Title	シミュレーションと多目的最適化による病院資源管理滞在期間と医師割り当ての改善を通じた患者満足度の向上戦略
Author(s)	Chemkomnerd, Nittaya
Citation	
Issue Date	2024-09
Type	Thesis or Dissertation
Text version	ETD
URL	http://hdl.handle.net/10119/19379
Rights	
Description	Supervisor:HUYNH, Van Nam, 先端科学技術研究科, 博士

Doctoral Dissertation

Simulation and Multi-Objective Optimization Based Strategies for Enhancing Patient Satisfaction through Length of Stay and Physician Assignment in Hospital Resource Management

Nittaya Chemkomnerd

Supervisor: Van Nam Huynh

Graduate School of Advanced Science and Technology
Japan Advanced Institute of Science and Technology
Knowledge science

September 2024

Abstract

Patient well-being is crucial for effective healthcare systems, which face ongoing challenges in resource allocation and satisfaction improvement. This research develops a comprehensive integrated approach to enhance patient satisfaction, focusing on Length of Stay (LOS) and physician assignment, by combining discrete event simulation (DES) modeling, multi-objective optimization (MOO), and decision-making guidelines.

The study investigates the impact of resource allocation strategies, patient flow patterns, and physician assignment on clinic performance and patient satisfaction. Data collection involved surveys, observations, and interviews to understand the hospital environment comprehensively. A unique formula was derived to compute satisfaction scores from survey data, which informed the development of a simulation model. The research applies a weighted max-min fuzzy multi-objective optimization methodology to balance competing objectives. By incorporating priority weights and scenario analysis, this integrated approach enables decision-makers to effectively manage trade-offs between different goals.

A case study of the Ophthalmology department at Thammasat University Hospital (TUH) in Thailand demonstrates the practical application of this integrated approach. The outcomes provide tailored improvement suggestions for hospitals of different sizes. For large hospitals, enhancements positively impact both LOS and physician assignment satisfaction. For medium and small-sized hospitals, two distinct options focusing on either LOS satisfaction or physician assignment satisfaction.

The findings underscore the importance of patient satisfaction as a central objective in healthcare optimization efforts and highlight the potential of advanced modeling techniques in addressing complex healthcare challenges. This research offers an adaptable, comprehensive workflow applicable to other hospital departments, promoting a holistic strategy for healthcare system enhancement. Future research directions include aligning this integrated approach with sustainable development goals to ensure long-term improvements in healthcare quality and accessibility.

Keywords: Patient satisfaction, Resource management, Multi-objective optimization, Simulation, Healthcare

Acknowledgement

I would like to express my deepest gratitude to those who have supported and contributed to the successful completion of this dissertation. First and foremost, I extend my sincere thanks to my supervisor, Professor Van-Nam Huynh, for his invaluable guidance, continuous support, and encouragement throughout my research. His expertise and insightful feedback have been crucial to the development of this work.

I would like to express my gratitude to my second advisor, Professor Hieu Chi Dam, for his guidance, support, and expertise throughout this research.

I would like to extend my deepest appreciation to my external advisor, Associate Professor Warut Pannakkong. His exceptional guidance, insightful advice, and unwavering support have been instrumental in the completion of this dissertation. His patience and encouragement have been invaluable, particularly during the most challenging phases of this project.

I would like to express my heartfelt gratitude to Associate Professor Tanatorn Tanantong for his invaluable assistance in facilitating contact with the hospital. His support was crucial in making this research possible.

I am also deeply thankful to the hospital staff, especially those in the Ophthalmology department of Thammasat University Hospital, for providing essential information and insights that greatly contributed to the success of this study.

I extend my sincere thanks to the dual doctoral degree scholarship awarded by Sirindhorn International Institute of Technology (SIIT) Thammasat University, National Science and Technology Development Agency (NSTDA), and Japan Advanced Institute of Science and Technology (JAIST). Their financial support and commitment to academic excellence made this research achievable.

My heartfelt appreciation goes to my colleagues in Huynh's Lab and all Thai's friends, whose companionship and collaboration have been a source of motivation and inspiration.

Finally, I am eternally grateful to my family and my partner, Aon, for their unwavering support, patience, and love. This achievement would not have been possible without their constant support. Thank you all for your contributions to this journey. This dissertation is dedicated to you.

Contents

List of Figures

List of Tables

Abbreviations and Acronyms

AR	Auto-Refractometry Test
D	Dilation
DES	Discrete-event simulation
ET	Eye Tonometry Test
ICU	Intensive Care Unit
IOM	Intraocular Measurement
LOS	Length of stay
MOO	Multi-Objective Optimization
OCT	Optical Coherence Tomography test
OI	Ophthalmic Imaging test
OPD	Outpatient department
PA	Physician Assignment
TUH	Thammasat University Hospital
VAT	Visual Acuity Test
VF	Visual Field test

Chapter 1

Introduction

1.1 Background of the Study

With healthcare services being paramount for sustaining individual and societal well-being, healthcare facilities serve as the front line guardians of public health [1]. However, the challenges they face are as intricate as the human body itself. hospitals are constantly inundated with patients, operating at or near full capacity. [2, 3]. These challenges represent formidable barriers that hospitals encounter when attempting to implement operational improvements. The onset of the COVID-19 pandemic has cast a glaring spotlight on the vulnerabilities within healthcare systems worldwide, exposing deficiencies in resource management and operational resilience [4]. As hospitals contend with the unusual demands imposed by the pandemic, the need for optimized resource allocation has become increasingly urgent [5]. In the face of surging patient volumes and finite resources, the delicate balance between supply and demand pivots on the edge of hesitation.

At the core of our approach is the understanding that hospitals often face problems like overcrowding and limited resources, especially in outpatient department (OPD) [6, 7]. Overcrowding places immense pressure on resources and staff, leading to challenges in delivering quality care. This strain is exacerbated by the influx of both scheduled and walk-in patients in OPD. The result is a bunch of insights from data, showing ways to use resources better, make patients happier, and strengthen the whole system [8, 9]. We focused our search on a specialized area within the hospital, namely the Ophthalmology Department, dedicated to the diagnosis and treatment of disorders and diseases related to the eyes [10]. Given the prevalence of eye problems and the constant demand for medical attention concerning issues such as vision changes and eye pain, the department tends to be consistently busy [11, 12]. The workflow in the Ophthalmology Department is inherently complex, encompassing various crucial stages, including appointment scheduling, patient check-in, pre-examination procedures, consultation, diagnostic testing, treatment planning, surgical procedures, post-operative care, and communication with other departments [13–16].

In addition to managing resources efficiently, hospitals place a significant emphasis on ensuring high levels of patient satisfaction, recognizing its profound impact on overall hospital performance and reputation [17]. Patient satisfaction serves as a vital indicator of the quality of care provided, directly influencing patients' perceptions of the hospital and their likelihood of returning for future treatment [18, 19]. Moreover, satisfied patients are more likely to share positive experiences with others, contributing to the hospital's word-of-mouth reputation and attracting new patients [20, 21].

Several factors contribute to patient satisfaction [22–24], including the expertise and experience of physicians, the quality of interpersonal care received, and the overall waiting experience. Patients often place a premium on interacting with experienced and knowledgeable physicians, as their expertise can instill confidence and trust in the treatment process. Additionally, the manner in which healthcare providers communicate and interact with patients greatly influences their satisfaction levels. Warmth, empathy, and effective communication are essential components of patient-centered care that can significantly impact patients' overall experience and satisfaction. However, catering to patient preferences for experienced physicians in OPD can present challenges [25], particularly in terms of physician workload and scheduling [26]. Experienced physicians may be in high demand, leading to longer wait times for appointments and potentially overburdening these healthcare professionals. Balancing patient preferences with the need to ensure manageable workloads for physicians is crucial for maintaining high levels of patient satisfaction while safeguarding the well-being of healthcare providers [27].

Ultimately, by prioritizing patient satisfaction and concurrently addressing the needs of healthcare providers, hospitals can cultivate a positive and sustainable healthcare environment that fosters patient trust, loyalty, and well-being.

1.2 Problem Statement

Numerous studies have sought to optimize hospital systems, with a focus on resource allocation and operational enhancements. However, prior research, as exemplified by Tanantong *et al.* [28], has encountered a notable limitation: the absence of direct, real-time patient satisfaction scores. Instead, reliance was placed on feedback from healthcare professionals, predominantly nurses, to gauge patient satisfaction. While valuable insights were gleaned from this approach, it fell short of providing a precise and comprehensive understanding of patient satisfaction. Efforts to optimize various system aspects notwithstanding, significant gaps persist in accurately assessing patient satisfaction and its direct impact on service quality. Ala *et al.* [29] similarly identified limitations in prior work, including a reliance on objective measures such as waiting times, and staff interviews for evaluating satisfaction. Also, Fan *et al.* [30] show a lack of a direct correlation between dissatisfaction and overall patient satisfaction. Recognizing these shortcomings, our research endeavors to bridge these gaps. Our primary objective is to enhance the accuracy of patient satisfaction evaluation by converting the length of stay (LOS) into a reliable satisfaction score using a conversion technique derived from collected survey data. Moreover, our study aims to develop comprehensive guidelines for OPD improvements, considering patient satisfaction as a central consideration.

Our integrated approach seeks to address this gap by combining two critical aspects of patient satisfaction: satisfaction related to LOS and satisfaction related to physician assignment. Leveraging optimization techniques, this comprehensive workflow determines the optimal number of resources while factoring in associated costs. This strategy presents a holistic solution applicable to hospitals of all sizes, offering a multi-faceted vision for enhancing patient satisfaction in the healthcare setting.

1.3 Research Objectives

- **Development of a Comprehensive Integrated Approach for Hospital Resource Management:** The foremost objective of this research is to develop a comprehensive integrated approach for hospital resource management, specifically tailored for OPD operations. This comprehensive workflow aims to optimize resource allocation and operational efficiency within OPDs, which are critical for managing patient flow and ensuring timely medical services. The primary goal is to create a system that enhances patient satisfaction by effectively managing the LOS and physician assignment, two pivotal metrics in healthcare service quality. This objective emphasizes the importance of crafting solutions that are not only theoretically robust but also practically implementable. By achieving this goal, the research addresses the pressing need for more efficient and patient-centered resource management strategies in modern healthcare settings.

- **Bridging the Gap in Prior Research by Incorporating Critical Aspects of Patient Satisfaction:** This objective is to bridge the gap in prior research by incorporating two critical aspects of patient satisfaction: satisfaction related to LOS and satisfaction related to physician assignment. By addressing these specific elements, the research aims to provide a more nuanced and complete picture of patient satisfaction, which is essential for targeted improvements and overall service quality enhancement.

- **Development of a Method to Predict Patient Satisfaction:** The third objective is to develop a method that predicts patient satisfaction by converting the LOS and physician assignment aspect into a reliable satisfaction score using a technique derived from collected survey data. This approach aims to provide a comprehensive understanding of patient satisfaction, beyond traditional metrics, to capture the true patient experience. By achieving this objective, the research seeks to enhance feedback mechanisms and support better decision-making in healthcare management.

- **Development of a Comprehensive Guidelines for Improving OPD Operations:** The objective is to develop comprehensive guidelines for improving OPD operations, with a central focus on enhancing patient satisfaction. These guidelines will be based on empirical data and best practices, offering actionable insights for healthcare administrators. This objective emphasizes the need for scalable and adaptable solutions that can be implemented across all sizes of hospital. By achieving this goal, the research aims to contribute broadly to the field of healthcare management, offering insights and tools that can be used to improve patient care universally.

1.4 Chapter Organization

- **Chapter 1:** This chapter serves as the entry point to the dissertation's exploration. It adeptly introduces the concept of production rescheduling, underlining its importance in tackling dynamic manufacturing challenges. It concisely articulates the problem statement and outlines the well-defined research objectives, offering a clear road map for the study's direction. Furthermore, the chapter provides readers with a valuable road map by delineating the organization of the dissertation, ensuring seamless and comprehensive navigation through the subsequent content.

- **Chapter 2:** This chapter lays the foundation for the dissertation's narrative by delving into the extensive body of literature surrounding the topic. It serves as an expertly curated guide to the existing research landscape, providing a comprehensive overview of the patient satisfaction, simulation, and multi-objective optimization. The chapter synthesizes key findings and insights from previous scholarship, offering a critical analysis of the current state of knowledge. Additionally, it presents gaps, inconsistencies, and emerging trends in the literature, setting the stage for the dissertation's original contribution.

- **Chapter 3:** At the core of the dissertation lies this chapter, which delineates the innovative and comprehensive methodology for addressing dynamic healthcare system challenges. Painstakingly crafted to optimize decision-making processes amidst competing objectives, this methodology represents a significant contribution to the field. It aims to enhance healthcare system performance and efficiency, paving the way for informed decision-making and policy formulation. This chapter serves as a cornerstone of the research, providing a robust integrated approach for navigating the complexities of healthcare management and improving patient satisfaction.

- **Chapter 4:** This empirical chapter serves as the numerical demonstration and experimental validation of the developed integrated approach. It presents tangible evidence to corroborate the effectiveness of this comprehensive methodology through rigorous testing and analysis. By evaluating the performance and practical applicability of this systematic process using numerical examples and case studies, this chapter ensures that the research findings can be confidently applied in real-world healthcare scenarios. It provides a concrete illustration of how this holistic strategy can be implemented and its impact on decision-making processes, thereby enhancing the credibility and relevance of the research outcomes.

- **Chapter 5:** In the ensuing discussion chapter, the focus shifts to providing concise managerial insights drawn from the research outcomes. This section offers practical recommendations on how decision-makers can effectively utilize the integrated approach in healthcare management and policy formulation. It serves as a vital link between research findings and practical application, aiding decision-makers in making evidence-based decisions to enhance organizational performance and patient care.

- **Chapter 6:** This chapter encapsulates the contributions of the research, which extend across methodological implications, practical applicability, and advancements in the field of Knowledge Science. By delineating the multifaceted ways in which this research pushes the boundaries of knowledge, the chapter underscores the significance of the study's outcomes.

- **Chapter 7:** In this concluding chapter, the research journey reaches its pinnacle with the presentation of key findings and their implications. It also humbly acknowledges the encountered limitations, serving as an honest reflection on the study's scope. Additionally, this chapter offers valuable signposts for future research directions, igniting the torch for continued exploration and innovation in the field.

Chapter 2

Literature Review

2.1 Patient Satisfaction

Patient satisfaction is a critical measure of the quality of healthcare services. It reflects patients' perceptions of the care they receive, encompassing various aspects such as communication with healthcare providers, the environment of care, and the efficiency of service delivery [31]. High levels of patient satisfaction are associated with improved patient compliance, better health outcomes, and increased patient retention, making it an essential focus for hospital management and continuous quality improvement efforts.

Extensive research has been dedicated to understanding the factors that contribute to patient satisfaction and its implications for healthcare quality. Studies [22, 32] have identified several key determinants, including interpersonal interactions with healthcare providers, communication effectiveness, perceived quality of care, waiting times, and facility amenities.

Cleary and McNeil [33] found that higher quality of care, which includes the clinical quality of healthcare services such as the accuracy of diagnoses and the effectiveness of treatments, is strongly associated with higher levels of patient satisfaction. Additionally, Cleaver *et al.* [34] statistically demonstrated that effective communication has a positive impact on patient satisfaction. Diwan *et al.* [35] reported that increased LOS negatively affects patient satisfaction, highlighting the critical role of waiting times for consultations and treatments. Moreover, patient demographics, health status, and cultural background significantly influence satisfaction levels, as discussed by Young *et al.* [36]. These findings underscore the multifaceted nature of patient satisfaction and the importance of addressing various factors to improve healthcare quality.

Batbaatar *et al.* [22] reviewed various methodologies employed to gather patient satisfaction data, including surveys, interviews, and online reviews. Surveys and questionnaires are the most common methods, as noted by Al-Abri and Al-Balushi [37]. These tools typically ask patients to provide feedback on different aspects of their care and can be conducted post-visit or via follow-up calls. In-depth interviews offer qualitative insights into patient experiences and satisfaction. With the evolution of technology, online reviews and feedback forms are becoming increasingly prevalent, as highlighted by Hong [38]. Patients now frequently share their experiences through online platforms and hospital feedback forms. Selecting the most suitable method for collecting data is crucial, as it ensures the accuracy and comprehensiveness of the gathered information.

To enhance the understanding and management of patient satisfaction, predictive models have been developed across various fields. These models utilize statistical techniques and machine learning algorithms to forecast satisfaction levels based on various predictors. In other industries, predictive models have been successfully applied to understand customer satisfaction. For example, in retail, predictive analytics help in personalizing customer experiences [39], and in online services, they are used to enhance user satisfaction by predicting service needs [40]. However, the application of predictive models in healthcare to forecast patient satisfaction has been relatively limited. Many predictive models, such as regression and machine learning, are used to forecast satisfaction scores based on various customer-related factors, provider characteristics, and processes [41]. These predictive models offer insights into potential areas for improvement and enable organizations to proactively address customer needs and enhance satisfaction levels. Given the success in other fields, it is intriguing to explore the potential of predictive models in the healthcare sector to better understand and manage patient satisfaction.

Overall, the literature on patient satisfaction underscores its significance as a key indicator of healthcare quality and patient-centered care. By understanding the factors influencing satisfaction and leveraging innovative approaches to enhance patient experiences, healthcare organizations can improve patient outcomes, foster patient loyalty, and ultimately drive continuous quality improvement efforts. Recognizing the gap in predictive modeling for patient satisfaction within healthcare, this research introduces a novel approach to achieve reliable satisfaction scores. By converting LOS and other determinants into a quantifiable satisfaction score through advanced predictive techniques, this study aims to provide a comprehensive integrated approach for improving patient satisfaction in hospitals. The proposed method leverages data collected from patient surveys and integrates it into a simulation model to predict and enhance satisfaction outcomes.

2.2 Simulation

In particular, the healthcare system poses unique challenges due to its continuous operations, limited resources, and high investment costs, making physical changes difficult to implement. To address these complexities, simulation modeling emerges as a valuable tool for imitating system dynamics, revealing internal processes, and identifying hidden issues [42]. Compared to altering the real system, improvements can be more easily implemented within a simulation model, allowing for iterative testing and refinement. Discrete Event Simulation (DES) has gained prominence in healthcare research over the past decades. Leemis and Park [43] define DES as a stochastic, dynamic, and discrete model, encapsulating the randomness, time dependency, and state changes that occur with each event. Bhattacharjee and Ray's [44] study on patient modeling methods elucidates the conditions conducive to DES application, highlighting its effectiveness in analyzing complex patient flows, transient system performance, and various aspects of capacity planning, resource allocation, and scheduling. DES proves particularly useful in scenarios where patient flows exhibit complexity in terms of stages, classes, priorities, and routing probabilities, facilitating comprehensive analyses and informed decision-making processes within healthcare settings.

Numerous studies have employed DES to analyze patient flow across various hospital departments. DES model is built to represent patient flow through multiple departments [45], emergency department [46], and OPD [47] incorporating data mining techniques to derive input parameters. Their model successfully helped reduce patient time spent in the hospital. Similarly, Devapriya *et al.* [48] utilized electronic health record data in a DES model to evaluate bed allocation policies, enabling accurate forecasting of patient numbers, length of stay, and occupancy rates.

Queuing theory and queue management are critical considerations in healthcare, as excessive wait times can negatively impact patient experience, clinical outcomes, and operational efficiency. DES offers a powerful approach to analyzing and optimizing queuing systems within hospitals and clinics. By modeling the stochastic arrival patterns of patients, prioritization rules, resource availability, and service time distributions, DES allows researchers to identify bottlenecks, test alternative triage policies, and evaluate the impact of capacity changes on queue lengths and waiting times. For example, Luo *et al.* [49] utilized DES to improve patient prioritization and reduce wait times in a computed tomography scanning department with different patient priority levels. Their model implemented dynamic queue management strategies, leading to significantly reduced delays for lower-priority patients without compromising service for higher-priority cases. Similarly, DES has been applied to emergency departments [50], outpatient clinics, and diagnostic facilities to streamline patient flow, balance resource allocation, and minimize queuing-related inefficiencies, ultimately enhancing patient satisfaction and care quality. Regarding software choices, Arena and Simul8 have been identified as the most commonly used DES tools in healthcare studies.

Overall, the literature highlights the versatility and effectiveness of DES in addressing various challenges in healthcare systems, from patient flow optimization to resource allocation and queuing management. As healthcare organizations strive to enhance efficiency and quality of care, DES is likely to continue playing a crucial role in facilitating data-driven decision-making and process improvements.

2.3 Multi-objective Optimization

Multi-objective optimization (MOO) has gained increasing attention in healthcare research as a powerful approach for addressing the complex and often conflicting objectives inherent in healthcare decision-making [51]. Healthcare systems face numerous challenges [52], including resource allocation, cost containment, patient satisfaction, and clinical effectiveness, which necessitate the consideration of multiple competing objectives.

In recent years, a growing body of literature has focused on applying MOO techniques to various healthcare domains, including healthcare delivery [53], resource allocation [54], treatment planning [55], and healthcare facility design [56]. Yousefi *et al.* [57] reported that the objectives of MOO usually aim to enhance decision-making processes by simultaneously considering multiple objectives, such as maximizing patient outcomes, minimizing costs, and improving resource utilization.

For instance, MOO has been employed to optimize nurse scheduling, achieving a balance in workload distribution, minimizing overtime costs, and enhancing employee satisfaction [58]. Craft *et al.* [55] applied MOO techniques to improve treatment planning by optimizing planning time and enhancing the quality of care. Additionally, Sun *et al.* [59] used MOO to optimize patient and resource allocation during an influenza pandemic, which also allowed for the prediction of resource shortages during the outbreak. These examples illustrate the versatility and effectiveness of MOO in addressing the multifaceted challenges within healthcare, providing a robust framework for improving overall system performance.

It is important to note that hospitals may have different preferences for each objective, highlighting the importance of considering the weight assigned to each objective in the optimization process. By assigning appropriate weights to each objective, decision-makers can align the optimization process with the hospital's strategic goals and priorities. MOO methods that incorporate priority weights are essential for addressing complex decision-making problems [60]. These methods assign different weights to each objective based on their relative importance, reflecting the priorities of the decision-makers. For instance, Chen and Wang [54] study in emergency department (ED), objectives might include minimizing average patient LOS and medical resource wasted cost. By assigning higher weights to more critical objectives, MOO methods can produce solutions that better align with the hospital's strategic goals. Techniques such as weighted sum method, goal programming, and weighted max-min method are commonly used [61]. These approaches ensure that the optimization process respects the predefined priority levels, leading to more balanced and acceptable outcomes. This weighted consideration is particularly beneficial in healthcare, where resource constraints and the need to deliver high-quality care must be balanced carefully. Thus, incorporating priority weights in MOO provides a structured way to navigate the trade-offs and achieve a balance between competing objectives.

In conclusion, the literature on multi-objective optimization in healthcare highlights its potential to address the complex and multifaceted challenges facing healthcare systems. By considering multiple objectives simultaneously and providing decision-makers with an optimal solutions, MOO offers a powerful approach for optimizing healthcare decision-making and improving patient outcomes. Weighted MOO approaches are essential for incorporating hospitals' preferences and ensuring that optimization efforts align with organizational objectives and priorities.

2.4 Resource Management Framework

In the literature review, numerous studies have delved into the development of frameworks aimed at enhancing hospital systems. Existing research explores strategies for improving healthcare processes and patient satisfaction across various domains. These studies delve into the intricate dynamics of healthcare delivery, seeking innovative approaches to optimize resource allocation, streamline workflows, and enhance overall patient experience. Through comprehensive analyses and innovative methodologies, researchers have contributed to the advancement of simulation-optimization frameworks tailored to address the multifaceted challenges within healthcare systems. While some studies touch upon aspects of patient experience, few provide a holistic approach that integrates factors like LOS and physician assignment. The literature review identifies key studies in hospital management and patient satisfaction as in Table 2.1.

While, Cabrera *et al.* [62] demonstrated the application of an agent-based model to simulate operations in the ED. The study confirmed that increasing the number of ED staff within specific cost constraints led to a reduction in the average patient LOS. However, the study focused solely on optimizing resource numbers without integrating scenario analysis to enhance performance further. Chang *et al.* [63] focuses on examining factors influencing the satisfaction of both patients and their families in intensive care units (ICU) in hospital. It explores ICU operations, identifies key processes, and links them to satisfaction survey questions to understand their impact on patient and family satisfaction. The study utilizes a simulation model to improve ICU satisfaction by examining various scenarios of medical staff assignments and provides a precise and objective approach to allocate adequate medical staff based on different considerations, thereby enhancing satisfaction with ICU services. However, this study lacks of optimization to determine the optimal number of nurses and associated costs. Abo-Hamad and Arisha [64] emphasizing the need for optimized resource utilization to mitigate challenges such as uncertainty in demand and declining patient satisfaction. The framework incorporates process modeling, simulation, and balanced scorecard methodologies to analyze and optimize healthcare processes. Detailed implementation of the framework in an ED setting demonstrates its effectiveness in improving resource utilization without considering the cost. Norouzzadeh *et al.* [65] investigate the performance and resource utilization using DES in OPD. They explored various scenarios, including altering resource allocation, patient rooming, prioritization, and managing patient volume. The study highlighted significant improvements in resource utilization but did not achieve optimal resource utilization or clinic performance.

Others research [66, 67] have analyzed the impact of physical expansions or staffing levels on patient wait times and throughput in ED, but they do not consider factors such as physician skill levels or patient satisfaction. Cho *et al.* [68] addresses the importance of optimizing medical scheduling to reduce patient waiting time and enhance satisfaction. The study have developed decision support frameworks using simulation analysis and process mining techniques, but they do not incorporate optimization to find optimal solutions for decision-making.

While Fan *et al.* [30] have explored data-driven simulation models considering patient preferences and behaviors, they do not clarify the relationship between dissatisfaction and satisfaction. Additionally, studies by Chang and Zhang [69] that utilize artificial neural networks for simulation modeling and consider multiple doctors, patient classes, and service processes do not optimize resource allocation. Although comprehensive models by Ordu *et al.* [70] have been developed to link hospital services, forecasting, simulation, and optimization techniques, they do not explicitly address patient aspects or satisfaction. Similarly, Sasanfar *et al.* [71] aim to optimize resource allocation and staff allocation in ED do not incorporate optimization for considering changes in resource numbers or associated costs. While Tanantong *et al.* [28] have aimed to enhance patient satisfaction in front-end department, they have not consistently integrated reliable and accurate measures of patient satisfaction into their analyses. Despite efforts to improve healthcare processes and resource allocation, there is a need for more comprehensive guidelines that consider patient satisfaction as a central consideration, particularly in the OPD setting. Moreover, many studies have explored patient satisfaction in various healthcare settings, such as emergency departments and inpatient wards, there is a relative lack of research specifically focused on improving patient satisfaction in OPD settings.

Table 2.1: Detailed Information on Studies Related to Simulation Frameworks in the Healthcare System.

Reference	Scope	Objective	Main Constraint	Department	Approach	Decision Analysis Tool
Cabrera *et al.* [62]	Develop simulation modeling, Optimization	Min: LOS	Cost	ED	Single objective optimization	-
Chang *et al.* [63]	Develop simulation modeling, Applying patient satisfaction	Max: Patient satisfaction	-	ICU	Scenario analysis	-
Abo-Hamad and Arisha [64]	Bed management, Develop simulation modeling, Balanced scorecard	Max: Utilization Min: Waiting time, LOS	Waiting time limitation	ED	Scenario analysis	Multi-criteria decision analysis tool
Norouzzadeh *et al.* [65]	Develop simulation modeling	Max: Utilization	-	OPD	Scenario analysis	-
Cho *et al.* [68]	Process mining, Develop simulation modeling, Rescheduling	Min: Waiting time	-	ICU	Scenario analysis	-
Fan *et al.* [30]	Develop simulation modeling, Patient preferences	Max: Benefit Min: Dissatisfaction	-	OPD	MOO, Genetic algorithm	-
Ordu *et al.* [70]	Forecast demand, Develop simulation modeling, Optimization	Max: Throughput	Revenue and cost Occupancy rate	whole hospital	Single objective optimization	Operational-level decision support
Sasanfar *et al.* [71]	Develop simulation modeling, Resource allocation	Min: Waiting time	-	ED	Scenario analysis	-
Tanantong *et al.* [28]	Develop simulation modeling, Applying patient satisfaction, Optimization	Max: Patient satisfaction Min: Cost	-	Front-end department	Scenario analysis, MOO	Decision guideline
This research	Develop simulation modeling, Applying patient satisfaction, Optimization	Max: Patient satisfaction Min: Cost	Size of hospital related to investment cost	OPD	Scenario analysis, MOO	Multi-criteria decision guideline

Chapter 3

Methodology

This integrated approach serves as a clear guide for hospitals towards impactful improvements in their systems. It provides a structured methodology that healthcare institutions can follow to address shortcomings, optimize their operations, and enhance patient care. By implementing this comprehensive workflow, hospitals can make decisions that lead to a more effective and efficient healthcare system. This section describes the proposed process architecture as shown in Fig. 3.1. The systematic procedure consists of 5 phases: Data collection, Data preparation, Discrete event simulation modeling, Multi-objective optimization with priority weights, and Guideline development for queuing policy and resource management. A detailed explanation of each phase follows, elucidating the step-by-step process of this holistic strategy.

3.1 Data Collection

The research focuses on the OPD of the hospital, specifically, the ophthalmology department in this study. The collected data is obtained through three methods: a patient satisfaction survey, observations within the OPD, and interviews with the nurses.

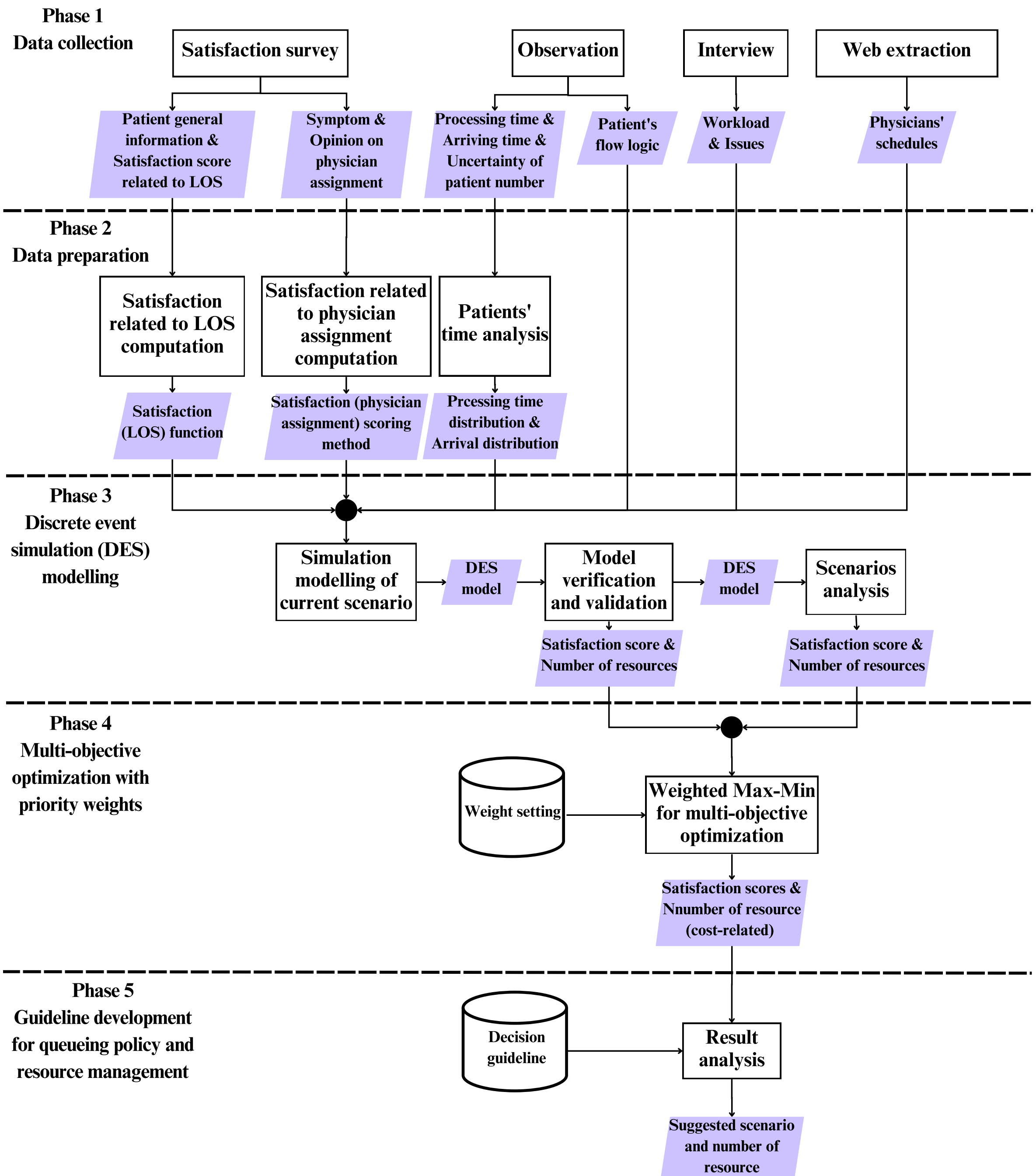

Figure 3.1: Proposed Integrated Approach

3.1.1 Satisfaction survey

Creating a satisfaction survey holds paramount importance as it allows us to tap directly into the realm of opinions and experiences [72]. By crafting a well-structured survey, we aim to capture these nuanced insights and experiences directly from patients. This not only provides a valuable window into their perspectives but also empowers healthcare providers and administrators with actionable feedback. Through this survey, we seek to uncover the multifaceted aspects of patient satisfaction, enabling us to make informed decisions and implement improvements that resonate with the very individuals we aim to serve. There are two types of satisfaction that we are interested in. The first is satisfaction related to LOS, which reflects the patient's feelings about the entire time spent in the hospital. The second is satisfaction related to physician assignment, which captures the patient's satisfaction with meeting their expected or desired physician.

The survey aims to determine two key aspects: (1) the relationship between the LOS and patient satisfaction, and (2) the satisfaction level related to physician assignment, specifically concerning the symptoms. The survey is separated into four parts: general information questions, questions related to satisfaction with the LOS, questions about satisfaction with physician treatment, and a section for suggestions. The satisfaction score is divided into five levels: 1 (very unsatisfied), 2 (unsatisfied), 3 (neutral), 4 (satisfied), and 5 (very satisfied). The questions asked in the survey are listed in Table 3.1.

In the survey, the times at which the patient enters and leaves each station are recorded to determine processing and arrival times as listed in question number 7 and 8 in Table 3.1. The data are also used to calculate LOS for each patient, which represents the time from when a patient enters the OPD until they leave.

The researcher approaches patients who completed their treatment and kindly requested their participation in the survey. On average, it took approximately 5 minutes for each patient to complete the survey. Patients were asked a series of questions based on the survey. Participation was entirely voluntary, and only those patients who were willing to provide feedback were approached.

Table 3.1: Patient Satisfaction Survey Questions

Part	Question
1. General information	1. Age
	2. Sex
	3. Were you a hospital patient?
	4. Were you an eye department patient?
	5. Were you have an appointment?
2. Questions related to satisfaction with the LOS	6. What time were you arriving at the hospital?
	7. What time were you arriving at the eye department?
	8. What time were you finish at the eye department?
	9. What is your satisfaction score in relation to the actual LOS? (rating 1 to 5)
	10. If the LOS is less than 1 hour, what would your satisfaction score be? (rating 1 to 5)
	11. If the LOS is in between 1-2 hour, what would your satisfaction score be? (rating 1 to 5)
	12. If the LOS is in between 2-3 hour, what would your satisfaction score be? (rating 1 to 5)
	13. If the LOS is more than 3 hour, what would your satisfaction score be? (rating 1 to 5)
3. Questions about satisfaction with physician treatment	14. What are your symptoms?
	15. With these symptom, which type of physician you are more preferable? (specialist, general, or no difference)
4. Suggestions	16. Choose 3 factors that have the most effectiveness on your satisfaction
	17. Suggestion

3.1.2 Observation

Observation emerges as a crucial tool in our pursuit of valuable insights within the healthcare setting [73]. In the face of resource constraints that often limit our ability to capture every piece of information, observation takes the spotlight. This method allows us to diligently gather essential data without overwhelming the already strained resources. By keenly observing the flow of patients within the hospital environment and systematically recording the time each patient spends at each process station, we can track critical details such as entry and exit times, the pathways patients follow, and the utilization of resources [74]. This approach not only optimizes resource allocation but also provides an authentic snapshot of real-time processes. Through detailed observation of each process in the department, we aim to harness the most pertinent data, enabling us to construct a comprehensive understanding of the hospital's operations and, subsequently, make informed decisions for enhancement.

Additionally, the flow path of the patient was collected during this observation. These data were subsequently utilized in constructing the simulation model.

3.1.3 Interview

The researcher engaged in discussions with the head nurse to gather essential workload information for the study. During these interactions, the nursing staff also highlighted any issues or problems occurring within OPD. Additionally, valuable insights into the physician schedule were obtained through interviews. This data was instrumentally employed in formulating scenarios aimed at addressing and resolving the identified problems within the OPD.

3.1.4 Web extraction

The researcher accessed data from the official website of the hospital to gather information on physicians' schedules. This involved retrieving details such as the names of physicians and their designated operating times. Additionally, if the hospital system provided similar information, it was also considered in the data collection process. The acquired data is systematically extracted and use in the development of the simulation model. By leveraging this real-time scheduling data, the simulation model aims to closely mirror the operational dynamics of the hospital, ensuring a more accurate and representative analysis of the physician assignment process.

3.2 Data Preparation

The raw data collected is transformed into information that can be used to build a simulation model. There are three methods for transforming the data based on data types: computation of satisfaction related to LOS, computation of satisfaction related to selecting a physician, and analysis of patients' time.

3.2.1 Satisfaction related to LOS computation

This process involves generating a function to predict the expected patient satisfaction score related to LOS. The data used for this process comes from questions in parts one and two of the satisfaction survey from Table 3.1: general information questions (question numbers 1-5) and questions related to satisfaction with the length of stay (question numbers 10-13). Each question has either binary answers (question numbers 1-5) or ordinal values (question numbers 10-13).

The suitable statistical method for this type of data is Ordinal Logistic Regression [75], which serves as a tool to create the predictive function for satisfaction scores based on influencing factors. The response variable of the function is the expected satisfaction score, derived from the patient's answers to questions 10 to 13. The explanatory variables include binary answers to questions 1 to 5 (yes or no) and the specified length of stay options mentioned in questions 10 to 13: less than one hour, between one and two hours, between two and three hours, and more than three hours. Subsequently, all variables are fitted into the ordinal logistic regression model using the Minitab software. The resulting output function, which represents the probability of occurrence for each satisfaction level, $P(S_a)$ as in (3.1), with S_a representing the satisfaction level a from 1 to 5. The variables are denoted as $b_{1,a}, ..., b_{n,a}$, with n variables in each satisfaction level a.

$$P(S_a) = \frac{1}{1 + e^{-(b_{1,a}+b_{2,a}+...+b_{n,a})}} \tag{3.1}$$

After computing the probability for each satisfaction level, the simulation model applies these probabilities. The simulation program generates a random number, $rand$, with a value between 0 and 1. Using this random number, the cumulative probability is calculated. Subsequently, the satisfaction score for each patient is determined based on the calculated probabilities. This process of calculating patient satisfaction related to LOS of each patient p, $PSLOS_p$, is illustrated as follows:

- $PSLOS_p = 1$,
  if $rand \leq P(S_1)$
- $PSLOS_p = 2$,
  if $P(S_1) \leq rand \leq P(S_1) + P(S_2)$
- $PSLOS_p = 3$,
  if $P(S_1) + P(S_2) \leq rand \leq P(S_1) + P(S_2) + P(S_3)$
- $PSLOS_p = 4$,
  if $P(S_1) + P(S_2) + P(S_3) \leq rand \leq P(S_1) + P(S_2) + P(S_3) + P(S_4)$
- $PSLOS_p = 5$,
  if $P(S_1)+P(S_2)+P(S_3)+P(S_4) \leq rand \leq P(S_1)+P(S_2)+P(S_3)+P(S_4)+P(S_5)$.

3.2.2 Satisfaction related to physician assignment computation

In this process, the researcher generates the method for computing the expected satisfaction score related to selecting a physician. The data used in this process comes from the survey question part three in Table 3.1. In question number 14, patients provide their symptom names, which can be too specific, and some symptoms might occur less frequently. To address this, the symptoms are categorized into three levels [76]: Easy (not severe, can be self-recovered), Hard (very severe, requiring immediate treatment), and Varied (severity varies and treatment depends on the causes). For instance, an eye stye falls into the 'Easy' category because the symptom typically resolves itself within two weeks [77]. On the other hand, glaucoma is categorized as 'Hard' because untreated cases can lead to loss of eyesight [77].

In question number 15 in Table 3.1, patients express their expectations toward meeting the physician using symptoms as a reference. There are three levels of expectation: being satisfied if meeting a general physician, being satisfied if meeting a specialist physician, and having no preference for any physicians. The probability of occurrence between symptoms and expected physician is then computed using the collected data.

After the patient meets with the physician, three possible events can occur. The first event is when the patient's expectation aligns with the actual physician meeting, resulting in a satisfaction score of 2. The second event occurs when the patient's expectation differs from the actual physician meeting, resulting in a satisfaction score of 0. The final event is when the patient's expectation is no preference, leading to a satisfaction score of 1 regardless of whether they meet a general or specialist physician. This method is later applied in the simulation model, and the equation for patient satisfaction related to physician assignment for each patient p, $PSPA_p$, is represented as in (3.2). The expected physician for each patient p is denoted as EXP_p, and the actual visiting physician is denoted as AP_p.

$$PSPA_p(EXP_p, AP_p) = \begin{cases} 2 & \text{if } EXP_p = AP_p \\ 1 & \text{if } EXP_p = \text{ no preference} \\ 0 & \text{if } EXP_p \neq AP_p \end{cases} \tag{3.2}$$

3.2.3 Patients' time analysis

This process utilizes data from observations, including collected processing time, arrival time, and the number of patients. Statistical methods are employed, utilizing the Input Analyzer program to analyze the collected processing time data, or another program that performs a similar task, to create the distribution of data. After fitting the data to the candidate distribution, a chi-squared goodness-of-fit test, which is a hypothesis test, is conducted [78]. A p-value > 0.05 indicates that the data best fits the distribution. The distribution of processing times is then fitted to represent the system's uncertainty. The patient arrival rate, which signifies the time when a patient arrives, is converted into the interarrival time which is the duration between patient arrivals.

Furthermore, the patient composition in each category changes over time. In the outpatient department, two primary types of patients exist: appointed patients and walk-in patients. Consequently, the number of patients in each category enters the department at varying rates as time progresses. Probability functions are integrated into the model during its creation to account for these dynamics.

3.3 Discrete Event Simulation Modelling

The discrete event simulation (DES) model is constructed using the Arena Simulation program. The model replicates the patient flow within the hospital's department, utilizing a case study for demonstration purposes. The simulation commences by generating entities representing patients entering the department and concludes as these entities exit the model, symbolizing patients leaving the department. The length of stay for each patient p, LOS_p, is calculated from their entry to exit, influenced by the summation of queue time (associated with the number of resources) and the processing time in all processes, as defined in (3.3) and the definition is shown in Table 3.2.

Table 3.2: Notations

Parameters	Definitions
i	Index of physician, $i \in I = \{1, ..., m\}$[1]
j	Index of resource, $j \in J = \{1, ..., n\}$[2]
p	Index of patient number, $p \in P = \{1, ..., l\}$[3]
D_i	Number of additional physician i
$CurrentD_i$	Number of current physician i
M_j	Number of resource j uses in the model
$Tr_{j,p}$	Processing time of patient p in resource j
$Tp_{i,p}$	Processing time of patient p when meeting physician i

[1] m: Total number of physician's type, [2] n: Total number of resource's type, [3] l: Total number of patient.

$$LOS_p = func_{queue}(CurrentD_i + D_i, M_j) + \sum_{j=1}^{J} \Delta Tr_{j,p} + \Delta Tp_{i,p} \qquad (3.3)$$

The simulation model incorporates an environment of uncertainty through the application of functions established in the analysis of patients' time section. The final processes prior to entity departure involve calculating satisfaction scores. The simulation model's performance metrics encompass both satisfaction scores obtained from LOS and physician assignment, each gathered separately.

3.3.1 Model verification and validation

Model verification aims to confirm the correctness of the model's logic, while model validation assesses the model's accuracy in representing the real system [79]. Verification involves testing the model under extreme conditions, such as when only one patient enters the system, and applying a constant processing time. The LOS serves as a key performance measure during this process. Simultaneously, LOS is manually calculated by summing up all processing times. A direct comparison of these values is made. If they match, it indicates that the model is correct and effectively represents the underlying assumptions.

Validation, on the other hand, is conducted using the model's output, particularly patient satisfaction related to LOS, which is compared with patient satisfaction data collected through a survey. The satisfaction scores derived from LOS are pivotal in validating the model's accuracy. The method used is the t-test, which compares the average value and standard deviation of two sets [80]. Using a 95% confidence interval, if the p-value is less than or equal to 0.05, the two sets are considered significantly different. Otherwise, the two sets are deemed the same. This validation is accomplished by comparing the model-generated satisfaction scores with those obtained from the satisfaction survey, specifically in question number 9 in Table 3.1. This comprehensive validation process ensures that the simulation model faithfully replicates the real-world system it intends to represent.

3.3.2 Scenario analysis

This research incorporates two simulation scenarios: the current scenario and our proposed scenario, each employing distinct queuing policies. In the current scenario, the queuing policy follows a 'first-come-first-serve' approach, as it is the typical operational procedure for the hospital. On the other hand, our proposed scenario introduces two changes to enhance patient satisfaction and system efficiency which are walk-in patients policy and shortest processing time queuing policy [81]. Walk-in patients are allowed to visit their preferred physician, provided the physician has fewer than five patients in the queue at that time. This queuing policy, based on the 'shortest processing time' approach, allows patients with predictably shorter consultation times to be seen first. This queue management technique relies on the nurses' experience to estimate the consultation length for each patient. The reason for selecting this policy is that scheduling patients with low variance in consultation times first is known to be effective in balancing patient waiting times and physician idle times. This dual approach aims to streamline patient flow, reduce waiting times, and improve overall patient satisfaction.

The process of building the DES model serves as a crucial foundation for subsequent multi-objective optimization efforts. In constructing the DES model, various inputs are carefully considered, including the queuing policy dictating patient prioritization and resource allocation, alongside factors like the number of resources such as physicians and equipment. The outputs generated by the DES model are satisfaction scores specifically related to patient LOS and physician assignment. The primary aim of this DES model is to construct a realistic representation of the OPD system, enabling the generation of satisfaction scores that accurately reflect real-world conditions. These scores are pivotal in identifying areas for improvement within the OPD, which can then be addressed through the subsequent multi-objective optimization process.

3.4 Multi-Objective Optimization with Priority Weights

The multi-objective optimization encourages decision-makers to cope with the conflict set of objectives, ensuring that the final solution forces a balance among competing goals. By considering multiple objectives simultaneously and harnessing the capabilities of fuzzy linear programming and weight sets, we pave the way for robust and adaptive solutions that align with the intricacies of real-world challenges. In the context of hospital system improvement, this methodology holds extensive potential to revolutionize resource allocation, enhance patient satisfaction, and elevate the overall quality of healthcare services. This optimization is carried out using OptQuest, an integrated application within the Arena program. OptQuest leverages heuristic algorithms and optimization techniques to fine-tune the parameters, striking an optimal balance between patient satisfaction and cost-effectiveness. Through this optimization process, the simulation model is improved to achieve the desired performance improvements.

3.4.1 Objectives

In formulating the multi-objective optimization, several key assumptions are made to ensure a realistic and practical optimization model. Firstly, the study assumes that resources, i.e. physicians and equipment, have a direct impact on patient satisfaction with LOS and patient satisfaction with physician assignment. It is assumed that increasing the number of resources can potentially reduce LOS and improve satisfaction. The model also assumes that these resources can be acquired or reallocated within the constraints of a given budget, allowing for the exploration of different resource configurations. Moreover, the optimization assumes a linear relationship between resource levels and associated costs. While this assumption may be a simplification of the real-world dynamics, it is necessary to facilitate the optimization process and ensure computational tractability. These assumptions provide an integrated approach for the multi-objective optimization to balance the trade-offs between maximizing patient satisfaction and minimizing costs through optimal resource allocation and process improvements.

The decision variables for the optimization include the number of additional physicians (D_i) and the amount of each resources (M_j). The objective functions, encompassing the goals of maximizing patient satisfaction related to LOS (Z_1), maximizing patient satisfaction toward physician assignment (Z_2), and minimizing investment costs (Z_3), are explicitly defined in Equation (3.4) – (3.6), respectively. The constraints for these objectives include ensuring that the number of additional physicians does not exceed the maximum allowable number of additional physicians as in (3.7), and that the number of resources remains at least at the current level or does not exceed the maximum allowable number of resources as in (3.8).

Objective function:

$$Max\,Z_1 = \sum_{p=1}^{N} \frac{PSLOS_p}{N} \tag{3.4}$$

$$Max\,Z_2 = \sum_{p=1}^{N} \frac{PSPA_p}{N} \tag{3.5}$$

$$Min\,Z_3 = \sum_{i=1}^{I} C_i D_i + \sum_{j=1}^{J} C_j (M_j - MCurrent_j) \tag{3.6}$$

Subjected to:

$$0 \leq D_i \leq MaxD_i \tag{3.7}$$

$$MCurrent_j \leq M_j \leq MaxM_j \tag{3.8}$$

,where C_i is cost of hiring one additional physician i, C_j is cost of adding one more resource j, $MCurrent_j$ is the number of resource j in current scenario, $MaxD_i$ is the maximum number of additional physician i, and $MaxM_j$ is the maximum number of resource j.

The objective of maximizing patient satisfaction related to LOS, maximizing patient satisfaction related to physician assignment, and minimizing investment cost present inherent conflicts. An increase in the number of resources, such as hospital staff and equipment, can lead to reduced wait times and shorter LOS, thereby improving patient satisfaction. Similarly, having a larger pool of physicians available increases the likelihood of patients being assigned to their preferred physician, enhancing satisfaction with physician assignment. However, expanding resources by hiring additional personnel or acquiring new equipment incurs substantial investment costs for the healthcare facility. Therefore, the objectives of maximizing patient satisfaction through reduced LOS and preferred physician assignments are at odds with the goal of minimizing investment costs. Striking the optimal balance between providing a high level of patient care and managing operational expenses becomes a complex trade-off, as improving one objective may come at the expense of another.

3.4.2 Optimization approach

Multi-objective optimization involves combining multiple objective functions and solving them simultaneously, with each objective assigned a different level of importance. This importance is determined by incorporating weights, denoted as w_o, into the objective function o. Through in-depth interviews with the experts of the hospital, it was determined that specific weights could not be assigned, as all objectives were considered important. The weight setting needed to be adjustable. Since the preferences from the hospital are not specified by the experts, a set of twenty-five weight configurations is presented as recommended from Yahia and Pradhan [82]. Each set contains weights for satisfaction objectives and the investment cost objective, as detailed in Table 3.3. Utilizing multiple weight settings in multi-objective optimization offers several benefits. By exploring different combinations of weighing factors, decision-makers can evaluate a range of scenarios, each representing a unique prioritization of the objectives, as all objectives were considered important and the weight setting needed to be adjustable. This approach provides decision-makers with a broader perspective and more options for selecting a solution that aligns with their specific preferences or situational requirements.

After running the single-objective optimization, the obtained results will be used to compute constraints for multi-objective optimization. Since the results are presented in different units, they need to be normalized for later combination. Zimmermann [83] introduced the fuzzy linear programming technique for normalizing the objective functions. The maximum and minimum values for each objective are gathered during single-objective optimization, denoted as the pessimistic values, Z_o^-, and optimistic values, Z_o^+. The method involves running single-objective optimization for each objective separately. The first objective, which is maximizing patient satisfaction related to LOS, provides the objective value referred to as the optimistic value for objective one. Similarly, objectives two and three yield their respective optimistic values. To

Table 3.3: Weight Settings of Each Objectives

Case	w_1	w_2	w_3	Case	w_1	w_2	w_3
1	1	0	0	15	0	2/6	4/6
2	0	1	0	16	0	3/6	3/6
3	0	0	1	17	0	4/6	2/6
4	1/6	5/6	0	18	0	5/6	1/6
5	2/6	4/6	0	19	1/6	2/6	3/6
6	3/6	3/6	0	20	1/6	3/6	2/6
7	4/6	2/6	0	21	1/6	1/6	4/6
8	5/6	1/6	0	22	1/6	4/6	1/6
9	1/6	0	5/6	23	2/6	1/6	3/6
10	2/6	0	4/6	24	2/6	3/6	1/6
11	3/6	0	3/6	25	2/6	2/6	2/6
12	4/6	0	2/6	26	3/6	1/6	2/6
13	5/6	0	1/6	27	3/6	2/6	1/6
14	0	1/6	5/6	28	4/6	1/6	1/6

w_1: Weight of satisfaction related to LOS objective, w_2: Weight of satisfaction related to physician assignment objective, w_3: Weight of cost objective

determine a pessimistic value for each objective, after completing all single-objective optimizations, in addition to the optimized objective value, other objective values are collected. For instance, the maximum patient satisfaction related to LOS is recorded, and using the same settings, patient satisfaction related to physician assignment and cost are also recorded. Subsequently, the worst value among these recorded objective values is used as the pessimistic value. The values are then used in the fuzzy set. The fuzzy set for normalization [84] is given as follows:

$$f_o(Z_o) = \begin{cases} \frac{Z_o^+ - Z_o}{Z_o^+ - Z_o^-} & for\, Min\, obj. \\ \frac{Z_o - Z_o^-}{Z_o^+ - Z_o^-} & for\, Max\, obj. \end{cases} \tag{3.9}$$

To conduct multi-objective optimization, we utilize the weighted max-min approach for fuzzy multi-objective optimization, as proposed by Lin [84]. This method enables the determination of an optimal solution within the feasible region, ensuring that the achieved levels closely match the weights' ratios. One of its advantages is its reduced computational complexity, making it more accessible to decision-makers or users who may not be familiar with complex mathematical models. Additionally, it enhances the comprehensibility of the application methodology. Amid *et al.* [85] also applied the model to handle the vagueness of input data for supplier selection. The objective function is defined to maximize the variable λ, as shown in (3.10). This variable is set between 0 and 1, as specified in (3.13). Constraint (3.11) represents the weight constraint, ensuring the maximization of the objective value while maintaining a balanced weighting. These constraints can be separated for each single objective function o, resulting in three constraints for this study. Constraint (3.12) ensures that the weights assigned to different objectives collectively represent the overall preference or importance of all objectives.

Objective function:

$$Max\, Z = \lambda \tag{3.10}$$

Subjected to:

$$w_o \lambda \leq f_o(Z_o), for\, o \subseteq \{1, 2, 3\} \tag{3.11}$$

$$\sum_{o=1}^{3} w_o = 1 \tag{3.12}$$

$$\lambda \in [0, 1] \tag{3.13}$$

This model is equivalent to solving (3.4) – (3.8) with new membership function as follows: for minimize objective function,

$$\mu_o(Z_o) = \begin{cases} 1/w_o & \text{for } Z_o \leq Z_o^- \\ f_o(Z_o)/w_o & \text{for } Z_o^- \leq Z_o \leq Z_o^+ \\ 0 & \text{for } Z_o \geq Z_o^+ \end{cases} \tag{3.14}$$

and for maximize objective function,

$$\mu_o(Z_o) = \begin{cases} 1/w_o & \text{for } Z_o \geq Z_o^+ \\ f_o(Z_o)/w_o & \text{for } Z_o^- \leq Z_o \leq Z_o^+ \\ 0 & \text{for } Z_o \leq Z_o^- \end{cases} \tag{3.15}$$

, where $\mu_o(x)$ is the achievement level of each objective function o.

3.5 Comparative Analysis

After performing the optimization, the results, which include the objective values of the optimized solution, are collected. The gathered data consist of the average satisfaction scores related to LOS, the average satisfaction scores related to physician assignment, and cost. These values are then compared to determine whether there are any differences. Two statistical methods, analysis of variance (ANOVA) and Tukey's test, are employed to identify differences between each set of weights. Each set of weights is referred to as a 'case,' total of 28 cases. The factors considered in the study include the cases, the scenarios, the interaction between cases and scenarios, and the replication, which will later be treated as a blocking factor. The responses measured are the patient satisfaction scores related to LOS and the patient satisfaction scores related to selecting a physician, computed separately. Using ANOVA, the null hypothesis of equal average satisfaction among all cases and scenarios is tested against the alternative hypothesis that they are not all equal. The accepted significance level is 95%, indicating that if the p-value is below or equal to 0.05, the null hypothesis is rejected. Subsequently, it is evident that the satisfaction scores among the cases and scenarios are not equal. Therefore, the utilization of Tukey's test is necessary to reorganize the data and determine the highest satisfaction score. The Tukey's involves comparing all pairs of satisfaction means and grouping together the satisfaction scores that show no significant difference. All statistical tests are conducted using Minitab 20.

After grouping, the base case serves as a benchmark for comparison. The events (cases and scenarios) with higher satisfaction scores than the benchmark are labeled as

'Higher' (not in the same group as the base case). The events in the same group as the base case are labeled as 'Unchanged'. The events with lower satisfaction scores than the benchmark are labeled as 'Lower'.

3.6 Decision Guideline Proposal

The Fig. 3.2 shows the logic of the decision guideline. The decision guideline logic, derived from a careful evaluation of each event's impact on patient satisfaction and investment costs, serve as a crucial compass in the complex landscape of healthcare system improvement. These rules are designed to guide decision makers in determining which events to prioritize when aiming to enhance patient satisfaction within the hospital system. The guiding logic is as follow:

1. Events with Both Lower: If both are labeled as 'Lower', the event is not recommended. This implies that if an event yields lower satisfaction levels for both objectives (LOS and physician assignment) compared to the base case, implementing this event is not advisable.

2. Events with One Lower and One Unchanged: If one satisfaction is labeled as 'Lower' and another is labeled as 'Unchanged', the event is not recommended. This implies that if there is no improvement in one objective and lower satisfaction in another, implementing the event is not advisable.

3. Events with Both Unchanged: If both are labeled as 'Unchanged', the event is not recommended. This implies that if there is no improvement in both satisfaction objectives, implementing the event is not advisable.

4. Events with Both Higher: In cases where both are labeled as 'Higher', the decision maker should consider the investment cost. If the investment cost falls within an acceptable range, as defined by the decision makers, the event is recommended. This implies that when the event leads to improvements in both satisfaction objectives and the cost is deemed reasonable, it is a recommended course of action.

However, if the investment cost exceeds the acceptable range, this event will be compared with other events in the next category.

5. Events with One Higher and One Unchanged: When one is labeled as ‘Higher’ and the other is labeled as ‘Unchanged’, the decision guideline rules take into account the investment cost. The event with the lowest investment cost should be recommended. This means that if an event results in an improvement in one satisfaction level (either LOS or physician assignment) and the cost is reasonable, it is recommended over an event that might yield a higher level but comes with a higher cost.

6. Events with One Higher and One Lower: Events, where one is labeled as ‘Higher’ and the other is labeled as ‘Lower’, are not recommended. This implies that events resulting in a decrease in one satisfaction level while improving the other are not advisable, as the reduction in satisfaction outweighs any gains.

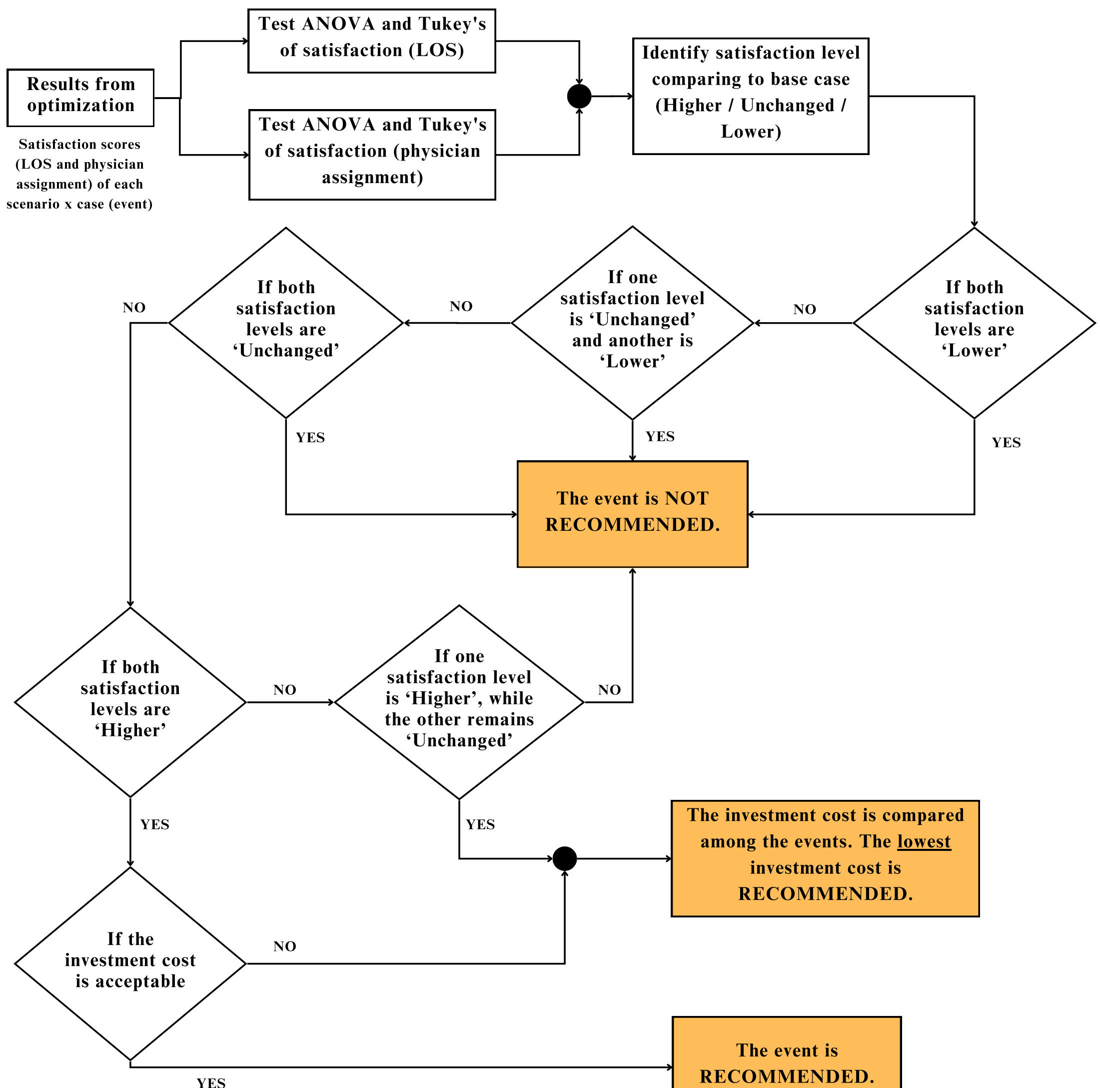

Figure 3.2: Decision Guideline Logic for Recommending the Event

Chapter 4

Case Study

The research utilizes a focused case study approach, in the Ophthalmology Department at the Thammasat University Hospital (TUH) in Pathum thani, Thailand. TUH stands out as a leading, large, public teaching hospital, widely recognized for its exceptional expertise across multiple medical specialties. Among these specialized domains, the hospital has garnered an impressive reputation for its allergy, neurology, cardiology, and ophthalmology services within the OPD.

With a remarkable capacity to serve over 2,000 outpatients daily and has over 800 beds for inpatients, TUH manages a high volume of scheduled appointments and walk-in patients in its OPD. This ophthalmology department is exceptionally popular, accounting for 10% of all outpatients at the hospital, making it the third most crowded department besides internal medicine and surgery. This department encompasses a comprehensive range of nine sub-specialties in addition to general ophthalmology services. The substantial patient load and diverse ophthalmological offerings underscore the department's vital role within the hospital's operations and highlight the imperative for efficient systems and processes to deliver optimal patient care.

4.1 Data Collection

In the data collection of the case study, four distinct methods were utilized to gather comprehensive data. Firstly, a satisfaction survey was conducted within the ophthalmology department, collecting feedback from patients regarding their experiences and overall satisfaction with the services provided. Secondly, observational data was collected by monitoring patient flow patterns and recording the time spent at each station within the department, providing insights into the efficiency and potential bottlenecks in the patient journey. Thirdly, interviews were carried out with nurses to identify pain points and problems encountered in the hospital, offering a valuable perspective on operational challenges and areas needing improvement. Lastly, web extraction techniques were employed to retrieve the physician schedule from the hospital's database, enabling an analysis of resource allocation and scheduling efficiency. Together, these data collection methods provide a robust foundation for understanding and addressing the multifaceted issues within the hospital's ophthalmology department. Data collection took place from February 10$^{\text{th}}$ to April 12$^{\text{nd}}$ 2022.

4.1.1 Satisfaction survey result

The satisfaction survey conducted within the ophthalmology department is presented in four distinct parts, providing a comprehensive overview of patient feedback. During a 12-day period, our survey collected responses from 232 participants. With a 95% confidence level, this sample size provides an accuracy within a 6% margin of error. This level of precision is considered acceptable in various research fields, ensuring that our findings are robust and reliable. This sample size strikes a balance between practical feasibility and statistical, capturing a representative snapshot of patient satisfaction for our study. The first part of the survey focuses on general information about the respondents. The summary of general information part is presented in Table 4.1. The findings reveal that most patients who participated in the survey are aged between 45 and 64 years. There is no significant gender variation among the respondents. Additionally, the majority of patients are not new to the hospital (88%) or the department (80%).

Table 4.1: Statistical Results of the Survey in General Information Questions

Question		Percentage	Number of patients
Age	18-24	10%	22
	25-44	29%	68
	45-64	40%	94
	65 up	21%	48
Sex	Female	55%	128
	Male	44%	102
	Not specified	1%	2
Previously treated at TUH	Yes	88%	204
	No	12%	28
Previously treated at Eye department	Yes	80%	186
	No	20%	46
Appointed patient	Yes	83%	192
	No	17%	40

Most respondents had scheduled appointments (83%), while the remaining 17% were walk-in patients.

The second part of the survey centers on patient satisfaction related to the LOS within the department. On average, patients reported spending approximately 3.5 hours during their visit to this department. Fig. 4.1 shows the summarize of satisfaction score related to actual LOS from respondents (question 9 in Table 3.1). Patient satisfaction displays a right-skewed distribution pattern, with a mean satisfaction score of 4.07 and a mode of 4. Further analysis of satisfaction scores, categorized by LOS, reveals that patients with a LOS of less than 1 hour express high satisfaction, predominantly scoring 5. For those with a LOS between 1 and 2 hours, satisfaction remains high but slightly decreases, with scores of 4. Patients experiencing a LOS between 2 and 3 hours tend to feel neutral, reflected by a score of 3, indicating neither strong satisfaction nor dissatisfaction. For patients with a LOS exceeding 3 hours, the scores drop to 2 or neutral, showing general dissatisfaction with the extended time spent. Fig. 4.2 presents the summarized satisfaction scores from questions 10 to 13, as outlined in Table 3.1. In conclusion, as the LOS increases, patients tend to exhibit lower satisfaction scores.

The third part of the survey addresses patient symptoms. The collected data en-

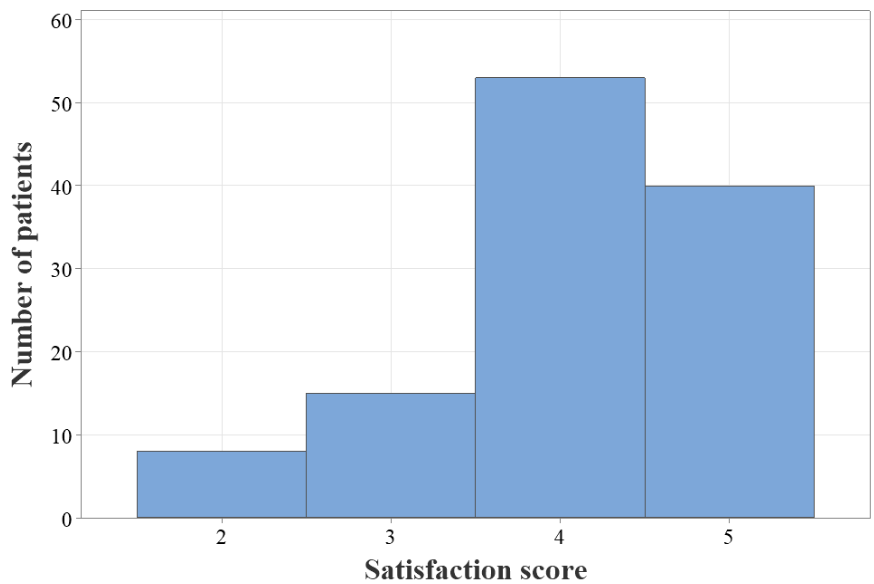

Figure 4.1: Summarize of Satisfaction Score in Relation to the Actual LOS

compasses a wide range of symptoms, as in the table 4.2, which are categorized into three types: easy, hard, and varied. Among the respondents, 33% reported symptoms classified as easy, 31% as hard, and 36% as varied, demonstrating a diverse range of clinical presentations within the department. This categorization helps provide clarity in understanding the nature and distribution of patient symptoms within the study.

The final part of the survey identifies factors significantly influencing patient satisfaction. The most frequently selected factor is the quality of the physician, indicating that the competence and care provided by the medical staff play a pivotal role in shaping patient contentment. Followed by pricing, suggesting that the cost considerations also weigh heavily on patient satisfaction levels. Then, the hospital's reputation, denoting its standing and credibility in the eyes of the patients. This highlights the critical role of healthcare providers' expertise and the perceived value of services in shaping patient satisfaction.

These survey findings provide valuable insights into patient demographics, satisfaction levels, symptom diversity, and key factors impacting satisfaction, offering a solid foundation for targeted improvements in the ophthalmology department.

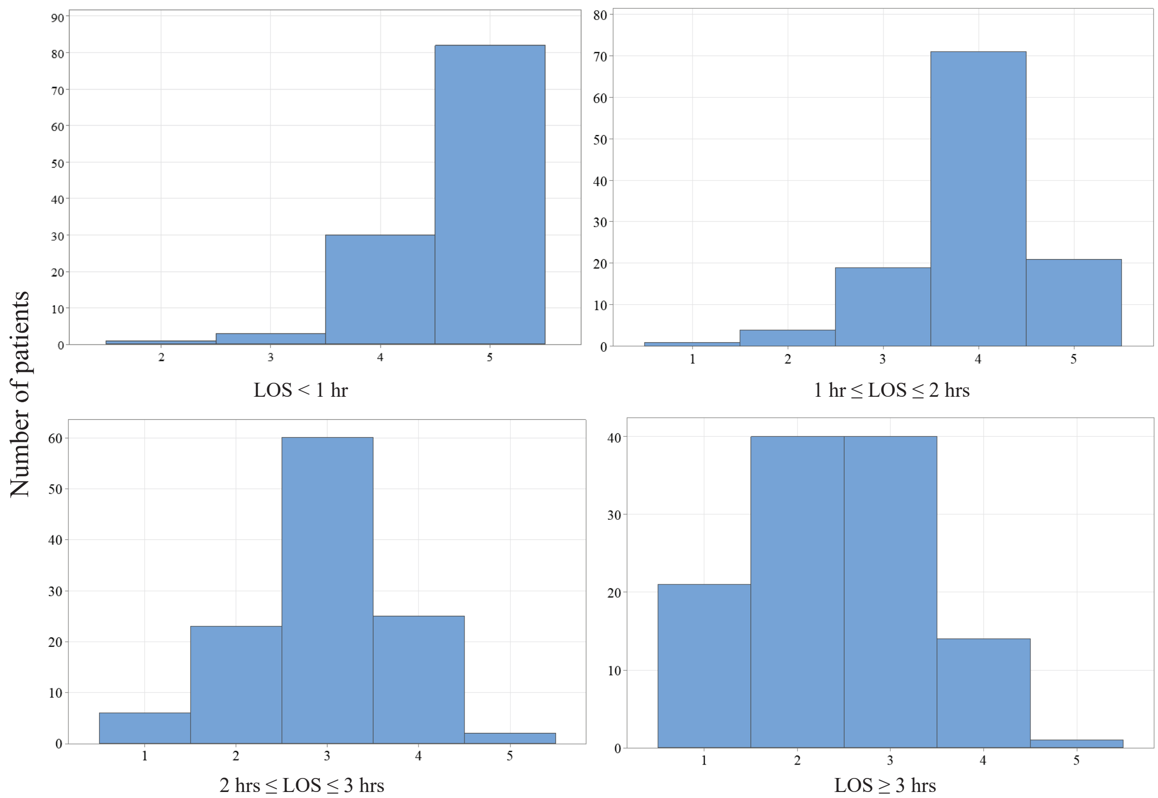

Figure 4.2: Survey Summary Histograms of Patient Satisfaction Scores Over Time Intervals for Four Questions. Each graph illustrates the distribution of satisfaction scores on the x-axis and the corresponding number of patients on the y-axis.

Table 4.2: Survey Responses: Patient Symptoms and Categories

Symptom	Type	Percentage	Number of Patients
Allergy		1.72%	4
By appointment		23.28%	54
Dry eyes		4.31%	10
Eye stye	Easy	0.86%	2
Insects in eyes		0.86%	2
Myopia		0.86%	2
Shingles		0.86%	2
Cataract		5.17%	12
Conjunctivitis blood vessels		0.86%	2
Corneal inflammation		1.72%	4
Diabetic retinopathy		12.07%	28
Fibrosis in eye		0.86%	2
Glaucoma	Hard	4.31%	10
Inability to see		0.86%	2
Inflamed eye cells		0.86%	2
Iriditis		2.59%	6
Lens move		0.86%	2
Papilloma		0.86%	2
Black spot		1.72%	4
Blurred vision		3.45%	8
Bulging eyes		0.86%	2
Check after surgery		11.21%	26
Clogged sebaceous glands		0.86%	2
Conjunctivitis		0.86%	2
Eye inflammation		0.86%	2
Eye pain	Varied	0.86%	2
Itching at corner of the eyes		0.86%	2
Laser		0.86%	2
Lazy eye		0.86%	2
Macular degeneration		5.17%	12
Pterygium		2.59%	6
Rash on eyes		0.86%	2
Stinging eyes		2.59%	6
Thyroid eye		1.72%	4
	Total	100%	232

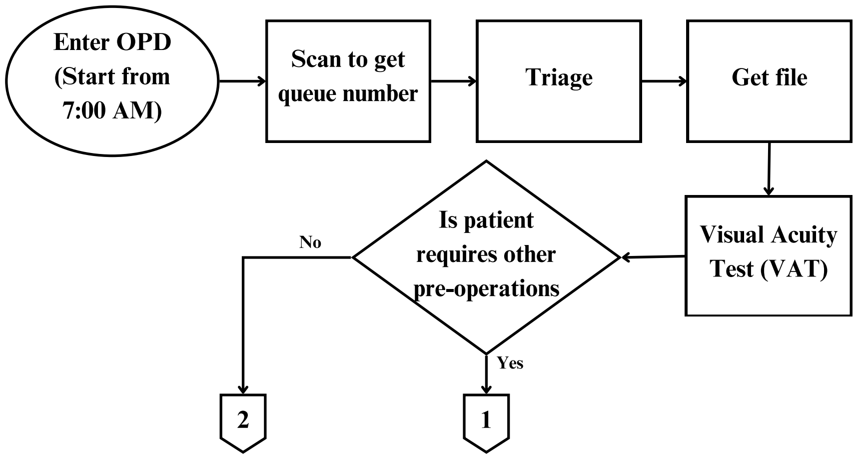

Figure 4.3: Flow Path of Patient in the Ophthalmology Department Part 1: Starting from Entering the Department Until Testing Visual Acuity.

4.1.2 Observation

The observation of patient flow within the ophthalmology department provides detailed insights into the journey of patients from arrival to departure. Upon arrival as shown in Fig. 4.3, patients scan the code from their appointment receipt or enter their hospital number, where their appointments are confirmed or new visit details are recorded, and receive a queue number. They are then directed to the waiting area, where they remain until called for their initial triage. Four main types of queues are established based on the appointment's type and time:

1. A queue type for appointment patients scheduled from 9:00 to 10:00 a.m.

2. A queue type for appointment patients scheduled from 10:00 to 11:00 a.m.

3. A queue type for appointment patients scheduled from 11:00 a.m. to 12:00 p.m.

4. A queue type for walk-in patients.

The next step involves a preliminary triage by a nurse, which includes basic diagnostic procedures and medical history updates. The triage process prioritize appointment patients over walk-in patients. For instance, if patients of types 1, 2, and 4 arrive at 9:00 a.m. and obtain their queue numbers through code scanning, type 1 patients will be triaged first, followed by type 2, and lastly type 4. Following triage, patients wait for no more than 30 minutes to receive their files, containing the necessary pre-operation steps before consulting with a physician.

Following this, patients proceed to the pre-operation process that is the Visual Acuity Test (VAT), which is a necessary procedure for most patients, excluding infants. If there are no other required pre-operations, patients proceed to wait for their physician consultation. For patients requiring additional pre-operative procedures, Fig. 4.4 outlines the supplementary pathway. This pathway begins with the Eye Tonometry Test (ET), followed by the Auto-Refractometry Test (AR), and Dilation (D). The subsequent four pre-operative tests—Optical Coherence Tomography (OCT), Ophthalmic Imaging (OI), Intraocular Measurement (IOM), and Visual Field Test (VF)—can be conducted in any order. Patients are directed to join the shortest queue for each required pre-operative test, with staff managing the flow. Once all pre-operative tests are completed, patients wait for their consultation with the physician.

Next step, the consultation with the physician for a comprehensive examination and diagnosis begins at 9:00 a.m., as illustrated in Fig. 4.5. Depending on the findings, patients may be required to undergo additional tests or post-consultation service, which could involve moving to specialized diagnostic rooms within the department. Following the conclusion of the consultation and post-consultation services, patients typically schedule follow-up appointments or receive prescriptions and care instructions. Once these steps are completed, patients can exit the department and proceed to the finance department for payment. This encapsulates the comprehensive process path for patients in the Ophthalmology department in the presented case study.

This entire process, from arrival to departure, is meticulously observed to identify any inefficiencies or bottlenecks that could impact the patient experience. By understanding these flow patterns and the time spent at each station, the department can implement targeted improvements to enhance operational efficiency and patient satisfaction.

The costs associated with hiring and other resources have been meticulously gath-

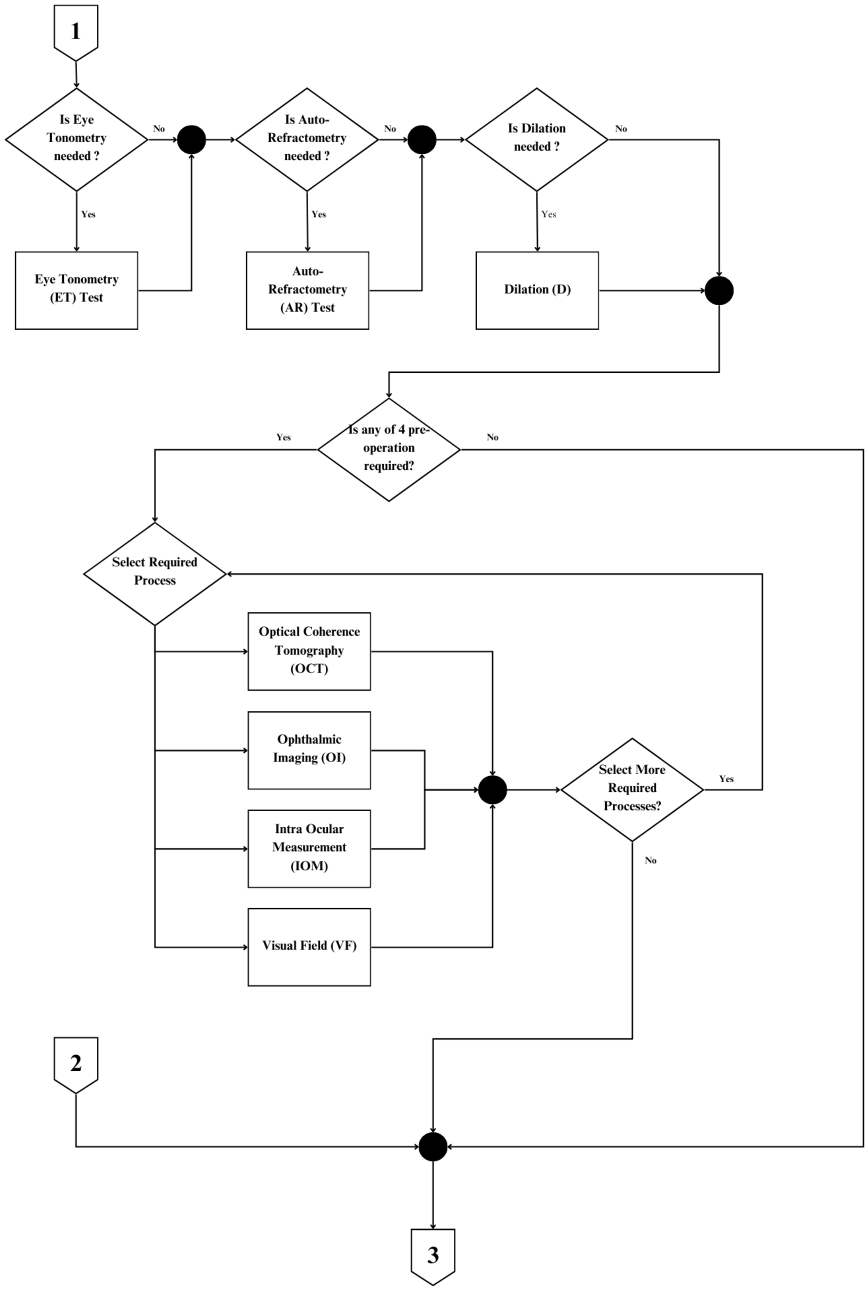

Figure 4.4: Flow Path of Patient in the Ophthalmology Department Part 2: Process in the Pre-operation Stations.

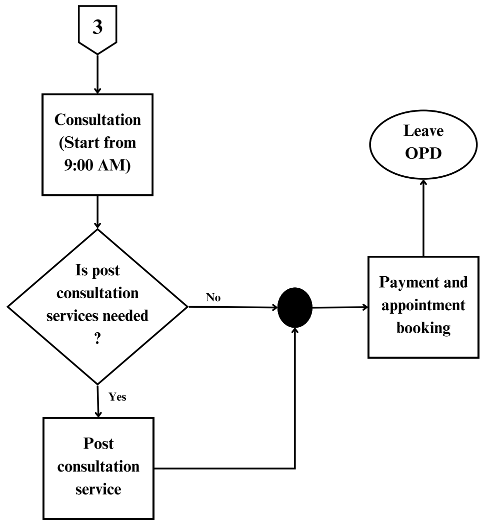

Figure 4.5: Flow Path of Patient in the Ophthalmology Department Part 3: Starting from Waiting to Consult until Leaving the Department.

ered from TUH hiring information website [86], ensuring accurate and up-to-date information. Table 4.3 presented succinctly summarizes these costs, providing a transparent overview of the monthly expenditures associated with various resources crucial to the hospital's operations. This comprehensive data serves as a reliable reference point for understanding the financial implications of resource allocation, aiding in informed decision-making and strategic planning within the hospital setting.

Table 4.3: Investment Cost of TUH

Resource	Monthly cost (Baht)
Physician	31,500
Triage nurse	24,750
VF machine	20,600
Queueing machine	13,000

4.1.3 Interview

An interview with the chief nurse of the ophthalmology department revealed significant challenges related to queue times. The primary issue identified is the variability in consultation durations among physicians. As a teaching hospital, the department is staffed not only by specialist physicians but also by residents, who are medical school graduates in training, and fellows, who are physicians training for specialization. The differing levels of experience among these healthcare providers result in varying consultation times. This inconsistency disrupts the scheduling system, causing queues to extend beyond the fixed timetable and leading to longer waiting times for patients. Addressing this variability is crucial for improving queue management and reducing patient wait times in the department.

4.1.4 Web extraction

The web extraction process provided detailed insights into the physician schedules within the ophthalmology department. In this case study, all of physician schedules were publicly available on the website [87]. The extracted data, organized by specialization, reveals that physicians do not work every day. For confidentiality, the names of the physicians have been omitted. The schedule in Table 4.4 indicates that Cornea specialists are available on Wednesdays and Fridays, while Glaucoma specialists work on Mondays, Tuesdays, and Wednesdays. Lasik specialists are scheduled on Thursdays and Fridays, and Lens specialists are available on Tuesdays. Pediatric ophthalmology specialists work on Tuesdays and Thursdays. Reconstructive surgery specialists are present on Mondays, Wednesdays, and Fridays, and Retina specialists are available every weekday. Uveitis specialists work on Mondays and Tuesdays. Additionally, there are seven fellows and residents working every day, ensuring continuous coverage and support across the department. This scheduling information is crucial for optimizing patient appointments and managing the flow within the department.

Table 4.4: Ophthalmology Department Physician Weekly Schedule

Specialization	Monday	Tuesday	Wednesday	Thursday	Friday
Cornea			X		X
Cornea			X		
Glaucoma	X	X	X		
Glaucoma	X	X			
Glaucoma			X		X
Lasik				X	X
Lens		X			
Pediatric-Ophthalmology		X		X	
Recon surgery	X			X	
Recon surgery	X				
Recon surgery			X		X
Retina			X	X	
Retina				X	X
Retina		X		X	
Retina		X			X
Retina	X		X		
Uveitis	X	X			

4.2 Data Preparation

The raw data collected has been transformed into usable information for building a simulation model. This transformation process involved three distinct methods based on the data types: calculating patient satisfaction related to LOS, assessing satisfaction associated with physician assignment, and analyzing patient time metrics.

4.2.1 Satisfaction related to LOS computation

The process of calculating patient satisfaction related to LOS involved fitting the data throughout the ordinal logistic regression and is presented in Table 4.5. This analysis revealed several significant variables that notably influence satisfaction levels. Initially, a regression analysis was conducted to assess the significance of each factor using the p-value. With a significance level set at 0.05, a p-value less than or equal to 0.05 indicates a statistically significant association between the response variable and the factor. In the results, variables such as LOS, hospital patient status, and ophthalmology (Oph) patient status exhibit statistical significance with p-values less than 0.05.

Table 4.5: Logistic Regression Model Fitting All Factors

Predictor	Coef	SE Coef	z	p	Odds Ratio	95% CI	
						Lower	Upper
Const(1)	-7.25136	0.818807	-8.86	<0.0001			
Const(2)	-5.52026	0.798820	-6.91	<0.0001			
Const(3)	-3.44020	0.782176	-4.40	<0.0001			
Const(4)	-0.610074	0.750927	-0.81	0.417			
LOS							
1-2hr	2.39118	0.299042	8.00	<0.0001	10.93	6.08	19.63
2-3hr	4.80260	0.358458	13.40	<0.0001	121.83	60.34	245.96
>3hrs	5.89143	0.379425	15.53	<0.0001	361.92	172.05	761.35
Age							
18-24	-0.639138	0.767392	-0.83	0.405	0.53	0.12	2.37
25-44	-0.110935	0.711966	-0.16	0.876	0.89	0.22	3.61
45-64	-0.661788	0.709848	-0.93	0.351	0.52	0.13	2.07
>65	-0.263091	0.732513	-0.36	0.719	0.77	0.18	3.23
Sex							
Not specify	1.62379	0.975903	1.66	0.096	5.07	0.75	34.35
Female	0.174750	0.195666	0.89	0.372	1.19	0.81	1.75
Hospital patient							
No	-0.540363	0.346463	-1.56	0.019	0.58	0.30	1.15
Oph patient							
No	0.697572	0.351071	1.99	0.047	2.01	1.01	4.00
Appointment							
No	-0.283282	0.340569	-0.83	0.406	0.75	0.39	1.47

The regression model was then refined by sequentially eliminating non-significant factors. Table 4.6 presents the final logistic regression model, which includes only the variables that were found to be statistically significant.

Table 4.6: Logistic Regression Model Fitting Significant Factors

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI	
						Lower	Upper
Const(1)	-7.40216	0.39081	-18.94	<0.0001			
Const(2)	-5.71580	0.34710	-16.47	<0.0001			
Const(3)	-3.67999	0.30548	-12.05	<0.0001			
Const(4)	-0.89979	0.20860	-4.31	<0.0001			
LOS							
1-2hr	2.34805	0.29669	7.91	<0.0001	10.47	5.85	18.72
2-3hr	4.70827	0.35362	13.31	<0.0001	110.86	55.43	221.71
More than 3hrs	5.77029	0.373317	15.46	<0.0001	320.63	154.25	666.46
Oph patient							
No	0.45828	0.26803	1.71	0.087	1.58	0.94	2.67
Hospital patient							
No	-0.49766	0.33244	-1.50	0.134	0.61	0.32	1.17

Considering other statistics, the Coef or coefficients are used to analyze how the probability of an outcome changes as predictor variables change. These coefficients represent the change in the link function for each unit change in the predictor, while holding other predictors constant. In this study, all predictors (factors) are categorical data. Here, the first event refers to satisfaction score 1, and the last event to satisfaction score 5. For instance, regarding the LOS predictor, which includes categories "less than 1hr", "1-2hr", "2-3hr", and "more than 3hr", with "less than 1hr" being the reference level, a positive coefficient associated with other levels indicates that patients with LOS more than 1 hr are more likely to have satisfaction score 1 compared to those with LOS less than 1hr. Similarly, for the Oph patient predictor with options "Yes" or "No", where "No" is the reference level, a positive coefficient with the level "No" suggests that patients visiting the Ophthalmology department for the first time are more likely to have satisfaction score 1 than current patients in the department. Finally, for the hospital patient predictor with options "Yes" or "No", where "No" is the reference level, a negative coefficient with the level "No" implies that patients visiting the hospital for the first time are more likely to have satisfaction score 5 than current hospital patients.

The regression analysis produced probabilities for each satisfaction level based on significant factors, $P(S_a)$, as shown in Table 4.7 and 4.8. These probabilities will be utilized in the simulation model to predict patient satisfaction related to LOS. The significant factors identified, such as LOS, hospital patient status, and Oph patient status, provide a statistical basis for these probability estimates. This approach ensures that the simulation model accurately reflects the influence of these key variables on patient satisfaction levels.

Table 4.7: Probabilities of Patient Satisfaction Levels Based on Significant Factors from Regression Analysis: LOS less than 1 hr and LOS between 1 and 2 hr.

LOS	Less than 1 hr				1-2 hr			
Oph patient	Yes		No		Yes		No	
TUH patient	Yes	No	Yes	No	Yes	No	Yes	No
$P(S_1)$	0.001	0.000	0.001	0.001	0.006	0.004	0.010	0.006
$P(S_2)$	0.003	0.002	0.004	0.003	0.027	0.017	0.042	0.026
$P(S_3)$	0.021	0.013	0.033	0.021	0.176	0.118	0.243	0.170
$P(S_4)$	0.264	0.183	0.353	0.257	0.601	0.583	0.576	0.601
$P(S_5)$	0.711	0.802	0.609	0.719	0.190	0.279	0.129	0.196

Table 4.8: Probabilities of Patient Satisfaction Levels Based on Significant Factors from Regression Analysis: LOS between 2 and 3 hr and LOS more than 3 hr.

LOS	Less than 1 hr				1-2 hr			
Oph patient	Yes		No		Yes		No	
TUH patient	Yes	No	Yes	No	Yes	No	Yes	No
$P(S_1)$	0.063	0.039	0.097	0.061	0.164	0.106	0.236	0.158
$P(S_2)$	0.204	0.142	0.269	0.199	0.350	0.285	0.389	0.346
$P(S_3)$	0.469	0.448	0.450	0.469	0.376	0.440	0.302	0.382
$P(S_4)$	0.242	0.335	0.171	0.249	0.102	0.157	0.068	0.106
$P(S_5)$	0.022	0.035	0.014	0.023	0.008	0.012	0.005	0.008

4.2.2 Satisfaction related to physician assignment computation

To compute patient satisfaction related to physician assignment, patient symptoms were first categorized into three levels: easy, hard, and varied, as shown in Table 4.2. Based on this categorization, the probabilities of expected satisfaction for each patient, derived from the collected data, were calculated. Table 4.9 presents these probabilities, detailing the expected satisfaction levels for patients based on their symptom category. For instance, patients with symptoms classified as easy have a 26% probability of being satisfied when seen by a general physician, a 29% probability of being satisfied when seen by a specialist physician, and a 45% probability of having no preference for either type of physician.

Table 4.9: Probability of Expected Satisfaction by Symptom Level

Expectation	Symptom		
	Easy	Hard	Varied
Satisfied with general physician	0.26	0.33	0.33
Satisfied with specialist physician	0.29	0.64	0.61
No preference	0.45	0.14	0.06

These probabilities will be applied in the simulation to assign the expected physician that each patient would like to meet, denoted as EXP_p. Subsequently, the satisfaction score will be calculated using Eq (3.2). This approach helps in predicting patient satisfaction based on the type of physician they are likely to encounter, which is critical for optimizing physician assignments and improving the overall patient experience.

4.2.3 Patients' time analysis

For the patient time analysis, detailed time stamps were collected at each process station throughout the patient's journey. This data included the exact times at which patients arrived at and departed from each station. By using the Input Analyzer program, we were able to create precise distributions for both processing times and arrival times at these stations. These distributions help in understanding the flow and identifying potential bottlenecks within the department. The results, which are summarized in Table 4.10, provide critical insights into how long patients spend at each station and the intervals between their arrivals. This information is essential for building a more accurate and effective simulation model, enabling the identification of inefficiencies and the implementation of targeted improvements.

Table 4.10: Distribution of Processing and Arrival Times at Each Process Station

Operation	Distribution	Parameter (second)	Constant (second)	Expression
Interarrival rate	Exponential	Mean=0.496	1	1+EXPO(0.496)
Scan code	Triangular	Min=15 Mode=30 Max=45	-	TRIA(15,30,45)
Triage	Erlang	ExpMean=19.9 k=2	27	27+ERLA(19.9,2)
Get file	Triangular	Min=12 Mode=30 Max=60	-	TRIA(12,30,60)
VAT	Triangular	Min=52 Mode=108 Max=226	-	TRIA(52,108,226)
ET	Erlang	ExpMean=6.61 k=3	11.5	11.5+ERLA(6.61,3)
AR	Erlang	ExpMean=14.4 k=2	26	26+ERLA(14.4,2)
D	Discrete	CumP1=0.9 Val1=1200 CumP2=1 Val2=1800	-	DISC(0.9,1200,1,1800)
OCT	Triangular	Min=250 Mode=360 Max=600	-	TRIA(250,360,600)
OI	Triangular	Min=180 Mode=390 Max=600	-	TRIA(180,390,600)
IOM	Triangular	Min=300 Mode=480 Max=600	-	TRIA(300,480,600)
VF	Triangular	Min=1500 Mode=1800 Max=2400	-	TRIA(1500,1800,2400)
Consult	Uniform	Min=300 Max=900	-	UNIF(300,900)
Post-consult	Uniform	Min=300 Max=600	-	UNIF(300,600)
Payment and Appointment booking	Triangular	Min=60 Mode=120 Max=180	-	TRIA(60,120,180)

4.3 DES Modeling

After gathering all information from the data collection and data preparation sections, a DES model was constructed. This model integrates the various data sets and findings to simulate the patient flow and satisfaction within the ophthalmology department. The raw data, transformed into actionable information, includes patient satisfaction related to LOS, physician assignment probabilities based on symptom categories, and time distributions for each process station. These components were critical in creating a comprehensive and realistic simulation. By combining these elements, the DES model offers a powerful tool to analyze and optimize the department's operations. It can be used to identify bottlenecks, test the impact of staffing changes, and ultimately enhance patient satisfaction by streamlining processes and improving resource allocation. This comprehensive approach ensures that the simulation model is grounded in empirical data, making its predictions and recommendations highly reliable.

4.3.1 Parameter setting

To build the simulation model, in addition to the flow pattern and processing time, it is essential to define the setup parameters, which include the number of replications of the simulation run, the replication length of each run, and the warm-up period to allow the model to reach a stable state.

The number of replications, replication lengths, and warm-up periods are user-specified. Each replication in this study represents one week of working days, from Monday to Friday, between 7:00 and 15:00, equivalent to eight hours per day for five days. To account for potential variations where patient appointments might extend beyond eight hours, a buffer is added, resulting in a replication length of 10 hours. The total simulation time for each replication is set at 50 hours.

Initially, five replications were used, but the error calculation, following Kelton et al.'s method [27], exceeded an acceptable threshold of 5%. Consequently, the number of replications was recalculated, and ten replications were found to meet the acceptable error threshold which is 3.46%.

Notably, no warm-up period is included in this research. Although warm-up periods are common in simulation models, they are typically used when simulating the start of a business or environments with no initial customers, such as restaurants. In the hospital context, the system starts with no patients, and this study focuses on resource management from the beginning of the day until the end, rather than during a steady-state period.

4.3.2 Model verification and validation

Verification involves comparing the length of stay (LOS) calculated by summing all processing times with the LOS generated by the simulation model. Assuming no queuing during the process, the calculated sum of processing times is 78 minutes, which matches the LOS produced by the simulation model. This comparison confirms the accuracy of the simulation model's logic.

Validation is conducted by comparing the average patient satisfaction related to LOS from the simulation model with the average patient satisfaction scores collected during the survey. A t-test is used to assess any differences between the two datasets. As shown in Table 4.11, the p-value is 0.113, which exceeds the threshold of 0.05. Therefore, no statistically significant difference is observed between the results from the simulation model and the survey scores. This outcome validates the simulation model's ability to accurately represent the real system.

Table 4.11: t-Test Results Comparing Survey and Simulation Data on Patient Satisfaction Related to LOS

Data	n	Mean	SD	t-value	df	p-value
Survey	116	4.077	0.8660	1.59	119	0.113
Simulation	10	3.940	0.0956			

4.3.3 Base case

The process of building the DES model serves as a crucial foundation for subsequent multi-objective optimization efforts. Various inputs are carefully considered, including the queuing policy dictating patient prioritization and resource allocation, alongside factors like the number of resources such as physicians and equipment. The outputs generated by the DES model are satisfaction scores specifically related to patient LOS and physician assignment.

Following the establishment and validation of the model, simulations were executed using the current operational conditions, referred to as the "Current scenario". The simulation results exhibited a notable consistency with the operational dynamics of the actual hospital system.

In this scenario, we assumed zero investment cost, implying the absence of additional resource or physician allocation. The outcomes revealed an impressive average patient satisfaction score related to the LOS, with a mean value of 3.9936 and a standard deviation of 0.0446. Concurrently, the average patient satisfaction score associated with the physician assignment was computed to be 1.8928, accompanied by a standard deviation of 0.0295.

Beyond the output satisfaction scores, the model also identified bottlenecks in the DES model from resource utilization and queue times. The processes with the longest queue times and highest utilization rates were scan code, triage, and the VF test. These processes will be targeted to determine the optimum number of resources required to solve the bottleneck issues. These results, serving as the base case, provide the foundation for the forthcoming evaluation of the optimization's impact on the system.

4.4 Multi-Objective Optimization

The optimization phase of our study represents a critical stage where we sought to identify and implement scenarios that maximizes patient satisfactions while minimizing costs. This stage stands as a pivotal component in the comprehensive integrated approach for hospital system enhancement. We employed a robust approach, combining the principles of multi-objective optimization with fuzzy linear programming, reinforced by weight assignment. The outcome is the development of a resource allocation strategy that optimally caters to the specific needs of the hospital, in both efficiency and quality of care. The results of this optimization process are detailed below, showcasing the performance of both the current scenario and our proposed scenario. These outcomes offer invaluable insights into the practicality and feasibility of our proposed integrated approach to the hospital system.

The optimization process is facilitated by OptQuest, and each optimization run requires approximately 8-10 hours to complete. Two distinct optimization scenarios were considered, with each scenario yielding optimal solutions from a total of 28 cases as shown in Table 3.3. These cases encompass three solutions resulting from single-objective optimizations and 25 solutions originating from the multi-objective optimizations. The optimization objectives encompass patient satisfaction related to LOS (Z_1), patient satisfaction related to physician assignment (Z_2), investment costs (Z_3), and λ for the multi-objective optimization.

4.4.1 Current scenario optimization result

Table 4.12 presents the optimization results. For the single-objective optimization, the weight of the target objective is set to one, while all other weights are set to zero. The optimization results for the current scenario were obtained. In case 1, the objective is to maximize patient satisfaction related to the LOS. As a result, Z_1 is high, reflecting the focus on minimizing patient LOS and ensuring timely care. The optimization yields the highest satisfaction score related to LOS at 4.0344, a satisfaction score related to physician assignment of 1.9147, and an investment cost of 404,000 Baht.

In case 2, the goal is to maximize patient satisfaction regarding physician assignments. Comparing this case to Case 1, we observe that while Z_2 is high, the Z_1 decreases because the focus has shifted away from reducing the LOS to improving the match between patients and their preferred physicians. The optimization results in a satisfaction score related to LOS of 4.0051, the highest satisfaction score related to physician assignment at 1.9502, and an investment cost of 622,750 Baht.

In case 3, the objective in this case is to minimize additional costs associated with resource allocation. The function aims to minimize investments or additional expenses, resulting in a scenario where no additional resources are allocated. Consequently, this leads to a trade-off where cost savings are achieved at the expense of patient satisfaction metrics. The optimization leads to a satisfaction score related to LOS of 3.9936, a satisfaction score related to physician assignment of 1.8928, and an investment cost of 0 Baht.

These results illustrate the trade-offs inherent in focusing on different single objectives. Prioritizing one aspect, such as LOS or physician assignment, can negatively impact the other metrics, highlighting the need for a balanced approach in multi-objective optimization.

For the multi-objective optimization, considering different weight settings, the results show that the satisfaction scores related to LOS vary between 4.0017 and 4.0435, the satisfaction score related to physician assignment varies between 1.8831 and 1.9342, and the investment cost varies between 24,750 and 546,800 Baht.

4.4.2 Our proposed scenario optimization result

Table 4.13 displays the outcomes of the optimization process. In the case of single-objective optimization, the weight of the chosen objective is assigned a value of one, while all other weights are set to zero. When the goal is to maximize patient satisfaction related to LOS, the optimization attains the highest satisfaction score for LOS, which is 4.1382, along with a satisfaction score of 1.9336 related to physician assignment and an investment cost of 508,550 Baht. In the scenario aimed at maximizing patient satisfaction related to physician assignment, the optimization results in a satisfaction score for LOS of 4.0000, the highest satisfaction score for physician assignment at 1.9614, and an investment cost of 708,450 Baht. For the scenario that focuses on minimizing investment cost, the optimization produces a satisfaction score related to LOS of 3.7765, a satisfaction score for physician assignment of 1.7989, and an investment cost of 0 Baht. In this case, the resource and physician numbers remain the same as the current scenario without optimization.

In the context of multi-objective optimization, while exploring various weight settings, the outcomes indicate that the satisfaction scores associated with LOS exhibit a range between 3.9981 and 4.1095. Likewise, the satisfaction scores pertaining to physician assignment display variability within the range of 1.8586 to 1.9646. Additionally,

Table 4.12: The Obtained Optimization Results from Current Scenario

Case	Objective	λ	Z_1	Z_2	Z_3
1		-	4.0344	1.9147	404,000
2	Single	-	4.0051	1.9502	622,750
3		-	3.9936	1.8928	0
4		1	4.0017	1.9312	305,700
5		1	4.0098	1.9014	404,350
6		1	4.0123	1.8941	415,250
7		1	4.0132	1.8967	481,700
8		1	4.0247	1.8850	546,800
9		1	4.0098	1.9024	24,750
10		1	4.0434	1.8900	103,700
11		1	4.0213	1.8831	45,350
12		1	4.0259	1.9227	250,800
13		1	4.0435	1.8900	103,700
14		1	4.0101	1.9175	44,500
15		1	4.0046	1.9312	65,100
16	Multiple	1	4.0116	1.9342	100,7500
17		1	4.0105	1.9258	119,250
18		1	4.0048	1.9283	126,000
19		1	4.0109	1.9141	136,050
20		1	4.0018	1.9198	429,600
21		1	4.0144	1.9107	126,750
22		1	4.0084	1.9342	508,200
23		1	4.0166	1.9152	261,200
24		1	4.0073	1.9289	396,000
25		1	4.0221	1.9127	119,250
26		1	4.0192	1.9017	122,200
27		1	4.0196	1.9160	476,200
28		1	4.0259	1.9067	464,450

the investment cost spans a spectrum from 24,750 to 584,550 Baht.

Table 4.13: The Obtained Optimization Result from Our Proposed Scenario

Case	Objective	λ	Z_1	Z_2	Z_3
1		-	4.1382	1.9336	508,550
2	Single	-	4.0000	1.9614	708,450
3		-	3.7765	1.7989	0
4		1	4.0145	1.9449	337,200
5		1	4.0242	1.9165	400,200
6		1	4.0665	1.8586	445,550
7		1	4.0672	1.8923	553,050
8		1	4.0773	1.8841	584,550
9		1	3.9981	1.8981	24,750
10		1	4.0181	1.8965	132,250
11		1	4.0244	1.8819	45,350
12		1	4.0297	1.9205	250,800
13		1	4.1095	1.8919	121,350
14		1	4.0106	1.9052	56,250
15		1	4.0124	1.9132	65,250
16	Multiple	1	4.0108	1.9214	108,350
17		1	4.0132	1.9223	132,250
18		1	4.0257	1.9342	152,850
19		1	4.0277	1.9189	274,200
20		1	4.0275	1.9318	136,050
21		1	4.0349	1.9118	113,750
22		1	4.0337	1.9646	463,200
23		1	4.0353	1.8999	210,300
24		1	4.0413	1.8851	361,000
25		1	4.0048	1.9336	119,250
26		1	4.0755	1.8723	293,600
27		1	4.0585	1.9226	476,200
28		1	4.0124	1.9047	482,950

4.5 Comparative Result

Further statistical analysis was conducted to examine the differences among the optimization results. To achieve this, Tukey's test, a widely recognized post hoc test for multiple comparisons [88], was employed. The analysis aimed to identify statistically significant distinctions in satisfaction scores related to LOS and physician assignment, as well as variations in investment costs between different optimization scenarios. The results of the Tukey's test revealed significant differences among the various scenarios. These findings provide valuable insights into which optimization strategies yield superior outcomes and, in turn, assist in making informed decisions on resource allocation and process enhancements within the hospital system.

The ANOVA analysis, which includes the base case, reveals that the interaction between scenarios and cases is highly significant with a p-value less than 0.001 for both patient satisfaction related to LOS and physician assignment as shown in Table 4.14 and 4.15. This significance underscores that the combined influence of scenarios and cases significantly affects patient satisfaction scores in both categories. Following the ANOVA analysis, the next step involves running Tukey's test to rank the satisfaction values. This post hoc test will provide further insights into the specific differences among scenarios and cases, helping to identify which ones contribute to the observed significant variations in patient satisfaction.

Table 4.14: ANOVA Table of Patient Satisfaction Related to LOS

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Case	27	0.4005	0.0148	7.24	<0.001
Scenario	2	0.1640	0.0820	40.05	<0.001
Replication	9	0.2138	0.0238	11.60	<0.001
Case*Scenario	54	0.5858	0.0109	5.30	<0.001
Error	747	1.5296	0.0021		
Total	839	2.8937			

Table 4.15: ANOVA Table of Patient Satisfaction Related to Physician Assignment

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Case	27	0.1951	0.0072	6.03	<0.001
Scenario	2	0.0599	0.0300	25.03	<0.001
Replication	9	0.0930	0.0103	8.63	<0.001
Case*Scenario	54	0.1762	0.0033	2.72	<0.001
Error	747	0.8947	0.0012		
Total	839	1.4190			

In this study, events are defined as combinations of scenarios and cases. Table 4.16 shows the Tukeys' result of comparing satisfaction score related to LOS and Table 4.17 shows the comparing of satisfaction related to physician assignment. To analyze the patient satisfaction scores associated with LOS and physician assignment, events are grouped based on the average satisfaction values. The grouping consists of two dimensions: for LOS-related satisfaction, it ranges from Group A (highest) to Group D (lowest), and for physician assignment-related satisfaction, it ranges from Group A to Group J (lowest). Events with the same group letter are considered statistically similar.

The base case is an integral part of this comparison, defining the reference level for each event. For LOS-related satisfaction, the base case falls within Group C. Events grouped in Group A and B are labeled as 'Higher' indicating higher satisfaction levels. These events include those from scenario 2 and cases 1 and 13. Meanwhile, events in the same grouping as the base case are labeled as 'Unchanged'. Only one event, scenario 2 case 3 in Group D, is labeled as 'Lower', indicating lower satisfaction than the base case.

For satisfaction related to physician assignment, the base case ranges from Group E to I. Events in Groups A to D are labeled 'Higher' including events from scenario 2 and cases 1, 2, 4, 18, 22, and 25, along with those from scenario 1 and cases 2, 16, and 22. Events in Groups E to I are labeled as 'Unchanged'. Only one event, scenario 2, case 3, is in Group J, indicating lower satisfaction than the base case. The 'Cost' column represents the investment cost required to enhance the system for each event, with several events showing zero cost, including the base case and events focused on minimizing investment cost in a single-objective approach. The significance of these results will be discussed in the following section.

Table 4.16: Tukey's Test Results for Scenario and Case on Satisfaction Related to LOS with Labeled Comparisons. The base case is highlighted as the benchmark in comparison.

Scenario	Case	Mean LOS	Group	Labeled	Cost	Scenario	Case	Mean LOS	Group	Labeled	Cost
2	1	4.1382	A	Higher	508,550	2	4	4.0145	C	Unchanged	337,200
2	13	4.1095	AB	Higher	121,350	1	21	4.0144	C	Unchanged	126,750
2	8	4.0773	ABC	Unchanged	584,550	2	17	4.0132	C	Unchanged	132,250
2	26	4.0755	ABC	Unchanged	293,600	1	7	4.0132	C	Unchanged	481,700
2	7	4.0672	ABC	Unchanged	553,050	2	15	4.0124	C	Unchanged	69,250
2	6	4.0665	ABC	Unchanged	445,550	2	28	4.0124	C	Unchanged	482,950
2	27	4.0585	ABC	Unchanged	476,200	1	6	4.0123	C	Unchanged	415,250
1	10	4.0435	BC	Unchanged	103,700	1	16	4.0116	C	Unchanged	100,750
1	13	4.0435	BC	Unchanged	103,700	1	19	4.0109	C	Unchanged	136,050
2	24	4.0413	BC	Unchanged	361,000	2	16	4.0108	C	Unchanged	108,350
2	23	4.0353	BC	Unchanged	210,300	2	14	4.0106	C	Unchanged	56,250
2	21	4.0349	BC	Unchanged	113,750	1	17	4.0105	C	Unchanged	119,250
1	1	4.0344	BC	Unchanged	404,000	1	14	4.0101	C	Unchanged	44,500
2	22	4.0337	BC	Unchanged	463,200	1	5	4.0098	C	Unchanged	404,350
2	12	4.0297	BC	Unchanged	250,800	1	9	4.0098	C	Unchanged	24,750
2	19	4.0277	BC	Unchanged	274,200	1	22	4.0084	C	Unchanged	508,200
2	20	4.0275	BC	Unchanged	136,050	1	24	4.0073	C	Unchanged	396,000
1	12	4.0259	BC	Unchanged	250,800	1	2	4.0051	C	Unchanged	622,750
1	28	4.0259	BC	Unchanged	464,450	1	18	4.0048	C	Unchanged	126,000
2	18	4.0257	BC	Unchanged	152,850	2	25	4.0048	C	Unchanged	119,250
1	8	4.0247	BC	Unchanged	546,800	1	15	4.0046	C	Unchanged	65,100
2	11	4.0244	BC	Unchanged	45,350	1	20	4.0018	C	Unchanged	429,600
2	5	4.0242	BC	Unchanged	400,200	1	4	4.0017	C	Unchanged	305,700
1	25	4.0221	C	Unchanged	119,250	2	2	4.0000	C	Unchanged	708,450
1	11	4.0213	C	Unchanged	45,350	2	9	3.9981	C	Unchanged	24,750
1	27	4.0196	C	Unchanged	476,200	**0**	**0**	**3.9937**	**C**	**Base case**	**0**
1	26	4.0192	C	Unchanged	122,200	1	3	3.9937	C	Unchanged	0
2	10	4.0181	C	Unchanged	132,250	2	3	3.7765	D	Lower	0
1	23	4.0166	C	Unchanged	261,200						

Table 4.17: Tukey's Test Results for Scenario and Case on Satisfaction Related to Physician Assignment (PA) with Labeled Comparisons. The base case is highlighted as the benchmark in comparison.

Scenario	Case	Mean PA	Group	Labeled	Cost	Scenario	Case	Mean PA	Group	Labeled	Cost
2	22	1.9646	A	Higher	463,200	1	25	1.9127	CDEFG	Unchanged	119,250
2	2	1.9614	AB	Higher	708,450	2	21	1.9118	CDEFG	Unchanged	113,750
1	2	1.9502	AB	Higher	622,750	1	21	1.9107	CDEFGH	Unchanged	126,750
2	4	1.9449	AB	Higher	337,200	1	28	1.9067	DEFGH	Unchanged	464,450
1	22	1.9342	ABC	Higher	508,200	2	14	1.9052	DEFGH	Unchanged	56,250
1	16	1.9342	ABCD	Higher	100,750	2	28	1.9047	DEFGH	Unchanged	482,950
2	18	1.9342	ABCD	Higher	152,850	1	9	1.9024	DEFGH	Unchanged	24,750
2	1	1.9336	ABCD	Higher	508,550	1	26	1.9017	DEFGHI	Unchanged	122,200
2	25	1.9336	ABCD	Higher	119,250	1	5	1.9014	DEFGHI	Unchanged	404,350
2	20	1.9318	ABCDE	Unchanged	136,050	2	23	1.8999	DEFGHI	Unchanged	210,300
1	4	1.9312	ABCDE	Unchanged	305,700	2	9	1.8981	EFGHI	Unchanged	24,750
1	15	1.9312	ABCDE	Unchanged	65,100	1	7	1.8967	EFGHI	Unchanged	481,700
1	24	1.9289	ABCDE	Unchanged	396,000	2	10	1.8965	EFGHI	Unchanged	132,250
1	18	1.9283	ABCDE	Unchanged	126,000	1	6	1.8941	EFGHI	Unchanged	415,250
1	17	1.9258	ABCDE	Unchanged	119,250	1	3	1.8928	EFGHI	Unchanged	0
1	12	1.9227	BCDEF	Unchanged	250,800	**0**	**0**	**1.8928**	**EFGHI**	**Base case**	**0**
2	27	1.9226	BCDEF	Unchanged	476,200	2	7	1.8923	EFGHI	Unchanged	553,050
2	17	1.9223	BCDEF	Unchanged	132,250	2	13	1.8919	EFGHI	Unchanged	121,350
2	16	1.9214	BCDEF	Unchanged	108,350	1	10	1.8900	EFGHI	Unchanged	103,700
2	12	1.9205	CDEFG	Unchanged	250,800	1	13	1.8900	EFGHI	Unchanged	103,700
1	20	1.9198	CDEFG	Unchanged	429,600	2	24	1.8851	FGHI	Unchanged	361,000
2	19	1.9189	CDEFG	Unchanged	274,200	1	8	1.8850	FGHI	Unchanged	546,800
1	14	1.9175	CDEFG	Unchanged	44,500	2	8	1.8841	FGHI	Unchanged	584,550
2	5	1.9165	CDEFG	Unchanged	400,200	1	11	1.8831	FGHI	Unchanged	45,350
1	27	1.9160	CDEFG	Unchanged	476,200	2	11	1.8819	GHI	Unchanged	45,350
1	23	1.9152	CDEFG	Unchanged	261,200	2	26	1.8723	HI	Unchanged	293,600
1	1	1.9147	CDEFG	Unchanged	404,000	2	6	1.8586	I	Unchanged	445,550
1	19	1.9141	CDEFG	Unchanged	136,050	2	3	1.7989	J	Lower	0
2	15	1.9132	CDEFG	Unchanged	69,250						

Chapter 5

Discussion

In the discussion section, we will delve into three main areas of analysis. First, we will present our recommended guidelines, offering strategic suggestions based on the findings from the study. These guidelines aim to improve patient satisfaction and optimize resource management in hospital settings. Second, we will explore the patient satisfaction survey responses, examining potential biases and the methodologies used for data collection. This will provide insights into the reliability and validity of the feedback obtained. Finally, we will compare our proposed integrated approach with existing approaches in the literature, highlighting the improvements and addressing the challenges that our method seeks to overcome. This comparative analysis will underscore the contributions and potential of our approach in advancing healthcare management practices.

5.1 Recommendations and Guidelines

According to the guideline in Fig. 3.2 and the comparison table in Table 4.16 and 4.17, we explore into the comparison results and employ the decision guidelines to provide recommendations to the hospital on policy selection for improvement. According to the comparison results, we grouped the events using labels from each satisfaction type and concluded that the events can be categorized into four sections: Lower-

Lower, Unchanged-Unchanged, Unchanged-Higher, and Higher-Higher. The first section, 'Lower-Lower', represents cases where both satisfaction score are labeled as lower. This implies that when the number of resources or the scenario, or both, is changed, the satisfaction score becomes lower than the base case. Therefore, event in this section, i.e. scenario 2 case 3, is not considered as improving results and is eliminated.

The second section is 'Unchanged-Unchanged' signifying that both types of satisfaction scores remain unchanged from the base case. This implies that there is no difference from the base case even when the number of resources, scenario, or both are altered. Consequently, events in this section are also eliminated.

The other two sections, 'Unchanged-Higher' and 'Higher-Higher' represent scenarios that could potentially be recommended as shown in Table 5.1. However, choosing the appropriate policy to enhance hospital performance is a challenging decision, as improvement necessitates investment. The required investment amount depends on the size of the hospital. In the hospital domain, facilities are typically categorized into three sizes based on the number of beds [89]: large, medium, and small. A large hospital has over 500 beds, a medium-sized one has 101-499 beds, and a small hospital has fewer than 100 beds.

Table 5.1: Possible Recommended Results

Scenario	Case	Mean LOS	Group	Labeled	Mean PA	Group	Labeled	Cost
2	1	4.1382	A	Higher	1.9336	ABCD	Higher	508,550
2	13	4.1095	AB	Higher	1.8919	EFGHI	Unchanged	121,350
2	22	4.0337	BC	Unchanged	1.9646	A	Higher	463,200
2	18	4.0257	BC	Unchanged	1.9342	ABCD	Higher	152,850
2	4	4.0145	C	Unchanged	1.9449	AB	Higher	337,200
1	16	4.0116	C	Unchanged	1.9342	ABCD	Higher	100,750
1	22	4.0084	C	Unchanged	1.9342	ABC	Higher	508,200
1	2	4.0051	C	Unchanged	1.9502	AB	Higher	622,750
2	25	4.0048	C	Unchanged	1.9336	ABCD	Higher	119,250
2	2	4.0000	C	Unchanged	1.9614	AB	Higher	708,450

While our research used a case study approach to demonstrate the integrated methodology, the underlying principles and techniques are designed to be scalable and adaptable to hospitals of different sizes. This comprehensive workflow is built with modular components that can be customized based on the specific needs and capacities of different healthcare facilities. For instance, the simulation models and optimization strategies can be adjusted to reflect varying patient volumes, staffing levels, and resource availability.

Moreover, the algorithms used for patient flow simulation and resource optimization are scalable, meaning they can handle different scales of data, from small community hospitals to large metropolitan healthcare centers, without losing accuracy or effectiveness. The core concepts of patient satisfaction, resource allocation, and queuing theory remain universally applicable across various healthcare settings.

By tweaking the input parameters (e.g., patient arrival rates, service times, resource constraints), this systematic process can be tailored to fit the unique operational dynamics of any hospital. The case study serves as a proof of concept, demonstrating the practical application and benefits of this holistic strategy. The positive results obtained provide a benchmark and inspire confidence in its applicability to other settings. These points highlight that while the case study provides specific insights, the design of this multi-faceted approach allows it to be adapted and applied to hospitals of various sizes and contexts, ensuring its broader relevance and utility in the healthcare sector.

5.1.1 Recommended Management Approaches for Small-Sized Hospitals

For small-sized hospitals, the investment cost is expected to be lower compared to other hospital sizes. Decision-makers may prioritize the lowest investment option due to budget constraints. Among the recommended results in Table 5.1, the 'Higher-Higher' section is anticipated to have higher investment costs, making the 'Unchanged-Higher' section more suitable for small hospitals. In the pursuit of minimizing investment, decision-makers are presented with two viable choices: an investment of 121,350 Baht per month, resulting in a higher satisfaction score related to LOS, or an investment of 100,750 Baht per month, yielding a higher satisfaction score related to physician assignment.

The selection between these options hinges on the decision-maker's objectives. If the hospital prioritizes greater satisfaction in LOS, the 121,350 Baht investment is recommended, aligning with scenario 2, case 13. This scenario involves adjusting the queuing policy for consultations to prioritize patients with the shortest processing time, necessitating the hiring of two physicians, one triage nurse, acquiring an additional queuing machine, and obtaining another VF machine. The total investment cost is calculated by multiplying the number of resources with their respective costs from Table 4.3 and summing them all together. Table 5.2 shows the summation of the number of additional resources from the optimized result that is recommended to the small-sized hospital.

Conversely, the hospital may opt for the 100,750 Baht investment to achieve higher satisfaction related to physician assignment, corresponding to scenario 1, case 16. In this scenario, patients are served on a first-come, first-served basis for consultations, entailing the hiring of two additional physicians, one triage nurse, and acquiring an additional queuing machine. The total investment cost is again determined by summing the costs of the required resources.

Table 5.2: Summary of Additional Resources Recommended for Small-Sized Hospitals

Scenario	Case	Optimum Additional Number of Resource				Total Investment Cost
		Physician	Triage nurse	Queue machine	VF machine	
2	13	2	1	1	1	121,350 Baht
1	16	2	1	1	-	100,750 Baht

5.1.2 Recommended Management Approaches for Medium-Sized Hospitals

For medium-sized hospitals, the investment costs typically have a higher threshold compared to smaller hospitals. Consequently, the 'Higher-Higher' section in the results, which includes only one event exceeding an investment cost of 500,000 Baht, may potentially surpass the budget constraint. Therefore, the 'Unchanged-Higher' section presents more feasible options. For instance, if we set the budget at 400,000 Baht per month, five events in Table 5.1 have investments within this limit: 121,350 Baht per month, 152,850 Baht per month, 337,200 Baht per month, 100,750 Baht per month, and 119,250 Baht per month, respectively. Among these options, if the hospital prioritizes minimizing costs, the investment of 100,750 Baht per month could be recommended to significantly improve satisfaction related to physician assignment, corresponding to scenario 1, case 16. In this scenario, patients are treated on a first-come, first-served basis for consultations, with the investment covering the hiring of two additional physicians, one triage nurse, and the acquisition of another queuing machine. However, if the decision-maker aims to enhance satisfaction in LOS, the investment of 121,350 Baht per month may be recommended, corresponding to scenario 2, case 13. This scenario prioritizes patients with shorter expected processing times to see the physician first, with the investment involving the hiring of two physicians, one triage nurse, the acquisition of another queuing machine, and obtaining another VF machine. Table 5.3 shows the summation of the number of additional resources from the optimized result that is recommended to the medium-sized hospital.

Table 5.3: Summary of Additional Resources Recommended for Medium-Sized Hospitals

Scenario	Case	Optimum Additional Number of Resource				Total Investment Cost
		Physician	Triage nurse	Queue machine	VF machine	
2	13	2	1	1	1	121,350 Baht
1	16	2	1	1	-	100,750 Baht

5.1.3 Recommended Management Approaches for Large-Sized Hospitals

For large-sized hospitals, which typically claims more substantial budgets and resources, the investment amount might not be a limiting factor. Therefore, the decision-maker can choose the event in the 'Higher-Higher' section as the preferred policy for improvement. This section means that the satisfaction scores in both types significantly improve from the base case. Specifically, the event of scenario 2 case 1 is recommended. This scenario involves a change in the queuing policy for consultations, prioritizing the shortest processing time for patients to see the physician first. Table 5.4 shows the summation of the number of additional resources from the optimized result that is recommended to the large-sized hospital. The associated investment cost for this policy is 508,550 Baht per month, which involves the recruitment of 11 additional physicians, three more triage nurses, and the acquisition of two more queuing machines and three additional VF machines. However, it's crucial to note that this paper employs the case study of Thammasat University Hospital, a large-sized hospital, leading to potential variations in hiring costs and equipment expenses compared to smaller institutions.

Table 5.4: Summary of Additional Resources Recommended for Large-Sized Hospitals

Scenario	Case	Optimum Additional Number of Resource				Total Investment Cost
		Physician	Triage nurse	Queue machine	VF machine	
2	1	11	3	2	3	508,550 Baht

5.2 Analysis of Patient Satisfaction Survey Responses

Our analysis of the patient satisfaction survey reveals several important insights regarding its bias and data quality. This discussion will address key areas of concern and their potential impact on the survey's validity and reliability. The survey design effectively captures patient satisfaction related to LOS and physician assignment, with questions evaluated by experts for reliability and relevance. This approach strengthens the survey's content validity, ensuring that it measures the intended constructs. However, focusing specifically on LOS and physician assignment may overlook other important aspects of patient satisfaction, potentially limiting the survey's scope. With a sample size of 232 surveys, the study meets the statistical requirements for a 95% confidence level with a ±6% margin of error. While this sample size is adequate for basic analysis, it's relatively small for a healthcare setting, potentially limiting the ability to conduct more nuanced subgroup analyses or detect subtle trends. Future iterations might benefit from a larger sample to increase precision and allow for more detailed statistical analyses.

The data collection method, implemented after service completion, introduces potential recall bias. Patients' responses, particularly regarding their initial expectations, may be influenced by their recent experiences, potentially skewing results. This timing issue is especially critical for questions about patient expectations, as these might be retrospectively adjusted based on the care received. Consideration should be given to collecting expectation data at multiple time points, including pre-service, to capture a more accurate picture of patient perspectives.

The survey environment, characterized by the presence of other patients and potentially longer wait times, could lead to social desirability bias. Patients may show increased empathy towards staff and be less inclined to express dissatisfaction, particularly if they've observed high patient volumes or overworked staff. This bias could result in artificially inflated satisfaction scores, masking areas that truly need improvement. Future surveys might explore methods to reduce this bias, such as delayed follow-up surveys or anonymous online submissions.

The decision to remove incomplete surveys from the analysis, while maintaining data integrity, may introduce non-response bias. Patients who didn't complete the survey might have had systematically different experiences or opinions, potentially skewing the results. An analysis of the characteristics of non-respondents or partially completed surveys could provide insights into this potential bias.

Despite these limitations, the survey data quality appears sufficient to provide valuable insights within the acceptable margin of error. The careful design and expert validation of questions enhance the survey's reliability. However, the relatively small sample size and potential biases necessitate cautious interpretation of the results, particularly when making comparisons or drawing definitive conclusions.

In conclusion, while the current survey provides valuable insights into patient satisfaction regarding LOS and physician assignment, there is room for methodological improvements. By addressing the identified biases and expanding the scope and sample size, future iterations of this survey could provide even more robust and actionable data for improving patient care and satisfaction.

5.3 Framework Comparison with Previous Work

A comprehensive analysis of existing frameworks reveals both the advancements and limitations in addressing patient satisfaction and hospital resource optimization. Cabrera's work [62] enhances simulation and optimization operations, aiming to minimize

LOS. While it effectively highlights various factors affecting LOS, it falls short in practical application and fails to address multiple objectives simultaneously. This gap underscores the need for more holistic approaches that can be readily implemented in real-world healthcare settings. Chang's research [63] takes a step forward by linking patient and family demands to process improvement, demonstrating that increasing resources can elevate satisfaction levels. However, this framework lacks a robust optimization component to determine the optimal resource allocation, leaving healthcare administrators without clear guidance on efficient resource distribution. Fan's approach [30] introduces an innovative element by incorporating patient preferences and developing a predictive model based on patient behavior patterns. While this adds a personalized dimension to satisfaction assessment, its narrow focus on behavioral patterns may overlook other crucial aspects of patient satisfaction, such as quality of care or communication effectiveness.

Ordu's work [70] stands out for its comprehensive approach, optimizing hospital resources and integrating linear optimization across all hospital services. This holistic view is commendable, yet the framework's limited applicability to hospitals of varying sizes restricts its widespread adoption, highlighting the need for more flexible and scalable solutions. Tanantong's research [28] aligns closely with our objectives by optimizing satisfaction in relation to LOS and cost. However, the reliability of their satisfaction prediction model, based on expert opinions, raises concerns about its accuracy and generalizability across different healthcare contexts. In contrast, our proposed integrated approach addresses many of the limitations identified in these existing approaches. We have developed an optimization model that enhances patient satisfaction while efficiently allocating hospital resources. Our integrated approach distinguishes itself through several key features:

- Reliable Satisfaction Prediction: Unlike Tanantong's expert-opinion-based model, we have implemented a more robust and data-driven method for predicting patient satisfaction, enhancing the reliability of our optimization outcomes.

- Multi-Factor Optimization: Our integrated approach incorporates the optimization of two critical factors influencing patient satisfaction, providing a more nuanced approach compared to single-factor models like Fan's behavior-based system.

- Scalability and Flexibility: Addressing the limitation in Ordu's work, our decision guidelines are designed to be applicable across hospitals of all sizes, ensuring broader relevance and adaptability.

- Practical Applicability: In response to the practical limitations of Cabrera's work, we have demonstrated our integrated approach's efficiency through a comprehensive case study, bridging the gap between theoretical models and real-world implementation.

- Balanced Approach: By considering both resource optimization and patient satisfaction, our integrated approach offers a more balanced solution compared to Chang's resource-focused approach or Fan's satisfaction-centric model.

The case study results validate the efficiency of our integrated approach, showcasing its ability to optimize resource allocation while enhancing patient satisfaction. This dual focus addresses a critical gap in existing research, where methodologies often excel in one area at the expense of another.

Moreover, our comprehensive workflow's ability to provide decision guidelines applicable to hospitals of all sizes represents a significant advancement. This feature addresses the scalability issues present in previous models, such as Ordu's, making our solution more versatile and widely applicable in the diverse landscape of healthcare institutions.

In conclusion, while existing strategies have made valuable contributions to the field, our proposed multi-faceted model represents a significant step forward. By addressing the challenges and limitations identified in previous research, our systematic process offers a more comprehensive, reliable, and practically applicable solution for optimizing hospital resources and enhancing patient satisfaction. The demonstrated performance of this holistic approach in real-world scenarios underscores its potential to drive meaningful improvements in healthcare delivery and patient experience.

Chapter 6

Contribution to Knowledge Science

6.1 Theoretical Contribution

1. **Development of a Patient-Centered Resource Management Integrated Approach:** This research presents a novel integrated approach that embeds patient satisfaction directly into resource management strategies, offering a comprehensive solution for healthcare optimization. Unlike traditional models, which often emphasize operational efficiency at the expense of patient experience, this approach integrates patient-centric outcomes into resource allocation decisions. By placing patients at the center of the resource management process, the integrated approach aims to achieve a balanced optimization, improving resource use while simultaneously enhancing patient satisfaction.

2. **Enhanced Understanding of Patient Satisfaction Factors:** This research not only considers LOS as a crucial factor affecting patient satisfaction in the simulation model but also examines the impact of physician assignment on patient satisfaction. It highlights the importance of matching patient needs with appropriate physician expertise to optimize overall satisfaction. By incorporating these key elements, the study provides a more comprehensive understanding of the factors that shape patient experiences and perceptions within the healthcare setting.

3. **Innovative Conversion of LOS to Satisfaction Scores:** This research proposes a unique and innovative method of using ordinal logistic regression for transforming LOS into a reliable and accurate measure of patient satisfaction. Traditional patient satisfaction surveys often rely on self-reported measures, which can be susceptible to various biases and inconsistencies. By leveraging the relationship between LOS and patient satisfaction, this research introduces a novel approach to quantifying satisfaction levels objectively and systematically. This approach enhances the precision and relevance of satisfaction metrics in healthcare research, enabling a more comprehensive understanding of patient experiences and perceptions.

6.2 Practical Contribution

1. **Application in Real-World Settings:** The application of the proposed integrated approach in a real-world case study highlights its practical relevance and effectiveness in tackling specific challenges within hospital operations. By implementing this approach in an actual healthcare setting, the research moves beyond theoretical exploration, offering critical insights into real-world complexities and practical considerations. The case study evaluates the performance of the integrated approach within a specific hospital, rigorously testing its effectiveness in addressing multifaceted challenges, such as resource limitations, operational intricacies, and patient diversity. This real-world application underscores the approach's adaptability and resilience in healthcare environments.

2. **Comprehensive Guidelines for OPD Improvements:** This research offers comprehensive and theoretically grounded guidelines for optimizing OPD operations, bridging the critical gap between theoretical research and practical application. The guidelines proposed in this research are firmly rooted in established theoretical principles and empirical evidence, ensuring their validity and applicability across diverse healthcare settings. Recognizing the diverse nature of healthcare facilities, this research establishes a flexible integrated approach

that can be adapted to hospitals of various sizes, from small community clinics to large academic medical centers. By accounting for the unique constraints and challenges faced by different healthcare environments, the guidelines offer scalable and tailored solutions, facilitating their implementation across a broad spectrum of outpatient settings.

3. **Guidance for Hospital Administrators:** The real-world implementation of the integrated approach offers critical guidance for hospital administrators and decision-makers, delivering practical insights for enhancing both operational efficiency and patient satisfaction. By illustrating the application of this approach in healthcare settings, the research provides a strategic road map for hospital leaders, helping them effectively manage the complexities of resource allocation while prioritizing patient-centered care. This research serves as a valuable tool for administrators aiming to optimize resource use and improve the overall patient experience.

4. **Feasibility in Healthcare Environments:** The case study's successful outcomes demonstrate the integrated approach's capacity to handle the unique challenges and complexities found in various healthcare settings. Whether applied in large academic medical centers, smaller community hospitals, or specialized care facilities, the approach has proven to be adaptable and scalable, addressing the distinct needs and operational constraints of each institution. Its flexibility ensures that it can be customized to meet different resource limitations, patient demographics, and operational requirements, making it an essential tool for optimizing resource management and improving patient satisfaction across diverse healthcare environments.

6.3 Contribution to Knowledge Science

1. **Introduction of a Novel Integrated Approach:** This research introduces a groundbreaking integrated approach that incorporates patient satisfaction into hospital resource management strategies. By considering patient satisfaction

alongside traditional goals such as cost efficiency and resource utilization, this approach presents a more comprehensive solution for healthcare management. It addresses a significant gap in the literature by highlighting the role of patient-centered care in driving better healthcare outcomes, offering a balanced framework that optimizes both operational performance and patient experiences. This innovation represents a key advancement in healthcare management practices, fostering a more patient-focused perspective.

2. **Enriching Existing Knowledge:** Through empirical validation and theoretical development, this research enriches existing knowledge in the field of healthcare management and optimization. By synthesizing insights from various disciplines, including operations research, healthcare administration, and patient experience studies, the research expands the theoretical understanding of hospital resource management. Additionally, the application of advanced optimization techniques and simulation modeling contributes to the refinement of existing methodologies, enhancing their practical relevance and effectiveness in real-world healthcare settings.

3. **Promising Avenues for Future Research:** This research identifies several promising avenues for future research within the realm of healthcare optimization and patient satisfaction. By demonstrating the feasibility and effectiveness of the proposed integrated approach in a specific context, the research opens the door to further exploration and refinement in other healthcare environments. Future research endeavors may include the development of specialized optimization models for different hospital departments, the integration of additional patient satisfaction metrics, and the exploration of emerging technologies such as artificial intelligence and machine learning in healthcare management. Additionally, the research highlights the importance of ongoing evaluation and adaptation of optimization strategies in response to evolving patient needs and healthcare trends.

Chapter 7

Conclusion and Recommendation

7.1 Conclusion

In response to the hospital's paramount concern for patient satisfaction, specifically focusing on LOS and physician assignment issues, This research presents a comprehensive integrated approach for enhancing hospital resource management, specifically tailored to OPD operations. The integrated approach was developed to address the pressing challenges of optimizing resource allocation and improving patient satisfaction, which are critical metrics in healthcare service quality. Key contributions include the formulation of methods for analyzing satisfaction surveys and computing satisfaction scores. By converting LOS into a reliable satisfaction score, derived from collected survey data, the research provided a more precise and holistic understanding of patient satisfaction. This innovative approach ensured that the evaluation of patient experiences moved beyond traditional metrics, capturing a fuller picture of the patient journey.

Additionally, the integration of a simulation model, scenario analysis, and multi-objective optimization has been pivotal in evaluating and comparing various performance improvements. The research formulated comprehensive guidelines for improving OPD operations, emphasizing enhancements in patient satisfaction. A multi-criteria decision guideline has been devised to assist decision-makers in selecting the most effective enhancements. These guidelines, grounded in empirical data and best practices, offer actionable insights for healthcare administrators aiming to improve the efficiency and quality of their services. Furthermore, the comprehensive solution developed in this research is designed to be applicable to hospitals of all sizes. This scalability ensures that the insights and tools provided can be universally implemented, enhancing patient satisfaction and operational efficiency across diverse healthcare settings. The research has utilized the case study of TUH to demonstrate the practical application of the integrated approach.

Tailoring our considerations to different hospital sizes revealed distinct recommendations. For large hospitals, the suggested improvements demonstrated enhancements in both types of satisfaction scores. In contrast, medium and small-sized hospitals face a choice between improving satisfaction related to LOS or physician assignment. This tailored approach ensures that recommendations align with each hospital's budget constraints and specific needs.

It is essential to acknowledge the limitations of this study, notably the impact of the COVID-19 situation in Thailand on data collection, resulting in a reduced number of patient surveys. Additionally, the diverse range of patient experiences and levels of understanding within public hospitals made it challenging for some patients to complete the survey. Despite this constraint, the findings shed light on potential improvements, providing a valuable foundation for future investigations.

In summary, this research significantly advances the field of healthcare management by providing a detailed, patient-centered approach to resource management. By integrating patient satisfaction into the core of resource optimization strategies, this study offers a practical and effective solution for improving the quality and efficiency of healthcare services. The findings and methodologies presented herein lay a strong foundation for future research and practical applications in the ever-evolving landscape of healthcare management.

7.2 Future Work

To expand the scope of this research, a significant challenge lies in addressing the dynamic nature of physicians' schedules, particularly in public, large, and teaching hospitals. The schedule often changes due to teaching commitments and emergency calls. Simulating with changing physician scheduling is one of the future study directions. While our focus has been on a specific department, the methodology and insights gained can be extended to other departments and applied across various healthcare settings.

While the proposed integrated approach has demonstrated its utility in enhancing patient satisfaction and resource optimization for the current operational scenario at the hospital, its applications can be extended to align with sustainable development goals (SDGs). Future research could explore leveraging this integrated approach to support initiatives related to good health and well-being, quality education, decent work and economic growth, and reducing inequalities. As a leading specialist ophthalmology center receiving numerous referral cases from other hospitals, improving resource planning through this integrated approach could enable the hospital to accept and serve a larger volume of referred patients, contributing to the goal of good health and well-being. Moreover, with the upcoming challenges of an aging society, where eye-related symptoms are common among the elderly population, the proposed integrated approach could be employed to develop 5-10 year resource planning strategies tailored to meet the anticipated healthcare needs of this demographic. Additionally, given the potential for future pandemic situations, the integrated approach's capabilities in simulating and optimizing resource allocation could be invaluable for proactive planning, ensuring the hospital's preparedness and resilience in the face of such public health emergencies. By expanding the scope of this research, the proposed integrated approach can serve as a versatile tool for sustainable development and adaptability in the healthcare sector.

Bibliography

[1] M. A. Holdsworth, "Health, wellness and wellbeing," *Revue Interventions économiques. Papers in Political Economy*, no. 62, 2019.

[2] C. O. Eriksson, R. C. Stoner, K. B. Eden, C. D. Newgard, and J.-M. Guise, "The association between hospital capacity strain and inpatient outcomes in highly developed countries: a systematic review," *Journal of general internal medicine*, vol. 32, pp. 686–696, 2017.

[3] D. X. Peng, Y. Ye, B. Feng, D. X. Ding, and G. R. Heim, "Impacts of hospital complexity on experiential quality: Mitigating roles of information technology," *Decision sciences*, vol. 51, no. 3, pp. 500–541, 2020.

[4] B. Shahverdi, H. Ghayoomi, E. Miller-Hooks, M. Tariverdi, and T. D. Kirsch, "Regional maximum hospital capacity estimation for covid-19 pandemic patient care in surge through simulation," in *2022 Winter Simulation Conference (WSC)*, pp. 508–520, IEEE, 2022.

[5] G. Widjaja, "Impact of human resource management on health workers during pandemics covid-19: systematic review," *International Journal of Health and Medical Sciences*, vol. 4, no. 1, pp. 61–68, 2021.

[6] C. Delpachithra and S. Jayasinghe, "Overcrowding and "floor" patients in state hospitals: institutions can make a difference," *Ceylon Medical Journal*, vol. 46, no. 2, 2014.

[7] M. T. Choudhry and S. Iqbal, "Management of overcrowding in opds of public hospitals using health information technology: An evaluation of telemedicine technology using utaut model in tertiary care public hospitals in pakistan," *Journal of Business and Management Research*, vol. 2, no. 2, pp. 231–260, 2023.

[8] M. M. Günal and M. Pidd, "Discrete event simulation for performance modelling in health care: a review of the literature," *Journal of Simulation*, vol. 4, pp. 42–51, 2010.

[9] W. A. van Lent, P. VanBerkel, and W. H. van Harten, "A review on the relation between simulation and improvement in hospitals," *BMC medical informatics and decision making*, vol. 12, no. 1, pp. 1–8, 2012.

[10] I. E. Murdoch, S. S. Morris, and S. N. Cousens, "People and eyes: statistical approaches in ophthalmology," *British Journal of Ophthalmology*, vol. 82, no. 8, pp. 971–973, 1998.

[11] L. W. Lim, L. W. Yip, H. W. Tay, X. L. Ang, L. K. Lee, C. F. Chin, and V. Yong, "Sustainable practice of ophthalmology during covid-19: challenges and solutions," *Graefe's Archive for Clinical and Experimental Ophthalmology*, vol. 258, pp. 1427–1436, 2020.

[12] T. H. Lai, E. W. Tang, and K. K. Li, "The implications of covid-19 to ophthalmology," *Coronavirus Disease-COVID-19*, pp. 637–655, 2021.

[13] T. A. Ciulla, M. V. Tatikonda, Y. A. ElMaraghi, R. M. Hussain, A. L. Hill, J. M. Clary, and E. Hattab, "Lean six sigma techniques to improve ophthalmology clinic efficiency," *Retina*, vol. 38, no. 9, pp. 1688–1698, 2018.

[14] A. C. Sommer and E. Z. Blumenthal, "Implementation of lean and six sigma principles in ophthalmology for improving quality of care and patient flow," *Survey of ophthalmology*, vol. 64, no. 5, pp. 720–728, 2019.

[15] Y.-C. Tham, R. Husain, K. Y. C. Teo, A. C. S. Tan, A. C. Y. Chew, D. S. Ting, C.-Y. Cheng, G. S. W. Tan, and T. Y. Wong, "New digital models of care in

ophthalmology, during and beyond the covid-19 pandemic," *British Journal of Ophthalmology*, 2021.

[16] A. W. Kam, S. Collins, T. Park, M. Mihail, F. F. Stanaway, N. L. Lewis, D. Polya, S. Fraser-Bell, T. V. Roberts, and J. E. Smith, "Using lean six sigma techniques to improve efficiency in outpatient ophthalmology clinics," *BMC Health Services Research*, vol. 21, pp. 1–9, 2021.

[17] O. A. Bjertnaes, I. S. Sjetne, and H. H. Iversen, "Overall patient satisfaction with hospitals: effects of patient-reported experiences and fulfilment of expectations," *BMJ quality & safety*, vol. 21, no. 1, pp. 39–46, 2012.

[18] G. Pink, M. Murray, and I. McKillop, "Hospital efficiency and patient satisfaction," *Health Services Management Research*, vol. 16, no. 1, pp. 24–38, 2003.

[19] M. Wang, G. G.-E. Liu, N. Bloom, H. Zhao, T. Butt, T. Gao, J. Xu, and X. Jin, "Medical disputes and patient satisfaction in china: How does hospital management matter?," *The International Journal of Health Planning and Management*, vol. 37, no. 3, pp. 1327–1339, 2022.

[20] P. L. Hudak and J. G. Wright, "The characteristics of patient satisfaction measures," *Spine*, vol. 25, no. 24, pp. 3167–3177, 2000.

[21] D. M. Wolf, L. Lehman, R. Quinlin, T. Zullo, and L. Hoffman, "Effect of patient-centered care on patient satisfaction and quality of care," *Journal of nursing care quality*, vol. 23, no. 4, pp. 316–321, 2008.

[22] E. Batbaatar, J. Dorjdagva, A. Luvsannyam, M. M. Savino, and P. Amenta, "Determinants of patient satisfaction: a systematic review," *Perspectives in public health*, vol. 137, no. 2, pp. 89–101, 2017.

[23] J. Pan, D. Liu, and S. Ali, "Patient dissatisfaction in china: what matters," *Social Science & Medicine*, vol. 143, pp. 145–153, 2015.

[24] O. Rasouli and M. H. Zarei, "Monitoring and reducing patient dissatisfaction: a case study of an iranian public hospital," *Total Quality Management & Business Excellence*, vol. 27, no. 5-6, pp. 531–559, 2016.

[25] S. S. Li, N. L. Herrick, R. R. Deshpande, B. J. Cronin, C. M. Reid, M. G. Brandel, M. K. Dobke, C. A. Johnson, and A. A. Gosman, "The impact of residents on patient satisfaction," *Annals of Plastic Surgery*, vol. 80, no. 5S, pp. S247–S250, 2018.

[26] W. Rössler, "Stress, burnout, and job dissatisfaction in mental health workers," *European archives of psychiatry and clinical neuroscience*, vol. 262, pp. 65–69, 2012.

[27] B. E. Lacy and J. L. Chan, "Physician burnout: the hidden health care crisis," *Clinical gastroenterology and Hepatology*, vol. 16, no. 3, pp. 311–317, 2018.

[28] T. Tanantong, W. Pannakkong, and N. Chemkomnerd, "Resource management framework using simulation modeling and multi-objective optimization: a case study of a front-end department of a public hospital in thailand," *BMC Medical Informatics and Decision Making*, vol. 22, no. 1, pp. 1–21, 2022.

[29] A. Ala, V. Simic, M. Deveci, and D. Pamucar, "Simulation-based analysis of appointment scheduling system in healthcare services: A critical review," *Archives of Computational Methods in Engineering*, vol. 30, no. 3, pp. 1961–1978, 2023.

[30] X. Fan, J. Tang, C. Yan, H. Guo, and Z. Cao, "Outpatient appointment scheduling problem considering patient selection behavior: data modeling and simulation optimization," *Journal of Combinatorial Optimization*, vol. 42, pp. 677–699, 2021.

[31] B. Williams, "Patient satisfaction: a valid concept?," *Social science & medicine*, vol. 38, no. 4, pp. 509–516, 1994.

[32] R. Ladhari and B. Rigaux-Bricmont, "Determinants of patient satisfaction with public hospital services," *Health marketing quarterly*, vol. 30, no. 4, pp. 299–318, 2013.

[33] P. D. Cleary and B. J. McNeil, “Patient satisfaction as an indicator of quality care,” *Inquiry*, pp. 25–36, 1988.

[34] S. L. Clever, L. Jin, W. Levinson, and D. O. Meltzer, “Does doctor–patient communication affect patient satisfaction with hospital care? results of an analysis with a novel instrumental variable,” *Health services research*, vol. 43, no. 5p1, pp. 1505–1519, 2008.

[35] W. Diwan, P. A. Nakonezny, and J. Wells, “The effect of length of hospital stay and patient factors on patient satisfaction in an academic hospital,” *Orthopedics*, vol. 43, no. 6, pp. 373–379, 2020.

[36] G. J. Young, M. Meterko, and K. R. Desai, “Patient satisfaction with hospital care: effects of demographic and institutional characteristics,” *Medical care*, vol. 38, no. 3, pp. 325–334, 2000.

[37] R. Al-Abri and A. Al-Balushi, “Patient satisfaction survey as a tool towards quality improvement,” *Oman medical journal*, vol. 29, no. 1, p. 3, 2014.

[38] Y. A. Hong, C. Liang, T. A. Radcliff, L. T. Wigfall, and R. L. Street, “What do patients say about doctors online? a systematic review of studies on patient online reviews,” *Journal of medical Internet research*, vol. 21, no. 4, p. e12521, 2019.

[39] M. Zaghloul, S. Barakat, and A. Rezk, “Predicting e-commerce customer satisfaction: Traditional machine learning vs. deep learning approaches,” *Journal of Retailing and Consumer Services*, vol. 79, p. 103865, 2024.

[40] S. H. Lee, H. Lee, and J. H. Kim, “Enhancing the prediction of user satisfaction with metaverse service through machine learning.,” *Computers, Materials & Continua*, vol. 72, no. 3, 2022.

[41] A. R. Almasri, N. Yahaya, and S. S. Abu-Naser, “Instructor performance modeling for predicting student satisfaction using machine learning-preliminary results,” *Journal of Theoretical and Applied Information Technology*, vol. 100, no. 19, pp. 5481–5496, 2022.

[42] C. Yin and A. McKay, "Introduction to modeling and simulation techniques," in *Proceedings of ISCIIA 2018 and ITCA 2018*, Leeds, 2018.

[43] L. M. Leemis and S. K. Park, *Discrete-event simulation: A first course.* Pearson Prentice Hall Upper Saddle River, 2006.

[44] P. Bhattacharjee and P. K. Ray, "Patient flow modelling and performance analysis of healthcare delivery processes in hospitals: A review and reflections," *Computers & Industrial Engineering*, vol. 78, pp. 299–312, 2014.

[45] S. V. Kovalchuk, A. A. Funkner, O. G. Metsker, and A. N. Yakovlev, "Simulation of patient flow in multiple healthcare units using process and data mining techniques for model identification," *Journal of biomedical informatics*, vol. 82, pp. 128–142, 2018.

[46] R. Andrews, S. Suriadi, M. Wynn, A. H. ter Hofstede, and S. Rothwell, "Improving patient flows at st. andrew's war memorial hospital's emergency department through process mining," *Business Process Management Cases: Digital Innovation and Business Transformation in Practice*, pp. 311–333, 2018.

[47] E. Kim, S. Kim, M. Song, S. Kim, D. Yoo, H. Hwang, and S. Yoo, "Discovery of outpatient care process of a tertiary university hospital using process mining," *Healthcare informatics research*, vol. 19, no. 1, p. 42, 2013.

[48] P. Devapriya, C. T. Strömblad, M. D. Bailey, S. Frazier, J. Bulger, S. T. Kemberling, and K. E. Wood, "Stratbam: a discrete-event simulation model to support strategic hospital bed capacity decisions," *Journal of medical systems*, vol. 39, pp. 1–13, 2015.

[49] L. Luo, H. Liu, H. Liao, S. Tang, Y. Shi, and H. Guo, "Discrete event simulation models for ct examination queuing in west china hospital," *Computational and mathematical methods in medicine*, vol. 2016, 2016.

[50] M. Gul and A. F. Guneri, "A comprehensive review of emergency department simulation applications for normal and disaster conditions," *Computers & Industrial Engineering*, vol. 83, pp. 327–344, 2015.

[51] M. Brennan, J. D. Hagan, C. Giordano, T. J. Loftus, C. E. Price, H. Aytug, and P. J. Tighe, "Multiobjective optimization challenges in perioperative anesthesia: A review," *Surgery*, vol. 170, no. 1, pp. 320–324, 2021.

[52] P. Bhattacharjee and P. K. Ray, "Modelling and optimisation of healthcare systems: an overview," *International journal of logistics systems and management*, vol. 19, no. 3, pp. 356–371, 2014.

[53] S. Lucidi, M. Maurici, L. Paulon, F. Rinaldi, and M. Roma, "A simulation-based multiobjective optimization approach for health care service management," *IEEE Transactions on Automation Science and Engineering*, vol. 13, no. 4, pp. 1480–1491, 2016.

[54] T. Chen and C. Wang, "Multi-objective simulation optimization for medical capacity allocation in emergency department," *Journal of Simulation*, vol. 10, no. 1, pp. 50–68, 2016.

[55] D. L. Craft, T. S. Hong, H. A. Shih, and T. R. Bortfeld, "Improved planning time and plan quality through multicriteria optimization for intensity-modulated radiotherapy," *International Journal of Radiation Oncology* Biology* Physics*, vol. 82, no. 1, pp. e83–e90, 2012.

[56] W. Zhang, K. Cao, S. Liu, and B. Huang, "A multi-objective optimization approach for health-care facility location-allocation problems in highly developed cities such as hong kong," *Computers, Environment and Urban Systems*, vol. 59, pp. 220–230, 2016.

[57] M. Yousefi, M. Yousefi, and F. S. Fogliatto, "Simulation-based optimization methods applied in hospital emergency departments: A systematic review," *Simulation*, vol. 96, no. 10, pp. 791–806, 2020.

[58] G. J. Lim, A. Mobasher, and M. J. Côté, "Multi-objective nurse scheduling models with patient workload and nurse preferences," *Management*, vol. 2, no. 5, pp. 149–160, 2012.

[59] L. Sun, G. W. DePuy, and G. W. Evans, "Multi-objective optimization models for patient allocation during a pandemic influenza outbreak," *Computers & Operations Research*, vol. 51, pp. 350–359, 2014.

[60] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," *Cogent Engineering*, vol. 5, no. 1, p. 1502242, 2018.

[61] R. T. Marler and J. S. Arora, "Survey of multi-objective optimization methods for engineering," *Structural and multidisciplinary optimization*, vol. 26, pp. 369–395, 2004.

[62] E. Cabrera, M. Taboada, M. L. Iglesias, F. Epelde, and E. Luque, "Simulation optimization for healthcare emergency departments," *Procedia computer science*, vol. 9, pp. 1464–1473, 2012.

[63] H.-T. Chang, H.-Y. Jen, and S. M. Dahlgaard-Park, "Using service simulation to analyse the satisfaction with the processes of intensive care unit in the hospital: the perspective of the patient and the family," *Total Quality Management & Business Excellence*, vol. 24, no. 7-8, pp. 869–885, 2013.

[64] W. Abo-Hamad and A. Arisha, "Simulation-based framework to improve patient experience in an emergency department," *European journal of operational research*, vol. 224, no. 1, pp. 154–166, 2013.

[65] S. Norouzzadeh, N. Riebling, L. Carter, J. Conigliaro, and M. E. Doerfler, "Simulation modeling to optimize healthcare delivery in an outpatient clinic," in *2015 Winter Simulation Conference (WSC)*, pp. 1355–1366, IEEE, 2015.

[66] Samaha, Armel, and Starks, "The use of simulation to reduce the length of stay in an emergency department," in *Proceedings of the 2003 Winter Simulation Conference, 2003.*, vol. 2, pp. 1907–1911, IEEE, 2003.

[67] M. A. Ahmed and T. M. Alkhamis, "Simulation optimization for an emergency department healthcare unit in kuwait," *European journal of operational research*, vol. 198, no. 3, pp. 936–942, 2009.

[68] M. Cho, M. Song, S. Yoo, and H. A. Reijers, "An evidence-based decision support framework for clinician medical scheduling," *IEEE Access*, vol. 7, pp. 15239–15249, 2019.

[69] J. Chang and L. Zhang, "Case mix index weighted multi-objective optimization of inpatient bed allocation in general hospital," *Journal of Combinatorial Optimization*, vol. 37, pp. 1–19, 2019.

[70] M. Ordu, E. Demir, C. Tofallis, and M. M. Gunal, "A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach," *Journal of the operational research society*, vol. 72, no. 3, pp. 485–500, 2021.

[71] S. Sasanfar, M. Bagherpour, and A. Moatari-Kazerouni, "Improving emergency departments: Simulation-based optimization of patients waiting time and staff allocation in an iranian hospital," *International Journal of Healthcare Management*, vol. 14, no. 4, pp. 1449–1456, 2021.

[72] E. Shirley, G. Josephson, and J. Sanders, "Fundamentals of patient satisfaction measurement," *Physician leadership journal*, vol. 3, no. 1, p. 12, 2016.

[73] H. Higham, P. R. Greig, J. Rutherford, L. Vincent, D. Young, and C. Vincent, "Observer-based tools for non-technical skills assessment in simulated and real clinical environments in healthcare: a systematic review," *BMJ Quality & Safety*, 2019.

[74] J. Dooley, C. Bailey, and R. McCabe, "Communication in healthcare interactions in dementia: a systematic review of observational studies," *International Psychogeriatrics*, vol. 27, no. 8, pp. 1277–1300, 2015.

[75] S. Menard, *Applied logistic regression analysis.* Sage, 2002.

[76] P. Kraiphibul, *Eye disease*. Thailand: Amarin Corp. PLC., 2013.

[77] P. Gupta, "Eye infections: A review," *Ophthalmology and Vision Care*, vol. 1, no. 2, 2021.

[78] P. M. Bentler and D. G. Bonett, "Significance tests and goodness of fit in the analysis of covariance structures.," *Psychological bulletin*, vol. 88, no. 3, p. 588, 1980.

[79] J. P. Kleijnen, "Verification and validation of simulation models," *European journal of operational research*, vol. 82, no. 1, pp. 145–162, 1995.

[80] D. C. Montgomery and G. C. Runger, *Applied statistics and probability for engineers*. John wiley & sons, 2010.

[81] S. Fomundam and J. W. Herrmann, "A survey of queuing theory applications in healthcare," *IIE Transactions*, 2007.

[82] Z. Yahia and A. Pradhan, "Multi-objective optimization of household appliance scheduling problem considering consumer preference and peak load reduction," *Sustainable Cities and Society*, vol. 55, p. 102058, 2020.

[83] H.-J. Zimmermann, "Applications of fuzzy set theory to mathematical programming," *Readings in Fuzzy Sets for Intelligent Systems*, pp. 795–809, 1993.

[84] C.-C. Lin, "A weighted max–min model for fuzzy goal programming," *Fuzzy sets and systems*, vol. 142, no. 3, pp. 407–420, 2004.

[85] A. Amid, S. Ghodsypour, and C. O'Brien, "A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain," *International Journal of Production Economics*, vol. 131, no. 1, pp. 139–145, 2011.

[86] Thammasat University Hospital, "Thammasat University Hospital E-Recruitment." `https://tuh.hospital.tu.ac.th:9443/e-Recruitment/`. Accessed: February 20th 2022.

[87] Thammasat University Hospital, "Physician's schedule." `https://www.hospital.tu.ac.th/page/SearchDoctor/`. Accessed: February 1st 2022.

[88] F. Bretz, T. Hothorn, and P. Westfall, *Multiple comparisons using R.* CRC press, 2016.

[89] W. J. Carr and P. J. Feldstein, "The relationship of cost to hospital size," *Inquiry*, pp. 45–65, 1967.

Publication

International Journal

N. Chemkomnerd, W. Pannakkong, T. Tanantong, V-N. Huynh, and J. Karnjana, "A Simulation-based Multi-Objective Optimization Framework to Enhance Patient Satisfaction: A Case Study of Ophthalmology Department Management," *IEEE Access*, vol. 12, pp. 93197-93220, 2024.

International Conference

N. Chemkomnerd, W. Pannakkong, V-N. Huynh, and T. Tanantong, "Evaluating Patient Satisfaction Through Validated Predictive Classification Models," in *2024 16th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)*, pp. 337-342, IEEE, 2024.