) and continuous decision variables (e.g., position of nurses). Moreover, PSO's low computational time, easy implementation, and ability to identify a global best solution (Wu et al., 2021) are additional evidence for selecting this meta-heuristic.

In the proposed PSO approach, each particle is represented as a vector of decision variables ordered as follows: (i) bed position in a room (θ), and (ii) the nurse's position in (x, y) coordinates. An example of such vector may be $\{\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, x_1, y_1, x_2, y_2\}$, where positions #1 through #8 represent the bed position in each patient room, and (x_1, y_1) and (x_2, y_2) represent the coordinates of the first and second nurse's positions in the nursing station. We now explain our implemented PSO's subroutines in the following section.

3.4.3.1 Candidate Solution Subroutine

The purpose of this subroutine is to create random x and y coordinates that represent the positions of two nurses within the specified range of a nursing station, [Δ_N^{xmin}, Δ_N^{xmax}] and [Δ_N^{ymin}, Δ_N^{ymax}]. Additionally, this subroutine also determines the location of a bed (θ) by selecting a random value from the range of $\Phi \in [0, 5]$. The Φ value is then transformed into one of the five physical positions in the patient room considered in our model (see expression below).

$$\theta \begin{cases} = C, \text{ if } 0 \leq \Phi < 1 \\ = RC, \text{ if } 1 \leq \Phi < 2 \\ = R, \text{ if } 2 \leq \Phi < 3 \\ = LC, \text{ if } 3 \leq \Phi < 4 \\ = L, \text{ if } 4 \leq \Phi \leq 5 \end{cases}$$

After running this subroutine, a particle's decision variable vector could take the form of {*L, C, L, L, R, R, RC, C,* 120, 110, 180, 250}. Here, {*L, C, L, L, R, R, RC, C}* indicates the position of the bed in each room, and (120, 110) and (180, 250) represent the position of the two nurses in the nursing station.

3.4.3.2 Candidate Evaluation Subroutine

To evaluate each candidate solution, this subroutine employs the Visibility Estimator (see Section 3.4.1) to calculate function *f(.)* for each target *t* based on the particle's position vector and layout parameters. The resulting visibility values are then utilized to calculate the equity term in the objective function while ensuring that the effectiveness term for the ε-constraint is satisfied. For instance, assume an L-shaped layout with low obstruction, ε of 3.0, and a decision variable vector as {*L, C, L, L, R, R, RC, C,* 120, 110, 180, 250}. For this specific vector, this Candidate Evaluation Subroutine would return equity and effectiveness measures as 0.9 and 3.15, respectively.

3.4.3.3 Update Subroutine

This subroutine modifies the particle's position and velocity while updating the particle's individual best and the overall global best solutions. Moreover, this subroutine chooses a leader as the global best solution. Equations (4) and (5) are utilized to compute the particle's updated position.

$$V_{ij}^{t} = W(V_{ij}^{t-1} + C_1 r_1\left(Pbest_{ij}^{t-1} - X_{ij}^{t-1}\right) + C_2 r_2\left(leader_{ij}^{t-1} - X_{ij}^{t-1}\right)) \tag{4}$$

$$X_{ij}^{t} = X_{ij}^{t-1} + V_{ij}^{t} \tag{5}$$

At each iteration i, the position of the particle is represented by X_{ij}^{t} and velocity by V_{ij}^{t}. In expression (4), r_1 and r_2 are random variates that follow U[0, 1], and control the particle's movement towards its personal best position or a selected leader. The coefficients C_1 and C_2, known as acceleration constants, influence the particle's movement in the search space. During the search process, the inertia weight (W) and C_1 are set to 0.7282 and 2.05, respectively, per Clerc and Kennedy (2002). The value of C_2 is initially set to 1.5 and subsequently increased by 0.2 after 700 and 1000 iterations. We also reduce W over time to ensure that exploration and exploitation are favored. After the particle's position is updated, it is again evaluated by the Evaluation subroutine, and the process repeats until the termination criteria are met.

3.4.3.4 Termination Subroutine

This subroutine controls the iteration-based termination of the search process of the PSO algorithm. We tested with different iterations (from 500 to 5,000 iterations) and observed that 1,500 iterations were suitable for finding the n best solutions for the repository to get the best solution.

3.4.4 Repository Evaluator Routine

The repository evaluator routine refines each of the *n* solutions from the repository generator routine using the visibility estimator with a 0.1° interval size (as mentioned in Section 3.4.2). From the pool of refined solutions, a solution with the highest fitness score (highest equity measure) is ultimately chosen based on the computed fitness function scores at 0.1° intervals. For solutions with same equity measure, the effectiveness measure is used to compare and break the tie between those solutions.

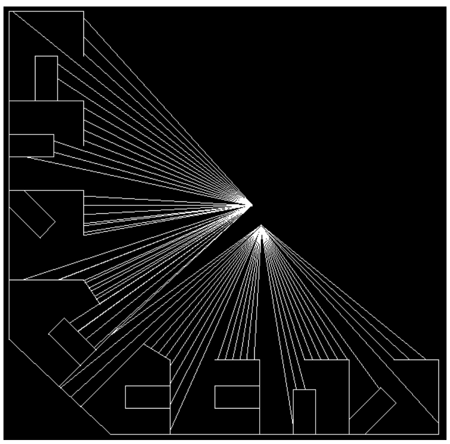

Figure 21a: Ray casting at 3° interval

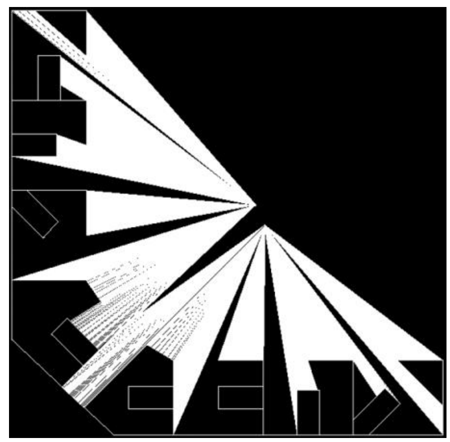

Figure 21b: Ray casting at 0.1° interval

Figure 21 Ray casting algorithm implementation at two ray intervals

Figure 21 demonstrates the application of this approach on one of the candidate solutions (among the n solutions). When the ray interval was 3°, certain areas in patient bed #2, #7 and #8 were not captured but are now covered using a finer 0.1° ray interval. This improvement ensures better accuracy in patient bed visibility while maintaining reasonable computational time.

By implementing this progressive refinement algorithm, we were able to reduce the total computational time by 68.75% compared to utilizing ray casting with a 0.1° interval (for 1500 iterations). Moreover, we managed to preserve the quality of the final solution using this approach.

3.5 Experimental Study

We conducted an experimental study that combined data from literature and our observations of hospital environments to generate valuable insights for inpatient unit designers. Below we detail our approach.

3.5.1 Data Collection and Experimental Factors

We assumed that the nurses are seated in chairs that allow for yaw (left and right) movement (Y_c) of 90°. Additionally, we considered the head and eye movements of the nurse, which can enhance their field of regard. Based on Parker and West (1972), we assumed a nurse's maximum head (H_E) and eye (E_E) movement to be 90°. Combined with the chair's yaw movement, this resulted in a nurse's field of regard (FoR) of 180°. We also assumed that the nurse's depth of view, or the distance they can see clearly, is 50 ft, in line with published literature.

We evaluated four distinct layout types - L-shaped, U-shaped, I-shaped, and R-shaped (as depicted in Section 3.5.2) - each with eight patient beds. In addition, to ensure safety and compliance with guidelines set by the US Centers for Disease Control and Prevention (CDC) and healthcare agencies (Occupational Safety and Health Administration 2021; Centers for Disease Control and Prevention, 2022), we set the minimum distance between two nurses in a nursing station at 6ft. Table 12 summarizes the dimensions of a typical layout we consider in our study based on recommendations in existing literature (Critical Care Medicine, 1995; CADdetails, 2021; Healthcare Facilities Today, 2021; AvaCare Medical, 2022).

Table 12 Dimension of layout component

Layout components	*Dimension*
Patient Room	12 ft × 10 ft
Patient Bed	6ft × 3ft
Corridor width	7 ft
Chair dimension	1.5 ft × 1.5 ft

It is worth noting that patient rooms may have varying obstructions that can hinder nurse-patient visibility. To replicate this in our study, we included two levels of obstruction, low (50%) and high (80%), depending on a combination of transparent glass door and window. Further, literature suggests that patient room doors can be positioned on either the left or right side of the room with respect to the nurse. Table 13 summarizes the parameters and values used in our experimental design. We calculated the target's visibility in the patient room using the methodology outlined in Sections 3.3 and 3.4.

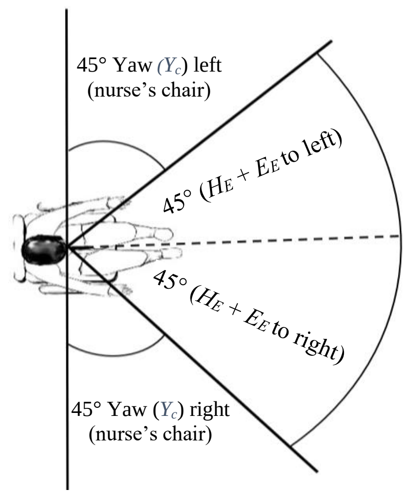

Figure 22 Nurse's visual parameters used in our experimental study

Table 13 Parameters values used in the experimental study

Parameters	*Levels*	*Values*
Layout types	4	L-shaped (16.5 ft × 17.5 ft), U-shaped (12 ft× 24 ft), I-shaped (26 ft× 11 ft), and R-shaped (25 ft× 11.5 ft)
Obstruction	2	Low (50%), High (80%)
Door position	2	Left (L), Right (R)

3.5.2 Results and Insights

We now present results based on the observations from our experiments per Table 13. On average, each experiment required 3.2 hours to achieve a reasonable solution quality. A solution is considered reasonable when no further improvement in final solution is observed over multiple replications and according to the termination criteria (Section 3.4.3.4). While Appendix D provides all the results, we illustrate a few of those later in this section as we discuss the insights.

It is important to note that, as our problem is modeled using an ε-constrained approach, there is no single optimal solution. Instead, we derive Pareto solutions that highlight the tradeoff between equity and effectiveness (see Figure 28). While inpatient unit designers can select any solution on the Pareto frontier based on their relative preference between equity and effectiveness, we discuss our insights based on the solution(s) that provided the highest equity (the primary objective term).

Insight 1: Joint determination of nurse and bed positions yields higher equity than optimizing nurse position alone.

This insight is based on a comparison of the best solution found from our approach with a baseline layout. The baseline layout had all bed positions assigned to the '*C*' position (see section 3.4 for reference), while the door position was set to '*RRRR*' across all rooms. Figure 23 provides an illustrative example of such a baseline configuration in a U-shaped layout. In the figure, blue and red dots represent to sample position of nurses inside the nursing station with their respective targets (beds) colored blue or red with dotted line representing a high obstruction setting.

We first optimized this baseline configuration by maximizing the equity measure with only the nurse position as a decision variable (as the bed position was set to ‘C’). Epsilon (ε) value was set to be the maximum allowable that would result in a feasible solution. Table 14 presents a comparative overview of results from various examined scenarios across all layout types and obstruction levels. The bold entries indicate the maximum achievable equity for a given layout type.

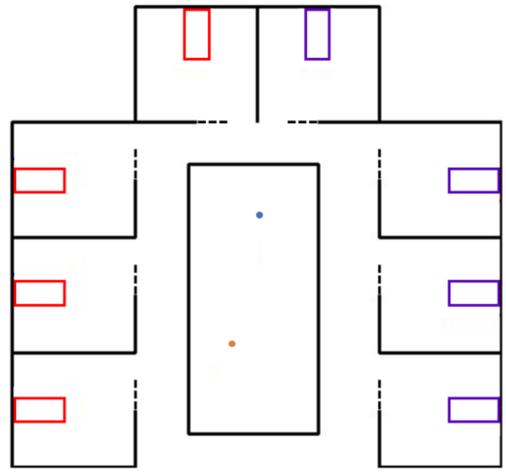

Figure 23 U shaped layout at low obstruction with all beds position on ‘C’

Table 14 shows that no instance with a baseline layout was identified that provides the optimal equity measure. However, there was a consistent improvement in all layout types when patient bed as a decision variable was incorporated into the model, thereby maximizing the objective function. Furthermore, we analyzed the effects of modifying the door position in conjunction with the bed and nurse positions, further elevating the objective function. These rows are labeled ‘Joint-O;’ i.e. joint optimization in Table 14. We can see that in most cases, the layout would benefit more when we also change the door position along with bed and nurse positions.

Table 14 Results summary from various scenarios considering both obstruction levels

Obs.	***Layout***	***Scenario***	ε	***Door position***	***Bed position***	***Nurse_1 position***	***Nurse_2 position***	***Eq.***
Low	L shaped	Baseline	2	RRRR	*C,C,C,C,C,C,C,C*	*(257,336)*	*(334,320)*	*0.59*
		Baseline-O	3.5	RRRR	*L,C,C,L,C,LC,C,RC*	*(258,342)*	*(256,252)*	*0.96*
		Joint-O	**3.5**	**RRRL**	***L,C,RC,L,R,LC,C,C***	***(256,279)***	***(338,342)***	***0.97***
	R shaped	Baseline	2.5	RRRR	*C,C,C,C,C,C,C,C*	*(379,42)*	*(275,54)*	*0.8*
		Baseline-O	3.5	RRRR	*C,R,R,R,LC,L,L,LC*	*(285,49)*	*(420,46)*	*0.93*
		Joint-O	**3.5**	**RRRL**	***C,R,RC,LC,RC,LC,L,LC***	***(320,57)***	***(410,42)***	***0.97***
	U shaped	Baseline	2	RRRR	*C,C,C,C,C,C,C,C*	*(240,170)*	*(240,73)*	*0.54*
		Baseline-O	3.5	RRRR	*L,C,RC,RC,C,L,L,C*	*(233,207)*	*(205,142)*	*0.87*
		Joint-O	**3.5**	**RRLR**	***LC,RC,R,C,C,LC,LC,R***	***(260,130)***	***(230,192)***	***0.98***
	I shaped	Baseline	1.5	RRRR	*C,C,C,C,C,C,C,C*	*(218,21)*	*(262,20)*	*0.54*
		Baseline-O	3	RRRR	*RC,L,L,LC,LC,LC,R,R*	*(254,21)*	*(302,24)*	*0.76*
		Joint-O	**3**	**RRRL**	***L,LC,C,L,RC,LC,RC,L***	***(192,21)***	***(282,20)***	***0.87***
High	L shaped	Baseline	2	RRRR	*C,C,C,C,C,C,C,C*	*(314,342)*	*(346,268)*	*0.58*
		Baseline-O	2	RRRR	*L,C,R,R,LC,LC,LC,C*	*(265,262)*	*(309,328)*	*0.79*
		Joint-O	**2**	**RRLR**	***R,R,L,R,LC,RC,LC,C***	***(328,276)***	***(286,325)***	***0.82***
	R shaped	Baseline	2	RRRR	*C,C,C,C,C,C,C,C*	*(417,55)*	*(275,56)*	*0.75*
		Baseline-O	2	RRRR	*R,R,C,R,LC,L,L,L*	*(456,53)*	*(293,46)*	*0.81*
		Joint-O	**2**	**RRLL**	***RC,RC,L,L,RC,RC,L,LC***	***(293,54)***	***(410,48)***	***0.87***
	U shaped	Baseline	2	RRRR	*C,C,C,C,C,C,C,C*	*(243,140)*	*(205,198)*	*0.52*
		Baseline-O	2.5	RRRR	*C,RC,LC,RC,LC,C,C,L*	*(240,164)*	*(224,227)*	*0.68*
		Joint-O	**3**	**RRLR**	***C,RC,LC,RC,L,LC,R,C***	***(236,191)***	***(208,132)***	***0.81***
	I shaped	Baseline	1	RRRR	*C,C,C,C,C,C,C,C*	*(178,21)*	*(248,20)*	*0.45*
		Baseline-O	2	RRRR	*C,C,LC,RC,LC,LC,R,R*	*(254,20)*	*(291,24)*	*0.59*
		Joint-O	**3**	**RRRL**	***L,C,RC,LC,RC,L,RC,R***	***(201,22)***	***(278,22)***	***0.79***

Figure 24 represent layouts with these improvements in equity measures against the baseline model across all layout types. The results indicate that regardless of the given layout, there is a significant potential for enhancing equity measures beyond those achievable by the baseline model. First, simply considering alternative door positions can improve the equity over baseline model. Further, by considering alternative door locations, and then jointly determining bed orientation and nurse position. However, note that we do not consider blockage of line of sight due to one nurse position on other.

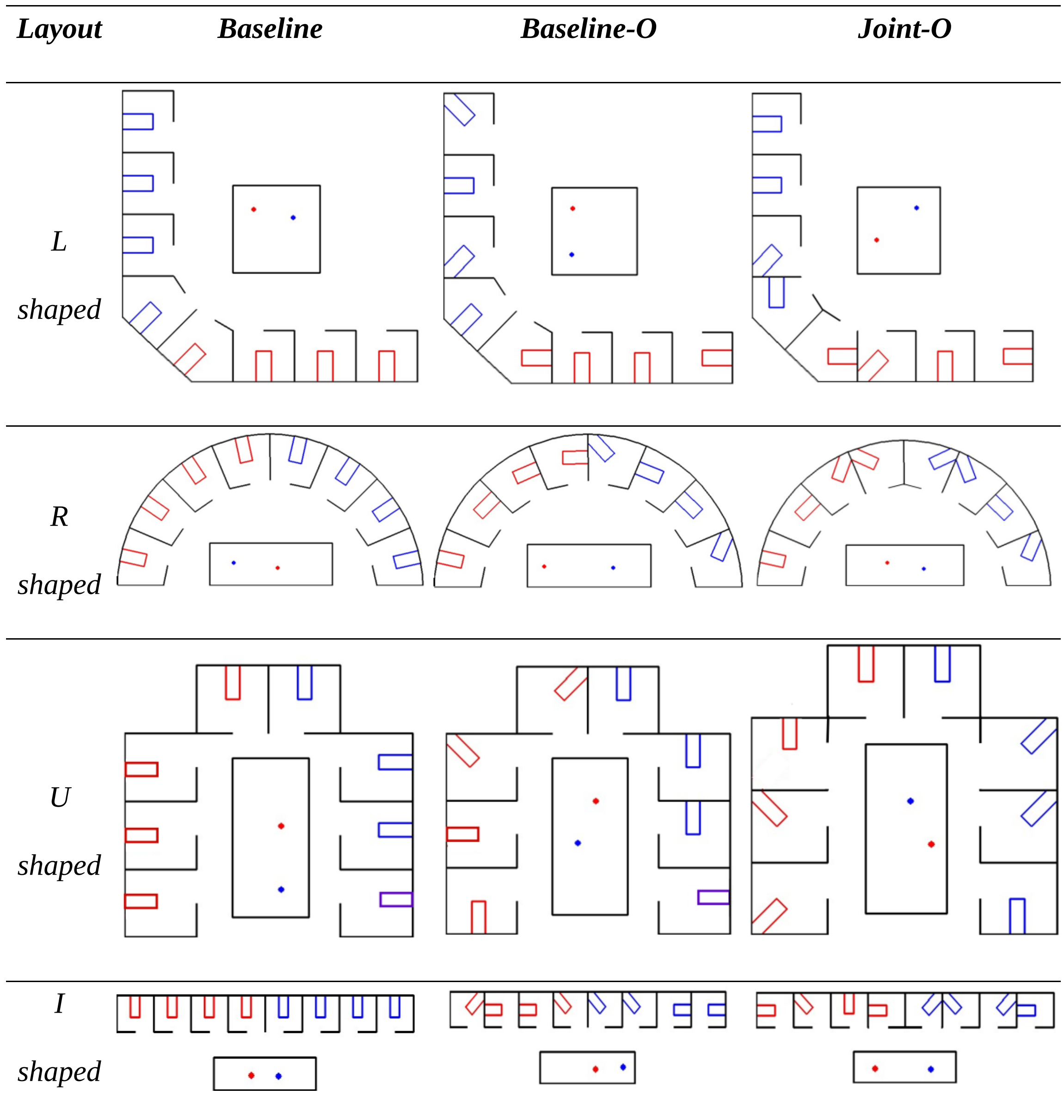

Figure 24 Results from different run cases for all layout types at low obstruction; Nurse 1 and 2 are depicted by Red and Blue dots, respectively

Insight 2: Angular layouts tend to be the most promising layout type.

The findings from our study consistently demonstrate that angular layouts – U-shaped, L-shaped, and R-shaped – yield the highest levels of equity across all ε values, surpassing the equity offered by an I-shaped layout. On average, angular layouts contribute to an increase of approximately 29% in low obstruction and 53% in high obstruction setting in the value of our objective function.

Note that the best layout among the three angular layouts appeared to fluctuate based on the specific parameters used in each experiment. Figure 25 offers a comparative analysis of equity measures produced by different layout types over multiple epsilon (ε) values for low and high obstruction settings. Clearly, the angular layouts consistently outperformed the I-shaped configuration in both obstruction settings.

The primary reason is the spatial depth of a layout; i.e., the arrangement of elements such as patient beds within the space (patient room). The I-shaped layout arranges patient beds linearly on a single plane, while angular layouts (i.e., U-, L-, and R-shaped) create spatial depth by positioning beds across multiple planes, offering diverse sightlines. Figure 26 shows that when positioning all patient beds to the exact location, the number of planes on which patient beds are arranged is higher in angular layout type than in I-shaped layout. For instance, in the case of U- and L-shaped layouts, beds were arranged in three different planes (shown inside three rectangles), while in the case of I-shaped, all beds were arranged in a single plane. This arrangement of patient beds in angular layouts creates an arc that synchronizes with the nurse's FoR making the patient beds visible with ease This, in turn, minimizes variance in the visibility values across patient beds, thus, lowering the equity value. Detailed results related to the optimal layout for specific parameters are presented in Appendix D.

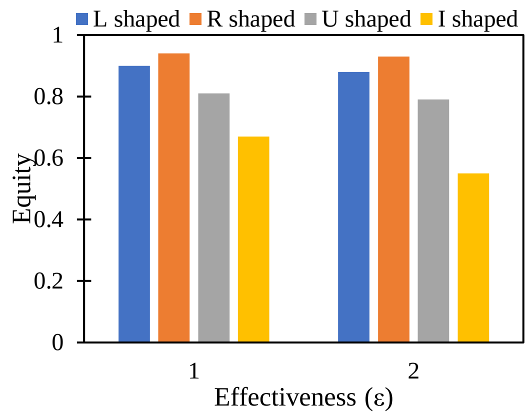

Figure 25a: Equity offered at low obstruction

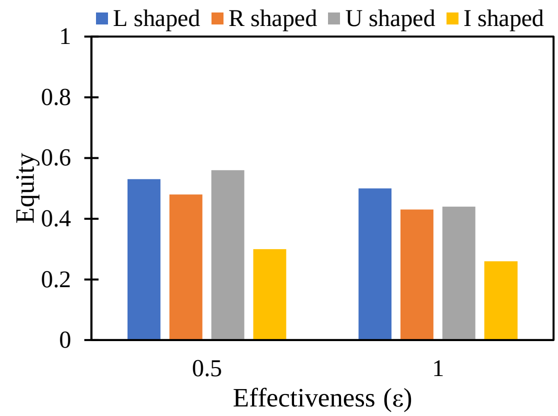

Figure 25b: Equity offered at high obstruction

Figure 25 Objective function value for all 4 layout types at different epsilon values

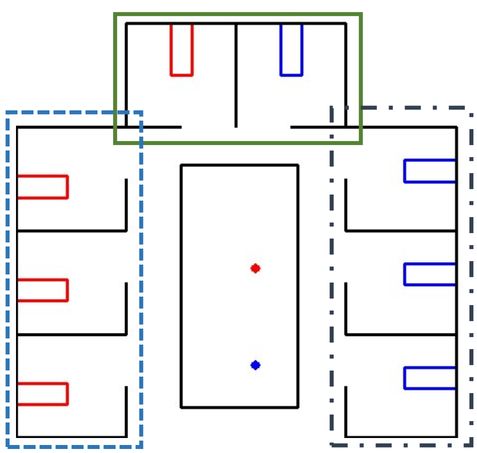

Figure 26a: U-shaped layout

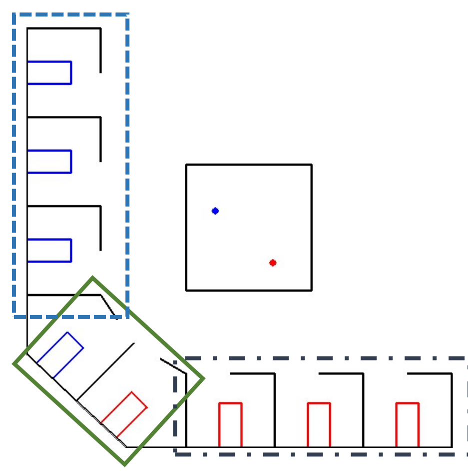

Figure 26b: L-shaped layout

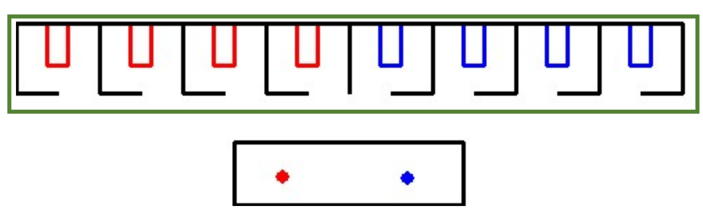

Figure 26c: I-shaped layout

Figure 26 Different planes created based on bed position for angular and I shaped layout

Insight 3: A higher spatial separation of nurses at the high obstruction level enhances equity of an angular layout.

We observed that a layout's potential to promote equity is enhanced when the nurses are spatially apart than closer. This is because the requirement of spatial vicinity (especially, <3 ft) constraints both nurses in achieving the best individual position to maximize equity among their assigned patients. For instance, if the model identifies the best position for Nurse 1 in terms of equity among their patients, then the decision variable for Nurse 2 must also be in that vicinity even though the corresponding equity among their patients is compromised. Increasing the required separation between them allows both nurses to identify a better position that maximizes equity among their patients.

To further exemplify this finding, we analyzed angular layouts, L-, U- and R-shaped, to compare the equity offered at various distances between two nurses. We present examples of such scenarios from an R-shaped layout in Table 15. This layout's equity is low when the nurses are placed nearby (between 1.5 ft and 3 ft), however, it improves when the distance between the nurses increases (between 6 ft and 9 ft or 9 ft and above); see also Figure 27. We noticed similar patterns in other angular layout types, including the L- and U-shaped layouts (see Appendix E).

Figure 27 shows an example of one of the cases from Table 15 for an R-shaped layout. More detailed results from all angular layouts can be found in Appendix E.

Similar to our findings from Contribution 1, this study also revealed a clear tradeoff between equity and effectiveness. The ability to distribute visibility equally among all patient beds diminishes as the model prioritizes the high visibility of beds in a layout. Hence, this directly impacts the equity measure, which balances visibility across all patient beds. Figure 28 visually represents this tradeoff across low and high obstruction settings from our experimental study. It illustrates how increased effectiveness— aimed at finding high visibility values—negatively impacts the equity measure. Therefore, the model struggles to attain higher equity values with an increase in the effectiveness measure.

Table 15 Results from varying nurse distance in R-shaped layout

Door position	***Nurses distance***	ε	***Nurse1 position***	***Nurse2 position***	***Equity***	***Distance***
RRRR	1.5 ft -3 ft	1.5	*(469,58)*	*(469,42)*	*0.62*	1.6
	3 ft - 6 ft	1.5	*(435,43)*	*(377,42)*	*0.82*	5.8
	6 ft - 9 ft	1.5	*(421,51)*	*(344,46)*	*0.82*	7.7
	9ft above	**1.5**	***(411,57)***	***(313,45)***	***0.87***	**9.9**
RRRL	1.5 ft -3 ft	1.5	*(465,60)*	*(469,40)*	*0.56*	2.0
	3 ft - 6 ft	1	*(469,60)*	*(420,40)*	*0.62*	5.3
	6 ft - 9 ft	2	*(449,60)*	*(384,57)*	*0.6*	6.5
	9ft above	**2**	***(458,51)***	***(339,45)***	***0.67***	**11.9**
RLLR	1.5 ft -3 ft	1	*(259,40)*	*(259,56)*	*0.52*	1.6
	3 ft - 6 ft	1	*(437,42)*	*(467,53)*	*0.59*	3.1
	6 ft - 9 ft	1	*(258,54)*	*(338,59)*	*0.61*	8.0
	9ft above	**1.5**	***(401,58)***	***(269,56)***	***0.5***	**13.2**
LRRR	1.5 ft -3 ft	1.5	*(433,59)*	*(441,40)*	*0.53*	2.1
	3 ft - 6 ft	1.5	*(469,40)*	*(428,40)*	*0.53*	4.1
	6 ft - 9 ft	1.5	*(469,58)*	*(381,53)*	*0.62*	6.5
	9ft above	**1.5**	***(416,52)***	***(298,48)***	***0.66***	**11.8**
LLRR	1.5 ft -3 ft	1	*(469,43)*	*(469,60)*	*0.45*	1.7
	3 ft - 6 ft	1	*(437,50)*	*(397,55)*	*0.44*	4.0
	6 ft - 9 ft	1	*(469,60)*	*(401,60)*	*0.51*	6.8
	9ft above	**1.5**	***(460,48)***	***(356,59)***	***0.56***	**10.5**
LLRL	1.5 ft -3 ft	1	*(469,41)*	*(469,60)*	*0.45*	1.9
	3 ft - 6 ft	1	*(366,57)*	*(308,58)*	*0.46*	5.8
	6 ft - 9 ft	**1**	***(353,40)***	***(264,40)***	***0.59***	**8.9**
	9ft above	1	*(313,53)*	*(435,59)*	*0.49*	12.2
LLLL	1.5 ft -3 ft	1	*(469,60)*	*(469,42)*	*0.26*	1.8
	3 ft - 6 ft	1	*(439,58)*	*(391,47)*	*0.41*	4.9
	6 ft - 9 ft	1	*(324,45)*	*(258,48)*	*0.56*	6.6
	9ft above	**1**	***(284,53)***	***(396,56)***	***0.71***	**11.2**

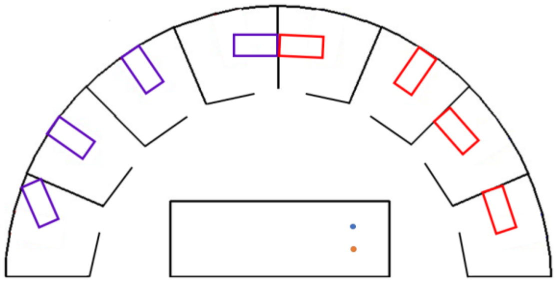

Figure 27a: Distance 1.5 ft to 3 ft (Equity = 0.62)

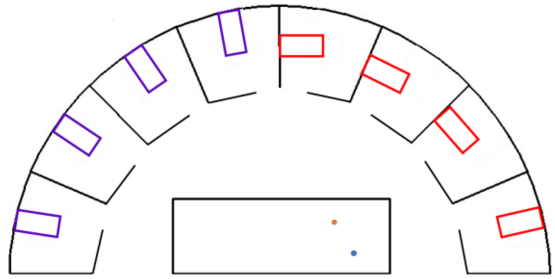

Figure 27b: Distance 3 ft to 6 ft (Equity = 0.82)

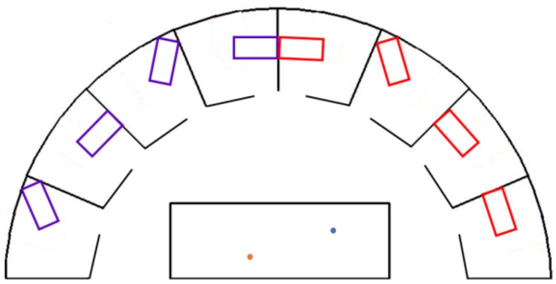

Figure 27c: Distance 6 ft to 9 ft (Equity = 0.82)

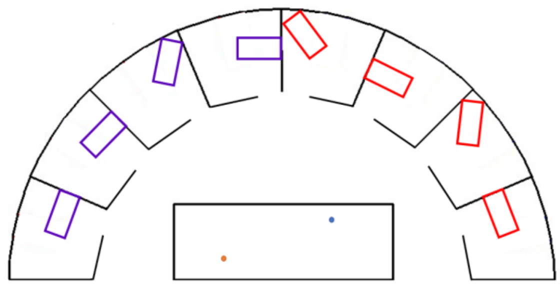

Figure 27d: Distance 9 ft above (Equity = 0.87)

Figure 27 Varying nurse distances in R-shaped layout at door position 'RRRR'

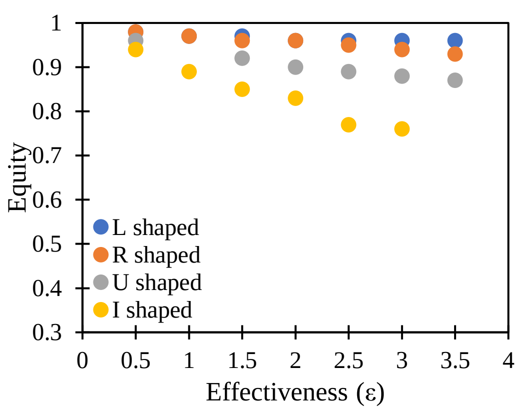

Figure 28a: Pareto frontier from low obstruction

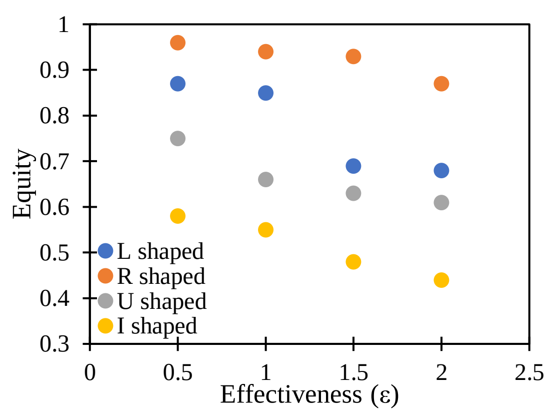

Figure 28b: Pareto frontier from high obstruction

Figure 28 Pareto frontier for two different obstruction setting

3.6 Conclusion And Future Research

The importance of hospital layout designs that enhance patient visibility is an essential aspect of healthcare architecture and significantly impacts the quality of patient care. One of the vital aspects of efficiency and timeliness of patient care is the design of physical space and the arrangement of layout design elements within an inpatient unit. However, prior research in this domain has focused predominantly on descriptive analyses of existing hospital layouts rather than suggesting optimal designs.

Realizing this gap in the literature, our study proposed a novel approach for inpatient unit layout with a focus on improving nurse visibility of patients. To address this, we considered an equitable distribution of patient visibility, while satisfying a minimum cumulative patient visibility in the layout. Our proposed optimization model jointly determines the position of two nurses and patient bed in each room to maximize equity in the visibility of all patients. The unique feature of our approach is that we incorporate nurses' field of regard in conjunction with typical layout design elements such as layout shape, door positions, and obstruction level. Because the estimation of patient visibility is complex and cannot be expressed in analytical form but only via a simulator, we proposed a progressive refinement approach embedded in the Particle Swarm Optimization framework to solve this model.

A comprehensive experimental study led to the following insights.

- In any given layout, while optimizing the position of nurses with a fixed bed position in each room can improve equity, substantial enhancements were observed when both the nurse and bed positions were jointly optimized.

- Angular layouts (e.g., U-shaped, L-shaped, R-shaped) enhanced the equity measure by an average of 29% compared to I-shaped layouts; this is because such layouts best align with a nurse's field of regard.
- At the high obstruction level, an increase in spatial distance between the two nurses was observed to increase equity in patient visibility in all three angular layouts.

Our study has several implications for inpatient unit designers. Our findings suggest that hospital designers, where feasible, should consider repositioning patient beds in the patient room (when possible) given the position of the assigned nurse. For instance, placing beds such that the clear glass door or glass window can provide a clear visual connectivity for the nurse. This may mean that some of the equipment in the room may have to be moved, but this alternative may be a lot inexpensive and feasible compared to retrofitting the room (e.g., taking down the walls, moving the door). This could also benefit nursing staff in terms of reduced frequency of visits to patient rooms prompted by false alarms from telemetry devices. Additionally, if a fall-prone patient were to move out of their bed, then instead of waiting for the telemetry devices to signal such events (e.g., detachment of leads), the direct visibility of the patient could lead to a prompt intervention (e.g., nurse walking over to the room to provide help) reducing a fall. Further, in scenarios involving various stakeholders in layout design, the Pareto frontier can facilitate the selection of solutions that are mutually acceptable to all parties.

There are several areas for future investigation of this research. First, deriving an analytical approximation for visibility estimation could enable the use of state-of-the-art optimization methods to solve the model. Second, extending our model to incorporate nurse's vertical field of regard can effectively capture the three-dimensional complexity in inpatient layouts, especially the obstruction phenomenon. However, this may increase the complexity of estimating of visibility in 3D, along with solving the optimization model. Furthermore, considering the layout redesign cost as an additional objective term could make the model comprehensive, especially in situations where the cost of repositioning a bed in a patient room is expensive. Finally, it would be interesting to adapt our approach to other healthcare facilities such as clinics, nursing homes, or rehabilitation centers with varying shapes of the nursing station and nurse-to-patient ratios to enhance our understanding of the effect of layout elements on nurse-patient visibility.

CHAPTER 4

CONCLUSIONS AND FUTURE RESEARCH

The significance of patient visibility in inpatient unit layouts design cannot be understated given that constant patient monitoring in hospital settings directly impacts quality of care. The key to optimizing patient visibility and satisfaction depends on the practical design of an inpatient unit layout that aligns with—and potentially leverages—the scanning behaviors of nurses in a nursing station. Our study comprehensively analyzed how alterations in layout design elements impact patient visibility.

The models developed in our research can serve as a foundation for further studies, facilitating the development of larger, more intricate models that consider additional design elements and unit-specific constraints. These could include multiple patient beds in each room, location of medical equipment, design of corridors, and navigation of nurses during rounding. For practitioners, our findings provide a valuable guideline based on derived insights to aid in exploring novel inpatient unit layouts and benchmarking existing ones. Below we summarize key contributions made through our research.

4.1 Summary of Contribution 1

Our study introduces a quantitative optimization-based approach, which combines analytical methods (e.g., dynamic adjustments of patient bed and nursing locations), computational rendering techniques (e.g., ray casting algorithm), and numerical methodology (e.g., bilinear approximation algorithm). These were implemented to estimate visibility from a nurse positioned in a designated nursing area to a target in the patient room (e.g., bed or head).

In an experimental investigation, we studied the effect of key layout design elements —unit shape, obstruction level, and patient bed (orientation)— on distribution of visibility of the target across all patient rooms. Our experimental findings included the following observations:

- Among three standard layout shapes examined, L-shaped, R-shaped, and I-shaped, each containing four patient beds and a single nurse in a nursing station, the R-shaped layout yielded the maximum equity in target visibility.
- A trade-off between effectiveness and equity was evident. For any particular layout, maximizing the cumulative visibility for all targets led to increased disparity in the distribution of visibility values (in turn, equity).
- Obstructions within a patient room can impede the line of sight from the nurse to the patient leading to a decline in patient visibility. Nurse position slightly away from the room, instead of closer, may help resolve this only if the increased distance does not impede visibility due to limited depth of vision.
- The orientation of patient beds depends on target area in the patient room. If the head/foot area was identified as a target, these parts of the bed are consistently oriented towards the room's entrance to optimize patient visibility.

4.2 Summary of Contribution 2

We extended our work to include (i) two nurses, instead of one, (ii) treating bed positions in each room as a decision variable, and (iii) accounting for door position in each room. For this extension, we proposed a non-linear optimization model that jointly determined positions of patient beds and multiple nurses in a nursing station to maximize the equity. This was achieved by first transforming our initial multi-objective problem into a single-objective problem by employing the ε-constrained method. We prioritized equity over effectiveness within the optimization model by setting effectiveness as the ε-constraint.

Given that the visibility estimation could still not be expressed in a closed analytical form, we proposed a multi-tier approach — the progressive refinement approach — that incorporated the visibility estimator (the ray casting algorithm) introduced in our first contribution. This approach was embedded in a Particle Swarm Optimization (PSO) framework. A comprehensive experimental study helped us generate several insights:

- By optimizing both nurse positions and patient bed position, we observed an average increase in layout equity of 45.2% in low and 26.5% in high obstruction, compared to solely optimizing the nurse position alone (for fixed bed position in each room).
- Angular layout shapes (R-shaped, L-shaped, and U-shaped) outperformed the I-shaped layout in terms of both equity and patient visibility due to their shapes more closely aligning with the nurses' field of regard.

- We also observed an effect of distance between two nurses in a nursing station on equity offered by a layout. In an angular layout with high obstruction setting, nurses close to each other were never favored, suggesting that considerable distance between nurses would aid in better equitable distribution of patient visibility.

4.3 Future Research

There are several promising directions to extend this research in the future. A key extension to our study could involve determining a closed-form approximation for patient visibility estimation, potentially enabling state-of-the-art commercial solvers. This could potentially help generate optimal solutions. Further, we only accounted for a combined head and eye movement range of 90°. Investigating more varied distributions of head and eye movement, such as smaller movements (60°) and larger ones (120°), could help compare our findings with them. For instance, some nurses may be able to make only a smaller movement (may be because their chair has no yaw or the effort for head movement is too much), while the others may be able to make a large movement. However, given the time-consuming nature of the visibility estimator using the ray casting algorithm, exploring improvements to the algorithm or alternative approaches to speed up patient visibility estimation would be beneficial.

We only considered a 2D version of the inpatient unit layout design. Extending it to 3D environment that includes the height of objects could make our model more realistic in modern hospital settings. In certain situations, the heights of objects within a nursing station (e.g., desks and computers) can obstruct the nurse's line of sight to the patient's room. Exploring these and related areas would be a worthwhile future endeavor.

We assumed that a bed could be freely relocated within a patient room without any barrier from room objects or elements. However, in practical scenarios, relocating a patient's bed necessitates the simultaneous relocation of medical equipment or adjusting the distance between the patient's bed and critical room elements such as the restroom. Thus, a viable extension to our study could involve considering the combined effects of these objects in a room in conjunction with patient bed relocation.

Finally, it would be worthwhile to model nurse walking behavior within a layout (e.g., when doing rounds) and estimate visibility in such a dynamic setting. This would increase the model's realism, but also complexity requiring the development of more advanced heuristic methods.

REFERENCES

1. Adler, L., Yi, D., Li, M., McBroom, B., Hauck, L., Sammer, C., Jones, C., Shaw, T., & Classen, D. (2018). Impact of inpatient harms on hospital finances and patient clinical outcomes. *Journal of Patient Safety*, 14(2), 67–73.
2. Alhammadi, H. Y., & Romagnoli, J. A. (2004). Chapter B4 - Process design and operation: Incorporating environmental, profitability, heat integration and controllability considerations. In P. Seferlis & M. C. Georgiadis (Eds.), *Computer Aided Chemical Engineering* (Vol. 17)
3. Alves, C., De Carvalho, M. V., & Clímaco, J. (2011). A multi-objective approach to nurse scheduling considering both personnel and patients. *International Transactions in Operational Research*, 18(6), 751-766.
4. AvaCare Medical. (2022). Hospital bed dimensions | Hospital bed size options |. *Retrieved from https://www.avacaremedical.com/bedroom/hospital-beds/hospital-bed-dimensions*
5. Baldi, P. (1995). Gradient descent learning algorithm overview: a general dynamical systems perspective. *IEEE Transactions on Neural Networks*, 6(1), 182–195.
6. Bayramzadeh, S., Joseph, A., San, D., Khoshkenar, A., Taaffe, K., Jafarifiroozabadi, R., & Neyens, D. M. (2018). The impact of operating room layout on circulating nurse's work patterns and flow disruptions: A behavioral mapping study. *Health Environments Research & Design Journal*, 11(3), 124-138.

7. Bernhardt, J., Lipson-Smith, R., Davis, A., White, M., Zeeman, H., Pitt, N., Shannon, M., Crotty, M., Churilov, L., & Elf, M. (2021). Why hospital design matters: A narrative review of built environments research relevant to stroke care. *International Journal of Stroke*, 17(4), 370–377.

8. Bor, J., Cohen, G. H., & Galea, S. (2017). Population health in an era of rising income inequality: USA, 1980–2015. *The Lancet*, 389(10077), 1475–1490.

9. Bosch, S. J., Apple, M., Hiltonen, B., Worden, E., Lu, Y., Nanda, U., & Kim, D. (2016). To see or not to see: Investigating the links between patient visibility and potential moderators affecting the patient experience. *Journal of Environmental Psychology*, 47, 33-43.

10. Boston Medical Center. (2016). Intensive care unit nurse-to-patient ratios. from *https://www.bmc.org/about-us/icu-nurse-ratios*

11. Burkey, M., Bhadury, J., & Eiselt, H. (2012). A location-based comparison of health care services in four U.S. states with efficiency and equity. *Socio-Economic Planning Sciences*, 46(2), 157–163.

12. CADdetails. (2021). Hillrom CAD, BIM and SPECS. from *https://www.caddetails.com/main/company/viewlistings?companyID=4794*

13. Cadenhead, C., & Anderson, D. (2010). Critical care design: Trends in award winning designs. *World Health Design*, 2, 72–77.

14. Cagan, J., Shimada, K., & Yin, S. (2002). A survey of computational approaches to three-dimensional layout problems. *Computer-Aided Design*, 34(8), 597-611.

15. Cai, H., & Zimring, C. (2012). Out of sight, out of reach: Correlating spatial metrics of nurse station typology with nurses' communication and co-awareness in an

intensive care unit. *Proceedings of the Eighth International Space Syntax Symposium*, Santiago, Chile.

16. Carvalho, A. & Pozo, A. (2009). Mining rules: a parallel multiobjective particle swarm optimization approach, *Swarm intelligence for multiobjective problems in data mining*, 242 179-198.

17. Castro, J.P., Landa-Silva, D., Pérez, J.A.M. (2009). Exploring feasible and infeasible regions in the vehicle routing problem with time windows using a multiobjective particle swarm optimization approach. *In: Krasnogor, N., Melián-Batista, M.B., Pérez, J.A.M., Moreno-Vega, J.M., Pelta, D.A. (eds) Nature Inspired Cooperative Strategies for Optimization (NICSO 2008). Studies in Computational Intelligence*, vol 236. Springer, Berlin, Heidelberg.

18. Centers for Disease Control and Prevention. (2022). Guidance and Tips for Tribal Community Living During COVID-19. *Retrieved from* *https://www.cdc.gov/coronavirus/2019-ncov/community/tribal/social-distancing.html*

19. Chaudhury, H., Mahmood, A., & Valente, M. (2009). The effect of environmental design on reducing nursing errors and increasing efficiency in acute care settings: A review and analysis of the literature. *Environment and Behavior*, 41(6), 755-786.

20. Cho, S. H., Ketefian, S., Barkauskas, V. H., & Smith, D. G. (2003). The effects of nurse staffing on adverse events, morbidity, mortality, and medical costs. *Nursing Research*, 52(2), 71–79.

21. Choi, Y. -S. (2011). The physical environment and patient safety: An investigation of physical environmental factors associated with patient falls. *PhD Thesis, Georgia Institute of Technology*, Atlanta, GA.

22. Critical Care Medicine (1995). Guidelines for intensive care unit design. 23(3):p 582-588.

23. Decherchi, S., & Rocchia, W. (2013). A general and Robust Ray-Casting-Based Algorithm for Triangulating Surfaces at the Nanoscale. *PLOS ONE*, 8(4), e59744.

24. Dehghani, M., & Ebrahimi, A. (2016). A robust optimization approach for outpatient facility layout problem. *The International Journal of Advanced Manufacturing Technology*, 87(1-4), 855-864.

25. Dehghani, M., & Ebrahimi, A. (2018). Designing a model for patient room layout using robust optimization. *Health Care Management Science*, 21(3), 428-438.

26. Department of Health, Victorian Government. (2015). Preventing adverse events. *Retrieved January 6, 2022, from https://www.health.vic.gov.au/patient-care/preventing-adverse-events*.

27. Devlin, A. (2014). Wayfinding in healthcare facilities: contributions from environmental psychology. *Behavioral Sciences*, 4(4), 423–436.

28. DHHS: U.S. Department of Health and Human Services. (2012.). Spotlight on … adverse events. Office of Inspector General, *U.S. Department of Health and Human Services*. *Retrieved January 5, 2022, from https://oig.hhs.gov/reports-and-publications/archives/spotlight/2012/adverse.asp*.

29. Dou, J., Su, C. L., & Zhao, X. (2020). Mixed integer programming models for concurrent configuration design and scheduling in a reconfigurable manufacturing system. *Concurrent Engineering*, 28(1), 32–46.

30. el Ansary, A., & Shalaby, M. (2014). Evolutionary optimization technique for site layout planning. *Sustainable Cities and Society*, 11, 48–55.

31. Enayati, S., Mayorga, M. E., Toro-Díaz, H., & Albert, L. A. (2019). Identifying trade-offs in equity and efficiency for simultaneously optimizing location and multi-priority dispatch of ambulances. *International Transactions in Operational Research*, 26(2), 415–438.

32. Eren Tokgöz, S., & Gürel, S. (2019). A multi-objective mathematical model for the flexible facility layout problem in hospitals. *Health Systems*, 8(1), 31-50.

33. Fay, L., Carll-White, A., Schadler, A., Isaacs, K. B., & Real, K. (2017). Shifting landscapes: The impact of centralized and decentralized nursing station models on the efficiency of care. *Health Environments Research & Design Journal*, 10(5), 80-94.

34. Fierce Healthcare (2016). 5 hospital-proven strategies to prevent patient falls. *Retrieved from. https://www.fiercehealthcare.com/healthcare/5-hospital-proven-strategies-to-prevent-patient-falls*

35. Freud, N., Duvauchelle, P., Létang, J. M., & Babot, D. (2006). Fast and robust ray casting algorithms for virtual X-ray imaging. *Nuclear Instruments & Methods in Physics Research Section B-beam Interactions With Materials and Atoms*, *248*(1), 175–180.

36. Frontera, J. A., & Kalb, T. (2015). The impact of environmental design on teamwork and communication in healthcare facilities: A systematic literature review. *Journal of Healthcare Architecture and Planning*, 1(1), 17-35.

37. Gaffney, A., & McCormick, D. (2017). The Affordable Care Act: implications for health-care equity. *The Lancet*, 389(10077), 1442–1452.

38. Gella, C. (2018). Improving communication to reduce patient falls in a 48- bed medical-surgical unit. *Nursing and Health Professions Research and Publications*, 124, 1-57.

39. Giant Bomb. (2019). Ray Casting (Concept). Retrieved May 19, 2022, *from https://www.giantbomb.com/ray-casting/3015-1517/.*

40. Goodman, J. C., Villarreal, P., & Jones, B. (2011). The social cost of adverse medical events, and what we can do about it. *Health Affairs*, 30(4), 590–595.

41. Gulwadi, G. B., & Calkins, M. P. (2008). The impact of the design of healthcare environments on patient falls. *The Center for Health Design*.

42. Gurascio-Howard, L., & Malloch, K. (2007). Centralized and decentralized nurse station design: An examination of caregiver communication, work activities, and technology. *HERD: Health Environments Research & Design Journal*, 1(1), 44–57.

43. Guthrie, B., & Parikh, P. J. (2019). Evaluating exposure of a retail rack layout in 3D. *Flexible Services and Manufacturing Journal*, 33(1), 107-135.

44. Hadi, K., & Zimring, C. (2016). Design to improve visibility: Impact of corridor width and unit shape. *HERD: Health Environments Research & Design Journal*, 9(4), 35-49.

45. Halawa, F., Madathil, S. C., Gittler, A., & Khasawneh, M. T. (2020). Advancing evidence-based healthcare facility design: A systematic literature review. *Health Care Management Science*, 23(3), 453–480.

46. Harvey, T. E., & Pati Pati, D. (2012). Keeping watch. HFM | *Health Facilities Management*. Retrieved February 10, 2022, *from https://www.hfmmagazine.com/articles/142-keeping-watch.*

47. Hassanain, A. A., Eldosoky, M. A. A., & Soliman, A. M. (2022). Evaluating building performance in healthcare facilities using entropy and graph heuristic theories. *Scientific Reports*, 12(1).

48. Healthcare Facilities Today (2021). Q&A on the required width of new corridor - Safety. *Retrieved from https://www.healthcarefacilitiestoday.com/posts/QA-on-the-required-width-of-new-corridor--9342*

49. Hignett, S., Griffiths, P., Sands, G., & Wolf, L. (2019). Applying human factors and ergonomics principles to the design of single-bed rooms in healthcare facilities. *Health Environments Research & Design Journal*, 12(2), 63-73.

50. Hitcho, E. B., Krauss, M. J., Birge, S., Dunagan, W. C., Fischer, I., Johnson, S., Nast, P. A., Costantinou, E., & Fraser, V. J. (2004). Characteristics and circumstances of falls in a hospital setting. *Journal of General Internal Medicine*, 19(7), 732–739.

51. Hörcher, D., & Graham, D. J. (2020). The Gini index of demand imbalances in public transport. *Transportation*, 48(5), 2521–2544.

52. Hua, Y., Becker, F., Wurmser, T., Bliss-Holtz, J., & Hedges, C. (2012). Effects of nursing unit spatial layout on nursing team communication patterns, quality of care, and patient safety. *Health Environments Research & Design Journal*, 6(1), 8-38

53. Intensive Care Unit Nurse-to-patient ratios. Boston Medical Center. (n.d.). *Retrieved July 28, 2022, from https://www.bmc.org/about-us/icu-nurse-ratios*

54. Johanes, M., & Atmodiwirjo, P. (2015). Visibility analysis of hospital inpatient ward. *International Journal of Technology*, 6(3), 400.f

55. Jones, D., Mirrazavi, S., & Tamiz, M. (2002). Multiobjective meta-heuristics: An overview of the current state-of-the-art. *European Journal of Operational Research*, 137(1), 1–9.

56. Joseph, A., & Rashid, M. (2007). The architecture of safety: hospital design. *Current Opinion in Critical Care*, 13(6), 714–719.

57. Joshi, R., Ossmann, M., & Joseph, A. (2022). Measuring potential visual exposure of physicians during shift-end handoffs and its impact on interruptions, privacy, and collaboration. *HERD: Health Environments Research & Design Journal*, 16(1), 175–199.

58. Kazemzadeh, R. B., & Hu, H. (2015). A location optimization model for healthcare facility planning. *Procedia Manufacturing*, 3, 5103-5110.

59. Kennedy, J. and Eberhart, R. (1995), "Particle swarm optimization," Proceedings of ICNN'95 – *International Conference on Neural Networks*, pp. 1942-1948 vol.4.

60. Kohler, M., Forero, L., Vellasco, M., Tanscheit, R., & Pacheco, M. A. (2016). PSO+: A nonlinear constraints-handling particle swarm optimization. *IEEE Congress on Evolutionary Computation (CEC)*.

61. Lapointe-Shaw, L., & Bell, C. M. (2019). Measuring the cost of adverse events in hospital. *Canadian Medical Association Journal*, 191(48).

62. Lasater, K. B., Aiken, L. H., Sloane, D. M., French, R., Martin, B., Reneau, K., Alexander, M., & McHugh, M. D. (2020). Chronic hospital nurse understaffing meets COVID-19: an observational study. *BMJ Quality & Safety*, 30(8), 639–647.

63. Lasater, K. B., Aiken, L. H., Sloane, D. M., French, R., Martin, B., Reneau, K., Alexander, M., & McHugh, M. D. (2020). Chronic hospital nurse understaffing meets COVID-19: an observational study. *BMJ Quality & Safety*, 30(8), 639–647.

64. Lê, L. (n.d.). Pin on Hospitals. Pinterest. Retrieved February 10, 2022 *from https://www.pinterest.com/pin/317644579943948020/.*

65. Lee, J. H., Ostwald, M. J., & Lee, H. (2017). Measuring the spatial and social characteristics of the architectural plans of aged care facilities. *Frontiers of Architectural Research*, 6(4), 431-441.

66. Lee, J., Lee, H., & Shepley, M. M. (2020). Exploring the spatial arrangement of patient rooms for minimum nurse travel in hospital nursing units in Korea. *Frontiers of Architectural Research*, 9(4), 711–725.

67. Lin, L., & Nazzal, D. (2014). Design of layout for an outpatient department using simulation-based optimization. *Journal of Medical Systems*, 38(2), 1-15.

68. Lin, Q., & Chen, J. (2013). A novel micro-population immune multiobjective optimization algorithm. *Computers & Operations Research*, 40(6), 1590–1601.

69. Lorenz, W. E., Bicher, M., & Wurzer, G. X. (2015). Adjacency in hospital planning. *IFAC-PapersOnLine*, 48(1), 862–867.

70. Lu, Y. (2010). Measuring the structure of visual fields in nursing units. *Health Environments Research & Design Journal*, 3(2), 48-59.

71. Lu, Y., & Seo, H. (2015). Developing visibility analysis for a retail store: A pilot study in a bookstore. *Environment and Planning B: Planning and Design*, 42(1), 95-109.

72. Lu, Y., & Zimring, C. (2012). Can intensive care staff see their patients? An improved visibility analysis methodology. *Environment and Behavior*, 44(6), 861-876.

73. Lu, Y., Ossmann, M. M., Leaf, D. E., & Factor, P. H. (2014). Patient visibility and ICU mortality: A conceptual replication. *Health Environments Research & Design Journal*, 7(2), 92–103.

74. Lu, Y., Peponis, J., & Zimring, C. (2009). Targeted visibility analysis in buildings: Correlating targeted visibility analysis with distribution of people and their interactions within an intensive care unit. *Paper presented at the 7th International Space Syntax Symposium*, Stockholm.

75. MarketScale. (2020). How much do patient falls cost in your medical facility? MarketScale. *Retrieved September 20, 2021, from https://marketscale.com/industries/healthcare/patient-falls-cost-medical-facility/.*

76. Massachusetts Hospital Association (2006). Patients First. [Electronic version]. *Available:* https://www.mhalink.org/MHA/MyMHA/Communications/MondayReportItems/Content/2018/09-10/MR-20180910.aspx?WebsiteKey=4749f948-ab0e-4978-a199-d93433f790dc/

77. Michael V, Azeem T, Pirwani M, Sharma J, Allen S (2000). An epidemiological study of falls on integrated general medical wards. *Int J Clin Pract*, 54:654–657.

78. Moerman, A., Jansen, G., & van der Voort, M. C. (2020). The effects of hospital ward design on healthcare professional communication, collaboration and patient outcomes: A systematic review. *Health Environments Research & Design Journal*, 13(4), 191-207.

79. Mohammadi, S., & Vizvari, B. (2016). A new mathematical model for optimal hospital layout problem. *International Journal of Industrial Engineering & Production Research*, 27(2), 131-144.

80. MohammadiGorji, S., Nubani, L., Bosch, S. J., Valipoor, S., & McElhinney, S. (2023). Using space syntax analysis to measure patient aggression risk. *Health Environments Research & Design Journal*, 16(2), 125-145.

81. Montazami, R., Wilson, R., & Nicol, F. (2019). The impact of nursing station design on the visibility of patients in the ward. *Architectural Engineering and Design Management*, 15(6), 460-474.

82. Montazer, A., & Saremi, S. (2014). A hybrid genetic algorithm for the design of a new integrated emergency department layout. *Journal of Industrial and Production Engineering*, 31(3), 130-146.

83. Mora, B., Jessel, J. & Caubet, R., (2002). "A new object-order ray-casting algorithm," *IEEE Visualization*, pp. 203-210.

84. Moslehi, G., & Mahnam, M. (2011). A Pareto approach to multiobjective flexible job-shop scheduling problem using particle swarm optimization and local search. *International Journal of Production Economics*, 129(1), 14–22.

85. Mowrey, C. H., Parikh, P. J., & Gue, K. R. (2018). A model to optimize rack layout in a retail store. *European Journal of Operational Research*, 271(3), 1100-1112.

86. Nelson, T., & Elvins, T. (1993). Visualization of 3D ultrasound data. *IEEE Computer Graphics and Applications*, 13(6), 50–57.

87. Nett, J. (2009), Bilinear Interpolation. Portland State University. Retrieved May 20, 2022, *from* http://web.pdx.edu/~jduh/courses/geog493f09/Students/W6_Bilinear%20Interpolation.pdf.

88. Norouzi, N., Tavakkoli-Moghaddam, R., Ghazanfari, M., Alinaghian, M., & Salamatbakhsh, A. (2011). A new multi-objective competitive open vehicle routing problem solved by particle swarm optimization. *Networks and Spatial Economics*, 12(4), 609–633.

89. Occupational Safety and Health Administration (2021). Protecting Workers: Guidance on Mitigating and Preventing the Spread of COVID-19 in the Workplace. *Retrieved from* https://www.osha.gov/coronavirus/safework

90. Owens, P. L., Limcangco, R., Barrett, M. L., Heslin, K. C., & Moore, B. J. (2018). HCUP-US statistical briefs chronological. *Agency for Healthcare Research and Quality*. Retrieved May 1, 2022, *from https://www.hcup-us.ahrq.gov/reports/statbriefs/statbriefs.jsp*.

91. Parker JF Jr., West, VR. (1972). Bioastronautics data book. *Biotechnology Inc.*, Falls Church VA.

92. Parsia, Y & Tamyez, P. F. (2018). Role of healthcare-facilities layout design, healing architecture, on quality of services, *International Journal of Civil Engineering and Technology*, 9(4), pp. 598–601.

93. Pati D, Harvey TE, Reyers E, et al. (2009). A Multidimensional Framework for Assessing Patient Room Configurations. *Health Environments Research & Design Journal*;2(2):88-111.

94. Pati, D., Harvey Jr, T. E., & Reyers, E. (2008). An examination of the relationships between room size, patient visibility and patient safety in ICU. *International Journal of Architectural Research*, 2(2), 117-128.

95. Pati, D., Harvey, T., & Cason, C. (2008). Inpatient unit flexibility design characteristics of a successful flexible unit. *Environment and Behavior*, 40(2), 205e232.

96. Pérez-Gosende, P., Mula, J., & Díaz-Madroñero, M. (2021). Facility layout planning: An extended literature review. *International Journal of Production Research*, 59(12), 3777–3816.

97. Piatkowski, M. (2020). The role of visibility in health care facilities. *Health Facilities Management*. Retrieved February 11, 2022, *from https://www.hfmmagazine.com/articles/3851-the-role-of-visibility-in-health-care-facilities*.

98. Piatkowski, M., Taylor, E., Wong, B. B. M., Taylor, D. L., Foreman, K. B., & Merryweather, A. (2021). Designing a Patient Room as a Fall Protection Strategy: The Perspectives of Healthcare Design Experts. *International Journal of Environmental Research and Public Health*, 18(16), 8769.

99. Poerwoningsih, D., Antariksa, Leksono, A. S., & Hasyim, A. W. (2016). Integrating visibility analysis in rural spatial planning. *Procedia - Social and Behavioral Sciences*, 227, 838–844.

100. Rabbani, M., Oladzad-Abbasabady, N., & Akbarian-Saravi, N. (2022). Ambulance routing in disaster response considering variable patient condition: NSGA-II and MOPSO algorithms. *Journal of Industrial & Management Optimization*, 18(2), 1035.

101. Rashid, M. (2007). A decade of adult intensive care unit design: A study of the physical design features of the best-practice examples. *Critical Care Nursing Quarterly*, 30(2), 113-128.

102. Rashid, M., & Boyle, D. K. (2017). The influence of nursing unit design on nurse–patient communication. *Journal of Nursing Administration*, 47(3), 147-153.

103. Rathert, C., Wyrwich, M. D., & Boren, S. A. (2013). Patient-centered care and outcomes: A systematic review of the literature. *Medical Care Research and Review*, 70(4), 351-379.

104. Reader, T. W., Gillespie, A., & Roberts, J. (2014). Patient complaints in healthcare systems: A systematic review and coding taxonomy. *BMJ Quality & Safety*, 23(8), 678-689.

105. Reiling, J. G. (2005). The impact of facility design on patient safety. *Amsterdam University Press*.

106. Rensburg, R. J., van der Merwe, A., & Crowley, T. (2020). Factors influencing patient falls in a private hospital group in the Cape Metropole of the Western Cape. *Health SA Gesondheid*, 25.

107. Reuter-Oppermann, M., & Becker, C. (2019). Evaluation of optimization algorithms for the patient room allocation problem. *Health Care Management Science*, 22(2), 251-266.

108. Rong, A., Figueira, J. R., & Lahdelma, R. (2015). A two phase approach for the bi-objective non-convex combined heat and power production planning problem. *European Journal of Operational Research*, 245(1), 296–308.

109. Ruder, S. (2016). An overview of gradient descent optimization algorithms. *arXiv preprint arXiv:1609.04747*.

110. Sadeghi, A., & Tavakkoli-Moghaddam, R. (2019). A novel mixed-integer linear programming model for a hospital layout problem: A case study. *Health Care Management Science*, 22(3), 430-443.

111. Savic, D. (2002). Single-objective vs. multiobjective optimisation for integrated decision support. *In Proceedings of the First Biennial Meeting of the International Environmental Modelling and Software Society* (pp. 7-12).

112. Schneider, S. & König, R. (2011). Visibility-based floor plan design - the automatic generation of floor plans based on isovist properties, *Proceedings of the International Symposium on Spatial Cognition for Architectural Design* (SCAD 2011), New York, USA.

113. Seo, H., Choi, Y., & Zimring, C. (2010). Impact of hospital unit design for patient-centered care on nurses' behavior. *Environment and Behavior*, 43(4), 443-468.

114. Shipley, M. (n.d.). Nursing home. Pinterest. Retrieved February 10, 2022, *from https://www.pinterest.com/pin/17451517277839240/?d=t&mt=login.*

115. Silva, C., & Mitchell, J. (1997). The lazy sweep ray casting algorithm for rendering irregular grids. *IEEE Transactions on Visualization and Computer Graphics*, 3(2), 142–157.

116. Sitthiyot, T., & Holasut, K. (2020). A simple method for measuring inequality. *Palgrave Communications*, 6(1).

117. Skelly, C.L., Cassagnol, M., & Munakomi, S. (2021). Adverse Events. StatPearls. *StatPearls Publishing*.

118. Smith, H. K., Harper, P. R., & Potts, C. N. (2013). Bicriteria efficiency/equity hierarchical location models for public service application. *Journal of the Operational Research Society*, 64(4), 500–512.

119. Sturdavant, M. (1960). Intensive nursing service in circular and rectangular units. Hospitals, *Journal (Academy of Hospital Administration (India))*, 34, 46-48, 71-78.

120. Sundberg, F., Fridh, I., Lindahl, B., & Kåreholt, I. (2020). Associations between healthcare environment design and adverse events in intensive care unit. *Nursing in Critical Care*, 26(2), 86–93.

121. Tavakkoli-Moghaddam, R., Azarkish, M., & Sadeghnejad-Barkousaraie, A. (2011). A new hybrid multiobjective Pareto archive PSO algorithm for a bi-objective job shop scheduling problem. *Expert Systems with Applications*, 38(9), 10812–10821.

122. Techopedia. (2017). Ray Casting. Techopedia.Com. *Retrieved from https://www.techopedia.com/definition/21614/ray-casting.*

123. The importance of the optimal nurse-to-patient ratio. (2020). Wolters Kluwer. *Retrieved from:* *https://www.wolterskluwer.com/en/expert-insights/the-importance-of-the-optimal-nursetopatient-ratio*

124. Tongur, V., Hacibeyoglu, M., & Ulker, E. (2020). Solving a big-scaled hospital facility layout problem with meta-heuristics algorithms. *Engineering Science and Technology, an International Journal*, 23(4), 951–959.

125. Trzpuc, S. J., & Martin, C. S. (2010). Application of Space Syntax Theory in the Study of Medical-Surgical Nursing Units in Urban Hospitals. Herd: *Health Environments Research & Design Journal*, 4(1), 34–55.

126. Ulrich, R. S., Zimring, C., Zhu, X., DuBose, J., Seo, H. B., Choi, Y. S., ... & Joseph, A. (2008). A review of the research literature on evidence-based healthcare design. *Health Environments Research & Design Journal*, 1(3), 61-125.

127. Ulrich, R.P., Quan, X., Zimring, C.P., Joseph, A., Choudhary, R. (2004). The role of the physical environment in the hospital of the 21st century: a once-in-a-lifetime opportunity. *The Center for Health Design*.

128. Ünal, A. N., & Kayakutlu, G. (2020). Multi-objective particle swarm optimization with random immigrants. *Complex & Intelligent Systems*, 6(3), 635–650.

129. Walshe, K. (2000). Adverse events in health care: issues in measurement. *Quality in Health Care*, 9(1), 47–52. *from https://qualitysafety.bmj.com/content/9/1/47*

130. Wang, Y., Eldridge, N., Metersky, M. L., Sonnenfeld, N., Rodrick, D., Fine, J. M., Eckenrode, S., Galusha, D. H., Tasimi, A., Hunt, D. R., Bernheim, S. M., Normand, S. L. T., & Krumholz, H. M. (2020). Association between medicare expenditures and adverse events for patients with acute myocardial infarction, heart failure, or pneumonia in the United States. *JAMA Network Open*, 3(4).

131. Wei, D., & Li, X. (2021). Measuring the spatial quality of bedrooms in nursing homes with visual environmental performance. *Frontiers of Architectural Research*, 10(2), 332-350.

132. Wei, Y., & Li, Y. (2021). Patient room design in healthcare facilities: A systematic literature review. *Building and Environment*, 192, 107661.

133. Welton, J. M., Unruh, L., & Halloran, E. J. (2006). Nurse staffing, nursing intensity, staff mix, and direct nursing care costs across Massachusetts hospitals. *Journal of Nursing Administration*, 36, 416-425.

134. Wolf L, Costantinou E, Limbaugh C, Rensing K, Gabbart P, Matt P. (2013). Fall prevention for inpatient oncology using lean and rapid improvement event techniques. *HERD: Health Environments Research & Design Journal*, 7:85–101.

135. Wolters Kluwer. (2020). The importance of the optimal nurse-to-patient ratio. from *https://www.wolterskluwer.com/en/expert-insights/the-importance-of-the-optimal-nursetopatient-ratio*

136. World Health Organization. (2019). Patient Safety. Retrieved January 5, 2022, *from https://www.who.int/news-room/fact-sheets/detail/patient-safety*.

137. Zahiri, S & Seyedin, S. (2009). Using multiobjective particle swarm optimization for designing novel classifier, *Swarm intelligence for multiobjective problems in data mining*, 242 65-92.

138. Zborowsky, T., Bunker-Hellmich, L., Morelli, A., & O'Neill, M. (2010). Centralized vs. decentralized nursing stations: Effects on nurses' functional use of space and work environment. *HERD: Health Environments Research & Design Journal*, 3(4), 19–42.

139. Zhang, J. & Chau, K. (2009). Multilayer ensemble pruning via novel multi-sub-swarm particle swarm optimization, *Journal of Universal Computer Science*,15no. 4 840-858.

140. Zhang, Q., & Li, H. (2007). MOEA/D: A multiobjective evolutionary algorithm based on decomposition. *IEEE Transactions on Evolutionary Computation*, 11(6), 712–731.

141. Zimring, C., Augenbroe, G., Malone, E., & Sadler, B. (2008). Implementing healthcare excellence: the vital role of the CEO in evidence-based design. *Health Environments Research & Design Journal*, 1(3), 7-19.

APPENDICES

Appendix A Bilinear Interpolation Technique

Bilinear interpolation is a resampling method that estimates the value of a desired point with a distance weighted average of four nearest points to this desired point. The weights used are inversely proportional to the length of the source and destination point (Nett, 2009).

In our implementation, the nursing station is first converted into uniform rectangular grids with a step size of *x* units. Then, we run a ray casting algorithm on each grid point in advance and record each grid point's visibility value, which are later used to estimate the visibility from any location in the grid.

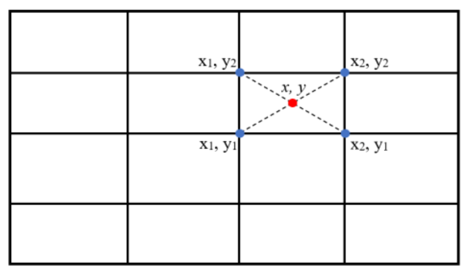

Figure A1: Example of bilinear interpolation method in a nursing station

For instance, in the Figure A1, assume that we need to calculate the visibility values at point (x, y), with the four nearest points in the grid system being (x_1,y_1), (x_1,y_2), (x_2,y_1), (x_2,y_2) and their respective visibility values, say (Q_{11}, Q_{12}, Q_{21}, Q_{22}). Firstly, we calculate the interpolation in the *x*-direction as follows:

$$R_1 = \frac{x_2 - x}{x_2 - x_1} Q_{11} - \frac{x - x_1}{x_2 - x_1} Q_{21} \qquad \text{and} \qquad (9)$$

$$R_2 = \frac{x_2 - x}{x_2 - x_1} Q_{12} - \frac{x - x_1}{x_2 - x_1} Q_{22}. \quad (10)$$

Then, we proceed by interpolating in the *y*-direction and calculating the interpolated value as follows:

$$P = \frac{y_2 - y}{y_2 - y_1} R_1 - \frac{y - y_1}{y_2 - y_1} R_2, \quad (11)$$

where *P* is the interpolated visibility value at point (*x*, *y*). The interpolated value of a target (bed or head) are used in the objective function of the optimization model. Table A1 shows the performance of the bilinear interpolation technique on a Pareto solution from an L-shaped layout with a low obstruction level.

Table A1: Accuracy of the bilinear interpolation technique

x	*y*	*Ray Casting*		*Bilinear Interpolation*		*Error*	
		Eff.	*Equity*	*Eff.*	*Equity*	*Eff.*	*Equity*
197.9	461.9	1.09	0.95	1.11	0.96	1.8%	1.0%
199.9	460.9	1.11	0.95	1.12	0.95	0.9%	0.0%
191.2	463.4	1.14	0.92	1.14	0.93	0.0%	1.1%
193.4	477.7	1.15	0.91	1.16	0.92	0.9%	1.1%
186.9	473.2	1.17	0.9	1.18	0.9	0.8%	0.0%
186	478.6	1.19	0.88	1.19	0.89	0.0%	1.1%
184.8	482.4	1.21	0.87	1.22	0.88	0.8%	1.1%
185.4	489.7	1.21	0.87	1.23	0.87	1.6%	0.0%
183.3	489.9	1.25	0.85	1.25	0.86	0.0%	1.2%
182.1	490.9	1.26	0.85	1.27	0.85	0.8%	0.0%
176.7	478.9	1.29	0.83	1.29	0.84	0.0%	1.2%
179	499.8	1.28	0.83	1.3	0.83	1.5%	0.0%
137.3	462.5	1.54	0.8	1.56	0.81	1.3%	1.2%
Average						**0.8%**	**0.7%**

Appendix B Result from Contribution 1

Table B1: Summary of results for patient's bed and head as target

Obs.	*Layout*	*Orientation (θ)*	*Max Z_1*	*Max Z_2*	*Max Z_1, min Z_2*	*Min Z_1, max Z_2*	*Diff in Z_1*	*Diff in Z_2*
Patient's bed as target								
Low	I-shaped	Front or Left	0.69	0.83	(0.69, 0.51)	(0.51, 0.83)	31.0%	57.2%
	L-shaped	Right or Back	0.96	1.56	(0.96, 1.11)	(0.81, 1.56)	4.0%	19.6%
	R-shaped	Front	1.00	1.94	(1.00, 1.91)	(0.99, 1.94)	0.0%	0.0%
High	I-shaped	Front or Left	0.50	0.47	(0.50, 0.30)	(0.29, 0.47)	49.5%	53.0%
	L-shaped	Right or Front	0.86	0.99	(0.86, 0.55)	(0.54, 0.99)	13.1%	1.0%
	R-shaped	Right or Back	0.99	1.00	(0.99, 0.67)	(0.68, 1.00)	0.0%	0.0%
Patient's head as target								
Low	I-shaped	Right	0.55	0.98	(0.55, 0.95)	(0.50, 0.98)	45.0%	50.0%
	L-shaped	Front	1.00	1.96	(1.00, 1.95)	(0.99, 1.96)	0.0%	0.0%
	R-shaped	Front	1.00	1.96	(1.00, 1.96)	(1.00, 1.96)	0.0%	0.0%
High	I-shaped	Right	0.5	0.5	(0.50, 0.04)	(0.25, 0.50)	50.0%	73.8%
	L-shaped	Front	0.74	1.03	(0.74, 0.65)	(0.57, 1.03)	26.0%	46.1%
	R-shaped	Front	1.00	1.91	(1.00, 1.77)	(0.99, 1.91)	0.0%	0.0%

*Abbreviations: Obs: Obstruction level; Z_1: Objective function (Equity); Z_2: Objective function (Effectiveness)

Appendix C Pareto Solutions from Two Different Nurse Position (Close and Away) in Insight 3 of Contribution 1

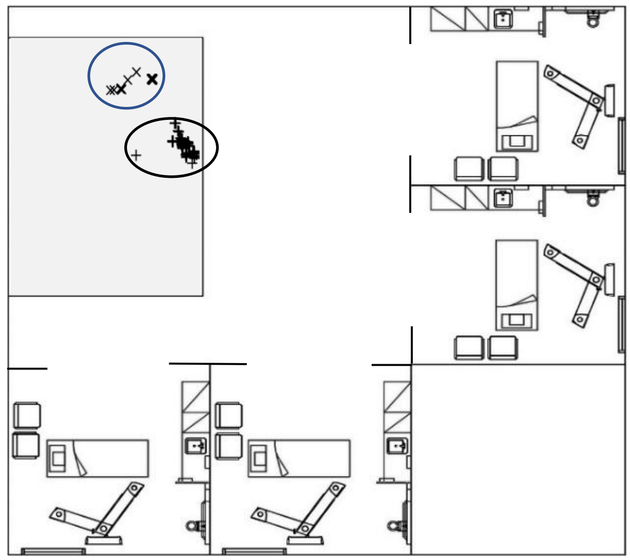

Figure C1: Pareto solutions for the nurse position in the nursing station (shaded) with bed as target (L-shaped layout)

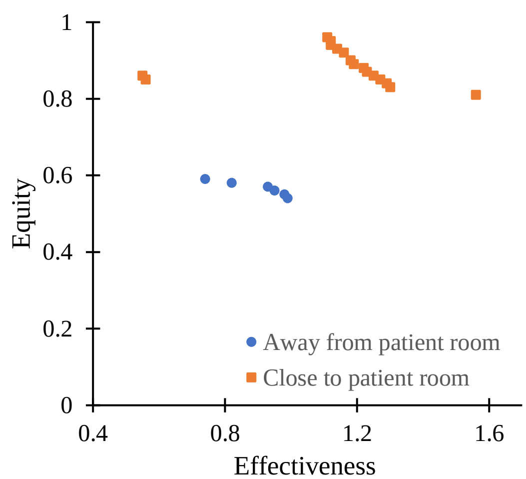

Figure C2: Pareto frontier based on solutions from Figure C1

Appendix D Results from Contribution 2

Table D1: Summary of results for low obstruction setting

Obs.	***Layout***	***Door position***	ε	***Bed Position***	***Nurse_1 position***	***Nurse_2 position***	***Equity***
Low	L shaped	RRRR	3.5	*L,C,C,L,C,LC,C,RC*	*(258,342)*	*(256,252)*	*0.96*
		RRRL	3.5	*L,C,RC,L,R,LC,C,C*	*(256,279)*	*(338,342)*	*0.97*
		RRLR	3.5	*C,R,C,R,LC,C,L,RC*	*(346,342)*	*(286,284)*	*0.95*
		RRLL	3.5	*C,C,C,LC,R,RC,RC,RC*	*(346,342)*	*(276,252)*	*0.92*
		RLRR	3.5	*L,L,R,R,LC,LC,RC,L*	*(289,253)*	*(345,342)*	*0.9*
		RLRL	3	*L,L,R,L,R,LC,RC,R*	*(291,255)*	*(259,336)*	*0.88*
		RLLR	3.5	*L,L,L,R,C,C,RC,RC*	*(346,342)*	*(346,270)*	*0.92*
		RLLL	3.5	*C,L,C,L,R,C,RC,L*	*(344,342)*	*(346,252)*	*0.9*
		LRRR	3	*L,C,R,R,LC,LC,LC,RC*	*(295,329)*	*(259,257)*	*0.76*
		LRRL	3	*L,C,R,L,R,LC,C,RC*	*(256,276)*	*(336,342)*	*0.84*
		LRLR	3	*R,C,L,R,LC,RC,LC,R*	*(339,265)*	*(259,332)*	*0.77*
		LRLL	2.5	*L,RC,LC,LC,R,R,L,RC*	*(297,266)*	*(346,329)*	*0.86*
		LLRR	2.5	*L,L,R,R,LC,L,RC,LC*	*(345,336)*	*(271,285)*	*0.84*
		LLRL	2.5	*L,L,R,L,R,L,RC,L*	*(322,342)*	*(256,274)*	*0.85*
		LLLR	3	*L,L,L,R,LC,RC,RC,LC*	*(337,292)*	*(257,280)*	*0.84*
		LLLL	2.5	*L,L,L,L,R,RC,RC,LC*	*(261,342)*	*(333,283)*	*0.82*
	R shaped	RRRR	3.5	*C,R,R,R,LC,L,L,LC*	*(389,49)*	*(450,46)*	*0.93*
		RRRL	3.5	*C,R,RC,LC,RC,LC,L,LC*	*(320,57)*	*(401,42)*	*0.97*
		RRLR	3.5	*R,R,L,RC,LC,RC,L,L*	*(369,43)*	*(430,40)*	*0.94*
		RRLL	3.5	*C,R,LC,L,RC,RC,L,LC*	*(315,57)*	*(407,52)*	*0.95*
		RLRR	3	*R,L,RC,C,L,LC,R,LC*	*(389,47)*	*(451,46)*	*0.93*
		RLRL	3.5	*R,LC,RC,LC,RC,LC,R,LC*	*(330,46)*	*(386,40)*	*0.92*
		RLLR	3.5	*C,LC,L,RC,LC,RC,R,L*	*(376,49)*	*(438,45)*	*0.92*
		RLLL	3	*C,LC,L,LC,RC,RC,R,L*	*(319,57)*	*(402,40)*	*0.93*
		LRRR	3.5	*LC,C,C,C,L,L,L,R*	*(468,40)*	*(381,40)*	*0.92*
		LRRL	3.5	*LC,C,RC,LC,RC,LC,L,R*	*(336,57)*	*(404,46)*	*0.92*
		LRLR	3.5	*LC,RC,LC,R,L,RC,L,R*	*(420,41)*	*(359,40)*	*0.91*
		LRLL	3.5	*LC,RC,L,C,RC,RC,LC,R*	*(304,52)*	*(400,45)*	*0.92*
		LLRR	3	*LC,L,R,R,LC,L,R,R*	*(385,42)*	*(447,42)*	*0.9*
		LLRL	3	*LC,LC,RC,LC,RC,LC,R,R*	*(296,41)*	*(396,44)*	*0.89*
		LLLR	3	*LC,LC,L,R,LC,C,R,R*	*(395,40)*	*(464,45)*	*0.89*
		LLLL	3	*LC,LC,LC,L,RC,RC,R,R*	*(337,51)*	*(413,43)*	*0.91*
		RRRR	3.5	*L,C,RC,RC,C,L,L,C*	*(233,207)*	*(205,142)*	*0.87*

	U shaped	RRRL	3	*LC,RC,L,L,RC,L,LC,R*	*(229,150)*	*(227,220)*	*0.82*
		RRLR	3.5	*LC,RC,LC,C,C,LC,LC,R*	*(218,146)*	*(230,210)*	*0.98*
		RRLL	3.5	*L,RC,L,LC,RC,LC,L,R*	*(223,147)*	*(226,213)*	*0.98*
		RLRR	3	*L,LC,RC,C,LC,RC,R,R*	*(227,211)*	*(227,148)*	*0.84*
		RLRL	3	*RC,RC,LC,LC,RC,C,LC,C*	*(205,70)*	*(205,138)*	*0.8*
		RLLR	3.5	*R,LC,R,C,LC,L,LC,L*	*(221,180)*	*(208,102)*	*0.98*
		RLLL	3.5	*RC,RC,R,LC,RC,L,R,R*	*(228,70)*	*(222,163)*	*0.95*
		LRRR	2.5	*L,RC,LC,C,L,L,C,LC*	*(240,93)*	*(205,233)*	*0.76*
		LRRL	2.5	*L,L,RC,LC,RC,L,L,L*	*(205,197)*	*(242,246)*	*0.69*
		LRLR	3	*RC,C,C,C,L,L,L,R*	*(208,233)*	*(205,129)*	*0.87*
		LRLL	3	*L,RC,R,LC,RC,C,L,L*	*(242,94)*	*(223,161)*	*0.81*
		LLRR	2.5	*RC,LC,R,L,LC,RC,C,RC*	*(238,225)*	*(220,70)*	*0.74*
		LLRL	2.5	*L,LC,LC,LC,RC,R,C,R*	*(209,125)*	*(241,71)*	*0.71*
		LLLR	3.5	*RC,LC,RC,R,L,L,C,R*	*(239,153)*	*(207,70)*	*0.92*
		LLLL	3	*RC,LC,R,LC,R,L,L,R*	*(214,185)*	*(213,75)*	*0.9*
	I shaped	RRRR	3	*RC,L,L,LC,LC,LC,R,R*	*(254,21)*	*(302,24)*	*0.76*
		RRRL	3	*L,LC,C,L,RC,LC,RC,L*	*(192,21)*	*(282,20)*	*0.87*
		RRLR	2	*C,L,L,LC,L,RC,L,LC*	*(272,20)*	*(302,24)*	*0.63*
		RRLL	2.5	*L,LC,L,C,RC,RC,L,L*	*(177,22)*	*(290,20)*	*0.73*
		RLRR	2	*C,L,L,C,L,C,C,RC*	*(262,25)*	*(302,20)*	*0.6*
		RLRL	2.5	*R,RC,LC,LC,RC,LC,LC,L*	*(221,21)*	*(256,23)*	*0.65*
		RLLR	1.5	*RC,C,RC,R,L,LC,L,LC*	*(302,23)*	*(177,20)*	*0.43*
		RLLL	1.5	*L,R,LC,LC,L,RC,L,C*	*(181,25)*	*(302,25)*	*0.58*
		LRRR	2.5	*L,RC,LC,R,LC,C,RC,LC*	*(252,22)*	*(295,20)*	*0.74*
		LRRL	3	*RC,LC,L,LC,RC,C,L,LC*	*(208,25)*	*(271,21)*	*0.85*
		LRLR	2.5	*R,R,LC,C,LC,RC,LC,LC*	*(177,23)*	*(302,22)*	*0.65*
		LRLL	2.5	*R,R,RC,LC,RC,L,RC,L*	*(195,24)*	*(252,20)*	*0.76*
		LLRR	2	*R,RC,R,R,LC,RC,LC,C*	*(270,24)*	*(235,21)*	*0.62*
		LLRL	2	*C,R,LC,LC,RC,R,C,LC*	*(219,21)*	*(249,24)*	*0.55*
		LLLR	1.5	*C,C,RC,R,L,LC,L,L*	*(302,20)*	*(181,25)*	*0.43*
		LLLL	1.5	*R,RC,LC,LC,RC,L,LC,R*	*(188,23)*	*(291,20)*	*0.58*

Table D2: Summary of results for high obstruction setting

Obs.	***Layout***	***Door position***	ε	***Bed Position***	***Nurse1 position***	***Nurse2 position***	***Equity***
High	L shaped	RRRR	2	*L,C,R,R,LC,LC,LC,C*	*(265,262)*	*(309,328)*	*0.79*
		RRRL	2.5	*C,L,L,L,R,LC,LC,L*	*(346,339)*	*(256,252)*	*0.69*
		RRLR	2.5	*C,R,R,R,LC,RC,L,LC*	*(260,320)*	*(323,280)*	*0.75*
		RRLL	2	*R,R,LC,R,R,RC,LC,L*	*(258,332)*	*(275,269)*	*0.68*
		RLRR	2	*C,C,C,R,LC,LC,RC,L*	*(276,252)*	*(346,342)*	*0.6*
		RLRL	2	*C,R,L,L,R,LC,RC,L*	*(256,268)*	*(346,342)*	*0.62*
		RLLR	2	*R,LC,L,R,LC,RC,L,C*	*(346,259)*	*(256,291)*	*0.68*
		RLLL	2	*R,C,L,R,R,RC,RC,LC*	*(334,259)*	*(283,342)*	*0.68*
		LRRR	2	*LC,R,C,R,LC,LC,LC,L*	*(340,338)*	*(281,252)*	*0.52*
		LRRL	2	*LC,C,L,L,R,LC,LC,C*	*(273,252)*	*(256,342)*	*0.59*
		LRLR	2	*C,R,C,R,LC,RC,L,C*	*(259,324)*	*(256,252)*	*0.6*
		LRLL	2	*R,R,LC,R,R,RC,LC,LC*	*(256,335)*	*(275,266)*	*0.54*
		LLRR	1.5	*C,LC,R,R,LC,LC,C,C*	*(269,275)*	*(333,259)*	*0.39*
		LLRL	1.5	*L,C,L,L,R,LC,RC,C*	*(294,252)*	*(341,342)*	*0.44*
		LLLR	1.5	*L,L,L,R,LC,RC,LC,RC*	*(346,342)*	*(319,252)*	*0.52*
		LLLL	1	*R,C,L,LC,R,RC,LC,L*	*(341,277)*	*(256,306)*	*0.61*
	R shaped	RRRR	2.5	*C,C,C,R,C,L,L,L*	*(468,60)*	*(258,50)*	*0.78*
		RRRL	2	*RC,C,C,R,C,L,L,RC*	*(458,51)*	*(339,45)*	*0.67*
		RRLR	2	*R,C,C,R,L,L,L,L*	*(464,49)*	*(262,50)*	*0.6*
		RRLL	2	*RC,RC,L,L,RC,RC,L,LC*	*(293,54)*	*(410,48)*	*0.87*
		RLRR	2	*RC,R,C,R,L,C,RC,L*	*(458,48)*	*(270,60)*	*0.69*
		RLRL	2	*RC,C,C,C,LC,L,L,L*	*(468,52)*	*(287,49)*	*0.58*
		RLLR	1.5	*RC,RC,L,C,L,LC,L,L*	*(466,40)*	*(266,59)*	*0.55*
		RLLL	1.5	*RC,LC,LC,L,RC,RC,R,L*	*(284,40)*	*(356,40)*	*0.69*
		LRRR	2	*LC,C,C,R,L,L,RC,C*	*(461,42)*	*(273,46)*	*0.59*
		LRRL	2	*LC,C,C,C,C,L,L,C*	*(468,60)*	*(296,60)*	*0.58*
		LRLR	2	*LC,C,R,R,LC,C,L,R*	*(456,52)*	*(281,40)*	*0.55*
		LRLL	1.5	*LC,RC,LC,LC,L,L,L,L*	*(352,50)*	*(258,49)*	*0.54*
		LLRR	1.5	*LC,R,C,C,L,C,RC,L*	*(460,48)*	*(356,59)*	*0.56*
		LLRL	1.5	*LC,R,C,R,L,L,L,L*	*(466,44)*	*(281,59)*	*0.55*
		LLLR	1	*RC,R,C,R,L,C,L,R*	*(429,48)*	*(266,51)*	*0.43*
		LLLL	1	*C,LC,L,L,RC,RC,C,L*	*(284,53)*	*(396,56)*	*0.71*
	U shaped	RRRR	2.5	*C,RC,LC,RC,LC,C,C,L*	*(240,164)*	*(224,227)*	*0.68*
		RRRL	2	*C,RC,LC,C,LC,C,C,LC*	*(241,178)*	*(209,233)*	*0.55*
		RRLR	3	*C,RC,LC,RC,L,LC,R,C*	*(236,191)*	*(208,132)*	*0.81*

		RRLL	2	*RC,LC,RC,R,LC,C,LC,R*	*(235,98)*	*(208,180)*	*0.63*
		RLRR	2	*RC,LC,LC,RC,LC,R,LC,R*	*(216,112)*	*(212,201)*	*0.57*
		RLRL	1.5	*RC,L,R,R,LC,C,R,LC*	*(227,72)*	*(211,133)*	*0.55*
		RLLR	3	*RC,LC,RC,RC,LC,R,C,RC*	*(216,119)*	*(205,189)*	*0.79*
		RLLL	2	*RC,L,R,R,C,LC,L,C*	*(212,74)*	*(209,157)*	*0.58*
		LRRR	2	*L,RC,LC,RC,L,L,C,RC*	*(238,166)*	*(207,233)*	*0.57*
		LRRL	1.5	*R,RC,L,C,LC,L,C,L*	*(241,167)*	*(212,233)*	*0.41*
		LRLR	2.5	*C,RC,LC,R,LC,LC,L,R*	*(233,223)*	*(205,154)*	*0.64*
		LRLL	1.5	*L,LC,C,R,L,L,RC,R*	*(241,123)*	*(207,70)*	*0.47*
		LLRR	1	*R,LC,C,RC,RC,C,C,R*	*(231,132)*	*(226,70)*	*0.45*
		LLRL	2	*RC,LC,R,R,L,RC,LC,L*	*(217,119)*	*(205,190)*	*0.64*
		LLLR	1.5	*C,C,LC,RC,L,C,L,L*	*(222,234)*	*(205,156)*	*0.52*
		LLLL	1.5	*RC,C,R,RC,LC,R,R,R*	*(240,74)*	*(210,153)*	*0.56*
	I shaped	RRRR	2	*C,C,LC,RC,LC,LC,R,R*	*(254,20)*	*(291,24)*	*0.59*
		RRRL	3	*L,C,RC,LC,RC,L,RC,R*	*(201,22)*	*(278,22)*	*0.79*
		RRLR	1	*LC,L,RC,R,L,C,R,LC*	*(254,22)*	*(302,22)*	*0.4*
		RRLL	2	*LC,LC,RC,C,RC,C,RC,RC*	*(204,25)*	*(274,25)*	*0.44*
		RLRR	1.5	*L,L,LC,R,L,RC,L,C*	*(257,22)*	*(222,22)*	*0.5*
		RLRL	2	*L,C,R,LC,RC,L,L,RC*	*(190,22)*	*(277,20)*	*0.58*
		RLLR	1	*C,LC,L,R,LC,LC,C,RC*	*(251,23)*	*(182,20)*	*0.28*
		RLLL	0.5	*L,RC,RC,C,LC,C,LC,RC*	*(210,24)*	*(177,25)*	*0.34*
		LRRR	1.5	*RC,RC,LC,R,L,RC,R,C*	*(259,22)*	*(212,23)*	*0.54*
		LRRL	2.5	*R,LC,R,LC,RC,L,LC,LC*	*(199,24)*	*(280,25)*	*0.68*
		LRLR	1	*RC,L,C,C,LC,LC,R,C*	*(267,21)*	*(302,22)*	*0.39*
		LRLL	1.5	*R,LC,RC,LC,RC,LC,RC,R*	*(197,22)*	*(278,21)*	*0.58*
		LLRR	1.5	*R,LC,LC,R,L,RC,LC,L*	*(259,20)*	*(220,22)*	*0.5*
		LLRL	2	*L,L,RC,LC,RC,LC,L,LC*	*(188,24)*	*(279,25)*	*0.5*
		LLLR	1	*RC,L,RC,R,LC,L,L,R*	*(302,20)*	*(177,20)*	*0.26*
		LLLL	0.5	*R,LC,R,RC,RC,L,R,LC*	*(270,20)*	*(230,24)*	*0.33*

Appendix E Result from Varying Nurses Distance in Angular Layout with High Obstruction

Table E1: Results for R-shaped layout

Layout	***Door position***	***Nurses distance***	ε	***Nurse1 position***	***Nurse2 position***	***Equity***	***Distance***
R shaped	RRRR	1.5 ft -3 ft	1.5	*(469,58)*	*(469,42)*	*0.62*	1.6
		3 ft - 6 ft	1.5	*(435,43)*	*(377,42)*	*0.82*	5.8
		6 ft - 9 ft	1.5	*(421,51)*	*(344,46)*	*0.82*	7.7
		9ft above	1.5	*(411,57)*	*(313,45)*	*0.87*	9.9
	RRRL	1.5 ft -3 ft	1.5	*(465,60)*	*(469,40)*	*0.56*	2.0
		3 ft - 6 ft	1	*(469,60)*	*(420,40)*	*0.62*	5.3
		6 ft - 9 ft	2	*(449,60)*	*(384,57)*	*0.6*	6.5
		9ft above	2	*(458,51)*	*(339,45)*	*0.67*	11.9
	RRLR	1.5 ft -3 ft	1.5	*(469,40)*	*(469,60)*	*0.66*	2.0
		3 ft - 6 ft	1.5	*(398,53)*	*(350,55)*	*0.62*	4.8
		6 ft - 9 ft	1.5	*(356,44)*	*(271,58)*	*0.66*	8.6
		9ft above	1.5	*(383,55)*	*(282,41)*	*0.61*	10.2
	RRLL	1.5 ft -3 ft	1.5	*(469,58)*	*(467,40)*	*0.58*	1.8
		3 ft - 6 ft	1	*(320,49)*	*(365,53)*	*0.79*	4.5
		6 ft - 9 ft	1.5	*(468,60)*	*(397,54)*	*0.61*	7.1
		9ft above	2	*(293,54)*	*(410,48)*	*0.87*	11.7
	RLRR	1.5 ft -3 ft	1	*(259,43)*	*(259,60)*	*0.49*	1.7
		3 ft - 6 ft	1	*(387,56)*	*(356,54)*	*0.67*	3.1
		6 ft - 9 ft	1	*(366,48)*	*(300,43)*	*0.67*	6.6
		9ft above	1	*(414,45)*	*(287,56)*	*0.7*	12.7
	RLRL	1.5 ft -3 ft	1	*(469,42)*	*(469,60)*	*0.45*	1.8
		3 ft - 6 ft	1	*(360,40)*	*(310,60)*	*0.64*	5.4
		6 ft - 9 ft	1.5	*(352,42)*	*(285,40)*	*0.64*	6.7
		9ft above	1.5	*(468,60)*	*(337,60)*	*0.58*	13.1
	RLLR	1.5 ft -3 ft	1	*(259,40)*	*(259,56)*	*0.52*	1.6
		3 ft - 6 ft	1	*(437,42)*	*(467,53)*	*0.59*	3.1
		6 ft - 9 ft	1	*(258,54)*	*(338,59)*	*0.61*	8.0
		9ft above	1	*(374,58)*	*(270,41)*	*0.54*	10.5
	RLLL	1.5 ft -3 ft	1	*(304,40)*	*(277,43)*	*0.68*	2.7
		3 ft - 6 ft	1	*(259,40)*	*(305,40)*	*0.81*	4.6
		6 ft - 9 ft	1.5	*(284,40)*	*(356,40)*	*0.69*	7.2
		9ft above	1.5	*(301,59)*	*(417,55)*	*0.66*	11.6

	LRRR	1.5 ft -3 ft	1.5	*(433,59)*	*(441,40)*	*0.53*	2.1
		3 ft - 6 ft	1.5	*(469,40)*	*(428,40)*	*0.53*	4.1
		6 ft - 9 ft	1.5	*(469,58)*	*(381,53)*	*0.62*	8.8
		9ft above	1.5	*(416,52)*	*(298,48)*	*0.66*	11.8
	LRRL	1.5 ft -3 ft	1.5	*(465,60)*	*(469,40)*	*0.43*	2.0
		3 ft - 6 ft	1.5	*(469,50)*	*(416,57)*	*0.5*	5.3
		6 ft - 9 ft	1.5	*(468,60)*	*(384,46)*	*0.59*	8.5
		9ft above	1.5	*(468,40)*	*(373,60)*	*0.53*	9.7
	LRLR	1.5 ft -3 ft	1	*(469,44)*	*(469,60)*	*0.51*	1.6
		3 ft - 6 ft	1	*(399,49)*	*(360,51)*	*0.53*	3.9
		6 ft - 9 ft	1	*(376,44)*	*(438,56)*	*0.7*	6.3
		9ft above	1.5	*(456,60)*	*(347,51)*	*0.5*	10.9
	LRLL	1.5 ft -3 ft	1	*(469,59)*	*(469,40)*	*0.38*	1.9
		3 ft - 6 ft	1	*(314,40)*	*(259,49)*	*0.54*	5.6
		6 ft - 9 ft	1	*(318,48)*	*(403,40)*	*0.76*	8.5
		9ft above	1.5	*(352,50)*	*(258,49)*	*0.54*	9.4
	LLRR	1.5 ft -3 ft	1	*(469,43)*	*(469,60)*	*0.45*	1.7
		3 ft - 6 ft	1	*(437,50)*	*(397,55)*	*0.44*	4.0
		6 ft - 9 ft	1	*(469,60)*	*(401,60)*	*0.51*	6.8
		9ft above	1.5	*(460,48)*	*(356,59)*	*0.56*	10.5
	LLRL	1.5 ft -3 ft	1	*(469,41)*	*(469,60)*	*0.45*	1.9
		3 ft - 6 ft	1	*(366,57)*	*(308,58)*	*0.46*	5.8
		6 ft - 9 ft	1	*(353,40)*	*(264,40)*	*0.59*	8.9
		9ft above	1	*(469,43)*	*(327,48)*	*0.55*	14.2
	LLLR	1.5 ft -3 ft	1	*(469,40)*	*(469,60)*	*0.42*	2.0
		3 ft - 6 ft	0.5	*(439,58)*	*(391,47)*	*0.41*	4.9
		6 ft - 9 ft	1	*(468,59)*	*(402,60)*	*0.43*	6.6
		9ft above	1	*(395,48)*	*(290,46)*	*0.43*	10.5
	LLLL	1.5 ft -3 ft	1	*(469,60)*	*(469,42)*	*0.26*	1.8
		3 ft - 6 ft	1	*(439,58)*	*(391,47)*	*0.41*	4.9
		6 ft - 9 ft	1	*(324,45)*	*(258,48)*	*0.56*	6.6
		9ft above	1	*(284,53)*	*(396,56)*	*0.71*	11.2

Table E2: Results for L-shaped layout

Layout	***Door position***	***Nurses distance***	ε	***Nurse1 position***	***Nurse2 position***	***Equity***	***Distance***
L shaped	RRRR	1.5 ft -3 ft	1.5	*(290,253)*	*(286,276)*	*0.75*	2.4
		3 ft - 6 ft	1.5	*(261,306)*	*(288,260)*	*0.78*	5.3
		6 ft - 9 ft	2	*(265,262)*	*(309,328)*	*0.79*	7.9
		9ft above	2	*(265,261)*	*(335,333)*	*0.75*	10.0
	RRRL	1.5 ft -3 ft	1.5	*(279,258)*	*(258,252)*	*0.69*	2.2
		3 ft - 6 ft	1.5	*(320,303)*	*(264,314)*	*0.67*	5.7
		6 ft - 9 ft	2.5	*(295,252)*	*(261,334)*	*0.68*	8.9
		9ft above	2.5	*(346,339)*	*(256,252)*	*0.69*	12.5
	RRLR	1.5 ft -3 ft	1.5	*(291,289)*	*(305,303)*	*0.69*	2.0
		3 ft - 6 ft	1.5	*(346,254)*	*(346,310)*	*0.73*	5.6
		6 ft - 9 ft	2.5	*(260,320)*	*(323,280)*	*0.75*	7.5
		9ft above	2.5	*(260,325)*	*(331,252)*	*0.74*	10.2
	RRLL	1.5 ft -3 ft	1.5	*(306,326)*	*(322,301)*	*0.66*	3.0
		3 ft - 6 ft	2	*(270,321)*	*(277,289)*	*0.64*	3.3
		6 ft - 9 ft	2	*(258,332)*	*(275,269)*	*0.68*	6.5
		9ft above	2	*(256,335)*	*(324,256)*	*0.65*	10.4
	RLRR	1.5 ft -3 ft	1	*(290,275)*	*(272,284)*	*0.56*	2.0
		3 ft - 6 ft	1	*(286,276)*	*(313,300)*	*0.55*	3.6
		6 ft - 9 ft	2	*(346,270)*	*(342,337)*	*0.57*	6.7
		9ft above	2	*(276,252)*	*(346,342)*	*0.6*	11.4
	RLRL	1.5 ft -3 ft	1.5	*(310,300)*	*(312,328)*	*0.58*	2.8
		3 ft - 6 ft	1.5	*(297,259)*	*(346,282)*	*0.54*	5.4
		6 ft - 9 ft	2	*(339,266)*	*(346,339)*	*0.59*	7.3
		9ft above	2	*(256,268)*	*(346,342)*	*0.62*	11.7
	RLLR	1.5 ft -3 ft	1.5	*(331,316)*	*(308,326)*	*0.51*	2.5
		3 ft - 6 ft	1.5	*(345,319)*	*(316,329)*	*0.58*	3.1
		6 ft - 9 ft	2	*(346,267)*	*(316,323)*	*0.64*	6.4
		9ft above	2	*(346,259)*	*(256,291)*	*0.68*	9.6
	RLLL	1.5 ft -3 ft	1	*(346,334)*	*(346,316)*	*0.49*	1.8
		3 ft - 6 ft	1.5	*(344,338)*	*(312,314)*	*0.42*	4.0
		6 ft - 9 ft	1.5	*(345,287)*	*(283,341)*	*0.66*	8.2
		9ft above	2	*(334,259)*	*(283,342)*	*0.68*	9.7
	LRRR	1.5 ft -3 ft	1	*(264,286)*	*(276,260)*	*0.53*	2.9
		3 ft - 6 ft	1.5	*(264,256)*	*(281,289)*	*0.53*	3.7
		6 ft - 9 ft	1.5	*(268,258)*	*(346,252)*	*0.59*	7.8
		9ft above	1.5	*(338,340)*	*(256,268)*	*0.54*	10.9

	LRRL	1.5 ft -3 ft	1.5	*(295,274)*	*(291,252)*	*0.49*	2.2
		3 ft - 6 ft	1.5	*(262,289)*	*(280,252)*	*0.52*	4.1
		6 ft - 9 ft	2	*(319,328)*	*(277,252)*	*0.54*	8.7
		9ft above	2	*(273,252)*	*(256,342)*	*0.59*	9.2
	LRLR	1.5 ft -3 ft	1.5	*(309,281)*	*(292,276)*	*0.54*	1.8
		3 ft - 6 ft	1.5	*(277,329)*	*(306,285)*	*0.49*	5.3
		6 ft - 9 ft	2	*(259,324)*	*(256,252)*	*0.6*	7.2
		9ft above	2	*(272,336)*	*(332,252)*	*0.6*	10.3
	LRLL	1.5 ft -3 ft	1	*(304,272)*	*(284,288)*	*0.44*	2.5
		3 ft - 6 ft	1.5	*(290,317)*	*(327,287)*	*0.46*	4.8
		6 ft - 9 ft	2	*(256,335)*	*(275,266)*	*0.54*	7.2
		9ft above	1.5	*(275,341)*	*(334,252)*	*0.55*	10.7
	LLRR	1.5 ft -3 ft	1	*(256,252)*	*(285,252)*	*0.31*	2.9
		3 ft - 6 ft	1	*(295,294)*	*(323,253)*	*0.37*	5.0
		6 ft - 9 ft	1	*(269,275)*	*(333,259)*	*0.39*	6.6
		9ft above	1	*(272,263)*	*(334,334)*	*0.5*	9.4
	LLRL	1.5 ft -3 ft	1	*(323,310)*	*(346,303)*	*0.38*	2.3
		3 ft - 6 ft	1	*(323,259)*	*(310,313)*	*0.37*	5.6
		6 ft - 9 ft	1.5	*(294,257)*	*(290,333)*	*0.4*	7.6
		9ft above	1.5	*(294,252)*	*(341,342)*	*0.44*	10.2
	LLLR	1.5 ft -3 ft	1	*(326,301)*	*(323,282)*	*0.56*	2.0
		3 ft - 6 ft	1	*(273,327)*	*(319,335)*	*0.57*	4.7
		6 ft - 9 ft	1.5	*(299,338)*	*(294,261)*	*0.44*	7.7
		9ft above	1.5	*(346,342)*	*(319,252)*	*0.52*	9.4
	LLLL	1.5 ft -3 ft	0.5	*(334,342)*	*(346,321)*	*0.46*	2.4
		3 ft - 6 ft	1	*(282,319)*	*(287,261)*	*0.34*	5.8
		6 ft - 9 ft	1	*(341,277)*	*(256,306)*	*0.61*	9.0
		9ft above	1	*(333,268)*	*(256,342)*	*0.49*	10.7

Table E3: Results for U-shaped layout

Layout	***Door position***	***Nurses distance***	ε	***Nurse1 position***	***Nurse2 position***	***Equity***	***Distance***
U shaped	RRRR	1.5 ft -3 ft	1.5	*(220,228)*	*(205,232)*	*0.61*	1.6
		3 ft - 6 ft	1.5	*(220,192)*	*(212,232)*	*0.61*	4.1
		6 ft - 9 ft	2.5	*(240,164)*	*(224,227)*	*0.68*	6.5
		9ft above	2	*(236,233)*	*(206,131)*	*0.54*	10.6
	RRRL	1.5 ft -3 ft	1	*(205,234)*	*(205,216)*	*0.47*	1.7
		3 ft - 6 ft	1	*(242,185)*	*(205,227)*	*0.47*	5.6
		6 ft - 9 ft	1.5	*(241,163)*	*(209,233)*	*0.56*	7.7
		9ft above	1	*(236,90)*	*(213,229)*	*0.54*	14.1
	RRLR	1.5 ft -3 ft	2.5	*(242,156)*	*(217,161)*	*0.67*	2.6
		3 ft - 6 ft	2.5	*(242,234)*	*(211,234)*	*0.68*	3.1
		6 ft - 9 ft	3	*(236,191)*	*(208,132)*	*0.81*	6.5
		9ft above	2.5	*(242,227)*	*(223,136)*	*0.75*	9.3
	RRLL	1.5 ft -3 ft	1.5	*(242,179)*	*(242,152)*	*0.51*	2.7
		3 ft - 6 ft	1.5	*(240,174)*	*(238,136)*	*0.68*	3.8
		6 ft - 9 ft	2	*(235,98)*	*(208,180)*	*0.63*	8.6
		9ft above	2	*(208,222)*	*(215,130)*	*0.6*	9.2
	RLRR	1.5 ft -3 ft	1.5	*(226,76)*	*(218,98)*	*0.64*	2.3
		3 ft - 6 ft	1.5	*(242,84)*	*(236,125)*	*0.64*	4.1
		6 ft - 9 ft	2	*(216,112)*	*(212,201)*	*0.57*	8.9
		9ft above	2	*(219,89)*	*(207,216)*	*0.56*	12.8
	RLRL	1.5 ft -3 ft	1	*(205,71)*	*(233,71)*	*0.44*	2.8
		3 ft - 6 ft	1	*(218,130)*	*(239,80)*	*0.46*	5.4
		6 ft - 9 ft	1.5	*(227,72)*	*(211,133)*	*0.55*	6.3
		9ft above	1.5	*(216,74)*	*(217,165)*	*0.44*	9.1
	RLLR	1.5 ft -3 ft	2	*(242,97)*	*(227,81)*	*0.63*	2.2
		3 ft - 6 ft	2	*(231,124)*	*(222,85)*	*0.74*	4.0
		6 ft - 9 ft	3	*(216,119)*	*(205,189)*	*0.79*	7.1
		9ft above	2.5	*(216,121)*	*(205,214)*	*0.69*	9.4
	RLLL	1.5 ft -3 ft	1.5	*(229,123)*	*(213,138)*	*0.49*	2.1
		3 ft - 6 ft	1.5	*(233,106)*	*(220,141)*	*0.54*	3.7
		6 ft - 9 ft	2	*(212,74)*	*(209,157)*	*0.58*	8.3
		9ft above	2	*(205,74)*	*(235,159)*	*0.57*	9.0
	LRRR	1.5 ft -3 ft	1	*(205,71)*	*(233,71)*	*0.44*	2.8
		3 ft - 6 ft	1	*(242,208)*	*(205,234)*	*0.46*	4.5
		6 ft - 9 ft	2	*(238,166)*	*(207,233)*	*0.57*	7.4
		9ft above	1.5	*(238,186)*	*(216,72)*	*0.42*	11.6

	LRRL	1.5 ft -3 ft	1	*(222,234)*	*(206,233)*	*0.37*	1.6
		3 ft - 6 ft	1	*(241,233)*	*(210,216)*	*0.45*	3.6
		6 ft - 9 ft	1.5	*(241,167)*	*(212,233)*	*0.41*	7.2
		9ft above	1	*(242,147)*	*(208,233)*	*0.37*	9.2
	LRLR	1.5 ft -3 ft	2	*(241,171)*	*(217,161)*	*0.59*	2.6
		3 ft - 6 ft	2	*(242,234)*	*(205,234)*	*0.6*	3.7
		6 ft - 9 ft	2.5	*(233,223)*	*(205,154)*	*0.64*	7.4
		9ft above	2.5	*(233,227)*	*(205,140)*	*0.63*	9.1
	LRLL	1.5 ft -3 ft	1.5	*(212,185)*	*(233,165)*	*0.38*	2.9
		3 ft - 6 ft	1.5	*(205,231)*	*(242,234)*	*0.42*	3.7
		6 ft - 9 ft	1.5	*(241,123)*	*(207,70)*	*0.47*	6.3
		9ft above	1.5	*(236,74)*	*(219,168)*	*0.4*	9.6
	LLRR	1.5 ft -3 ft	1	*(242,71)*	*(223,71)*	*0.45*	1.9
		3 ft - 6 ft	1	*(242,120)*	*(239,71)*	*0.45*	5.0
		6 ft - 9 ft	1	*(231,132)*	*(226,70)*	*0.45*	6.2
		9ft above	1	*(242,72)*	*(232,182)*	*0.37*	11.0
	LLRL	1.5 ft -3 ft	1	*(227,71)*	*(242,73)*	*0.29*	1.6
		3 ft - 6 ft	1	*(205,75)*	*(242,71)*	*0.31*	3.7
		6 ft - 9 ft	2	*(217,119)*	*(205,190)*	*0.64*	7.2
		9ft above	2	*(216,111)*	*(205,205)*	*0.61*	9.5
	LLLR	1.5 ft -3 ft	1	*(229,169)*	*(206,165)*	*0.41*	2.3
		3 ft - 6 ft	1.5	*(236,225)*	*(242,169)*	*0.47*	5.6
		6 ft - 9 ft	1.5	*(222,234)*	*(205,156)*	*0.52*	8.0
		9ft above	1.5	*(208,233)*	*(205,136)*	*0.44*	9.7
	LLLL	1.5 ft -3 ft	1.5	*(225,88)*	*(219,74)*	*0.43*	1.5
		3 ft - 6 ft	1.5	*(242,71)*	*(208,71)*	*0.48*	3.4
		6 ft - 9 ft	1.5	*(240,74)*	*(210,153)*	*0.56*	8.5
		9ft above	1	*(225,104)*	*(205,210)*	*0.5*	10.8

Appendix F List of Abbreviations

CDC	US Centers for Disease Control and Prevention
FoR	Field of Regard
HCMS	Health Care Management Science
MOPSO	Multi-Objective Particle Swarm Optimization
PSO	Particle Swarm Optimization
VGA	Visibility Graph Analysis

CURRICULUM VITAE

NAME:	Uttam Karki
EDUCATION:	Ph.D., Industrial Engineering University of Louisville, Louisville, KY, 2023
	M.S, Industrial and Human Factors Engineering Wright State University, Dayton, OH, 2019
	B.E., Industrial Engineering Tribhuvan University, Kathmandu, Nepal, 2017
PROFESSIONAL POSITIONS:	Data Scientist Bayer, MO, 2022