CHAPTER IV
RESULTS AND DISCUSSION

This chapter presents the numerical results of the proposed multi-stage framework for elective surgical planning and discusses its implications. The optimization model was solved using LINGO version 16.0, with real data from a tertiary hospital in Thailand. Solutions were generated within seconds, offering a practical approach to support strategic OR planning and patient scheduling under uncertainty.

In this chapter, the numerical results of the planning problem and the discussions are provided.

4.1 Stage 1: Multi-Objective OR blocks Allocation

In this section, we present the numerical experiment conducted for the deterministic operating room resource allocation (DORA) problem, along with a detailed discussion of the results obtained. The DORA model was solved using LINGO version 16, utilizing datasets obtained from the aforementioned hospital. The solution can be obtained within a few seconds, providing insights into optimal resource allocation and its impact on various metrics.

4.1.1 Comparative analysis: model solution versus current hospital setting

Figure 4.1.1 illustrates the number of OR blocks reallocated based on our model solution compared to the current allocation in the hospital. Notably, significant changes in OR block allocations have occurred across different surgical departments.

For instance, the ENT and GEN departments experienced increases from 5 to 8 blocks and from 8 to 10 blocks, respectively, while the OBG and URO departments experienced reductions from 3 to 2 blocks and from 8 to 7 blocks per week, respectively. The increase in OR blocks allocated to departments such as ENT, GEN, OTH directly address the patient waiting list demand for the surgical specialty surgical services within these specialties. By providing additional OR blocks, it can accommodate more surgeries, thereby reducing the backlog of cases and dramatically reducing average patient waiting time. Conversely, the reduction in OR blocks allocated to departments such as OBG and URO reflects a more efficient use of resources. By reallocating OR blocks from these two departments, the model solution can better match capacity with demand, thereby reducing underutilization of downstream resources and minimizing idle time in OR.

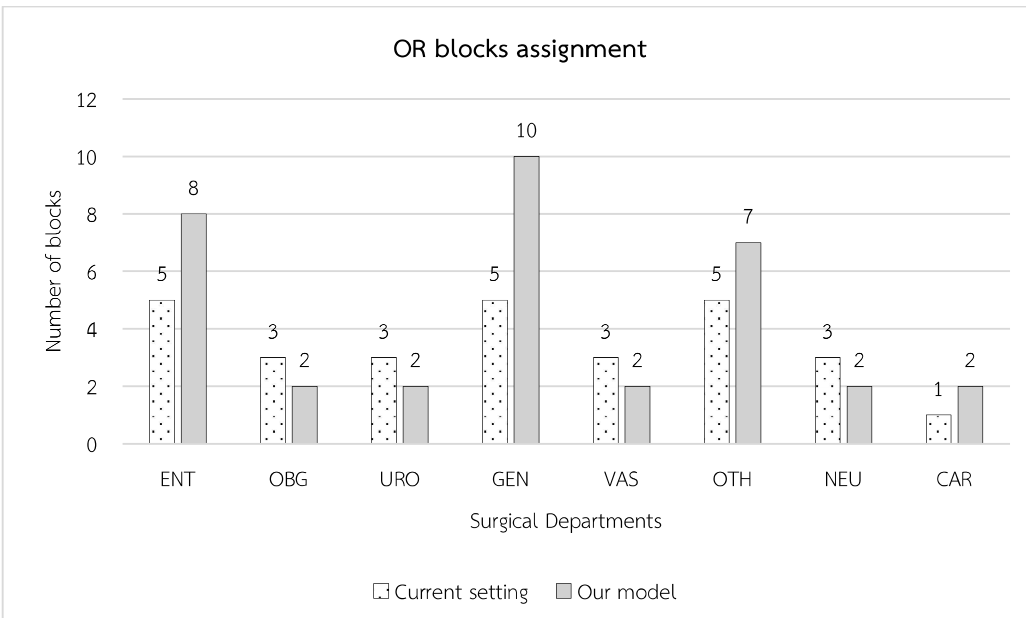

Figure. 4.1.1 Distribution of OR blocks across surgical departments

The outcomes presented in **Figure 4.1.2** show that the solution from our model substantially reduces the time required to clear the waiting list compared to the current setting. Departments such as ENT, GEN, OTH and CAR demonstrated a remarkable decrease in waiting list clearance times, transitioning from 43.68 to 27.3 weeks, 57.2 to 28.6 weeks, 59.8 to 42.71 weeks, and 52 to 26 weeks, respectively.

However, the OBG, URO, VAS and NEU departments showed an increase in waiting list clearance times, increasing from 31.2 to 46.8 weeks, 34.6 to 52 weeks, 28.88 to 43.33 weeks, respectively.

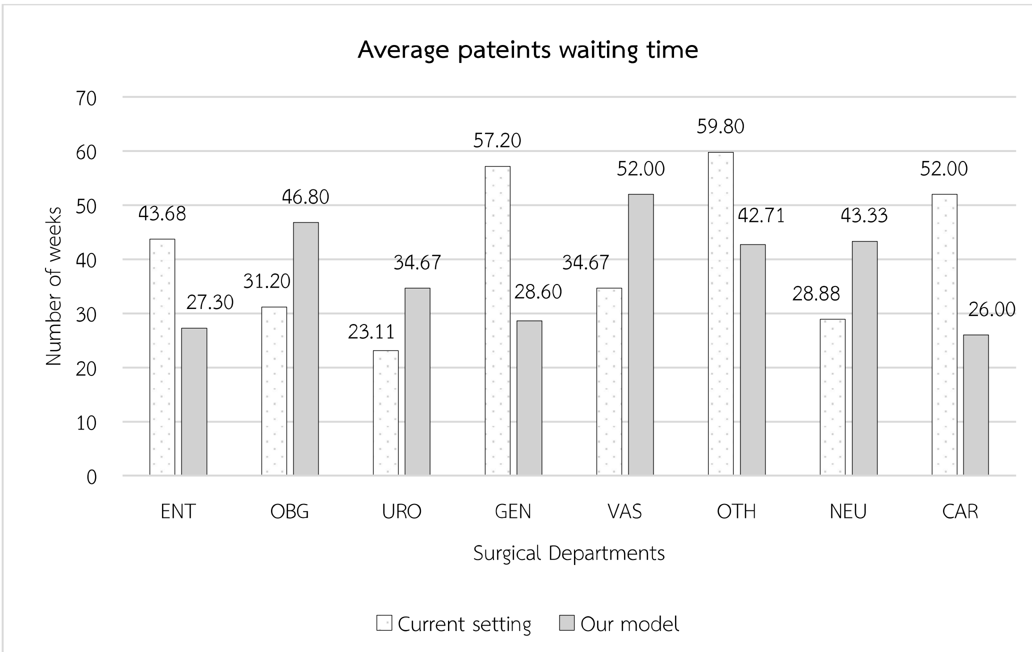

Figure. 4.1.2 Average waiting time of current setting vs our model

In addition, resource utilization across different facilities was compared between the current setting and our proposed model as shown in **Figure. 4.1.3**. The OR is 100% utilized based on our model solution while the current setting uses 80% of available capacity while downstream ICU and MCU utilization rates of 98.28% and 99.59%, compared to current resource utilization of 94% and 89.79%, respectively. And nursing time is relatively unchanged.

Table 1 shows a comparative statistical analysis between the model solution and current setting is presented. There is a notable decrease in both the objective value and average patient waiting time as well as improved resource utilization.

There is notably decrease Specifically, the mean and standard deviation patient waiting time decreased by approximately 8.81% and 28.87% respectively, while the objective value decreased by about 13.45%.

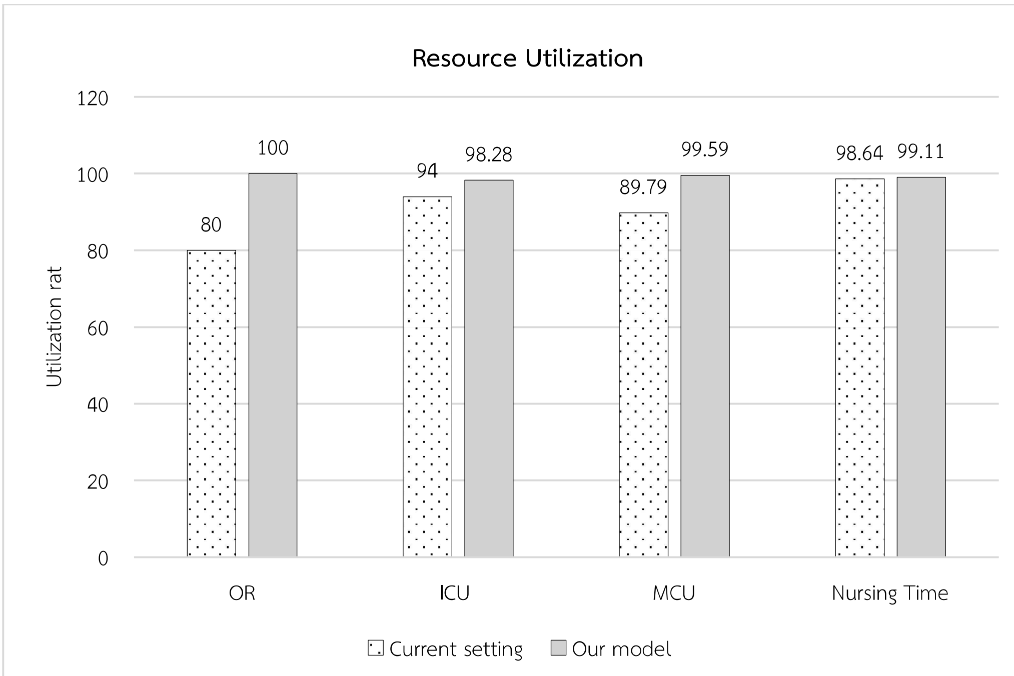

Figure. 4.1.3 Resource utilization

The mean resources utilization of resources is 99.25% and standard deviation 0.74% compared to the current hospital setting with average of 90.6% and standard deviation of 7.94%. The significant reduction in standard deviation implied that our model demonstrated better and more balance in terms of resource utilization across different resource facilities upstream and downstream.

The results highlight the effectiveness of our proposed model in optimizing OR block allocation within surgical departments. By reallocating OR blocks based on our model solution, the model solution achieved significant reductions in average patient waiting time and total incurred cost while also improving resource utilization across different resources facilities. These findings highlight the potential of modeling approaches for enhancing OR resources management and operational efficiency, ultimately leading to improved patient wait time. Although the model's solution offers improved OR resource allocation by reducing objective value, resource utilization deviation, and shortening patient waiting times across various surgical departments compared to current practices. Unfortunately, the model generates based on constrained resources and neglected the surgical department priority.

Table 4.1 Objective values of current setting vs our model

	Current setting	*Proposed Model*	*% Decrease (proposed model: current setting)*
Objective value (unit cost)	4725300	4089871	13.45%
Mean waiting time (weeks)	41.32	37.67	8.81%
Sd waiting time (weeks)	13.87	9.86	28.87%
Mean utilization (%)	90.60	99.25	8.7%
Sd utilization (%)	7.95	0.74	90%
Patient throughput	140	148	5.71%

Given the significant global burden of surgical backlog and the constraints posed by limited and costly overtime resources, it is vital for OR managers to consider prioritization techniques and allow overtime resources aid to address the surgical backlog. In scenarios where overtime is not possible due to hospital conditions, setting priorities among surgical departments becomes crucial.

This determines the order in which departments are granted access to OR blocks, impacting patient wait times and resource distribution. For instance, during crises such as pandemics or emergencies where resources are limited, decisions must be made wisely to allocate resources where they are most needed. Despite expensive overtime costs, from a crisis perspective, it is necessary to utilize overtime resources to help reduce the burden of the surgical backlog and patient waiting times. To better understand the trade-off between overtime resource allowance and additional costs incurred, the study conducts a cost-benefit analysis to assess the financial implications of such increases and strike a balance between reducing patient waiting times and considering financial aspects.

Through this analysis, hospital administrators can gain insights into the trade-offs between total additional overtime costs and average patient waiting time on the waiting list. This information provides valuable support for decision-making within hospitals regarding long-term and short-term investments in resource facilities and ensures efficient resource allocation.

For these reasons, the sensitivity analysis about surgical department priority and overtime allowances will be carried out. In the next subsection, we will continue performing sensitivity analysis with the aim of further improving the allocation of OR resources.

4.1.2 Sensitivity analysis

In this section, a comprehensive sensitivity analysis is done on two key critical parameters: surgical department priority and overtime resources allowance. OR managers should set these parameters through their strategies while other parameters such as surgery duration and patient length of stay in ICU and MCU are not under control of managers.

For generalization purposes, this study offers valuable insights to support better decision-making and alignment with hospital goals by proposing four different scenarios of prioritization setting.

1) 1.Priority based on clinical need: prioritizing departments based on their severeness.
2) Equal access: providing each department with equal right to access to resources in order to ensure fairness.
3) Tackling long waiting lists: prioritize department with long patient waiting list.

4) Prioritizing cases based on resource requirements (low and high): aims to optimize resource efficiency and utilization. Whereas, to assess the impact of overtime allowance on patient waiting time four variations in the overtime allowance are considered, ranging from 10% to 25% compared to the baseline no overtime.

The scenarios examined are as follows: Scenario 1: the overtime allowance increased by 10%; Scenario 2: 15%; Scenario 3: 20%; and Scenario 4: overtime allowance increased by 25%. These variations allow us to explore the impact of incremental changes in overtime allowances on patient waiting list clearance time as well as total overtime costs .

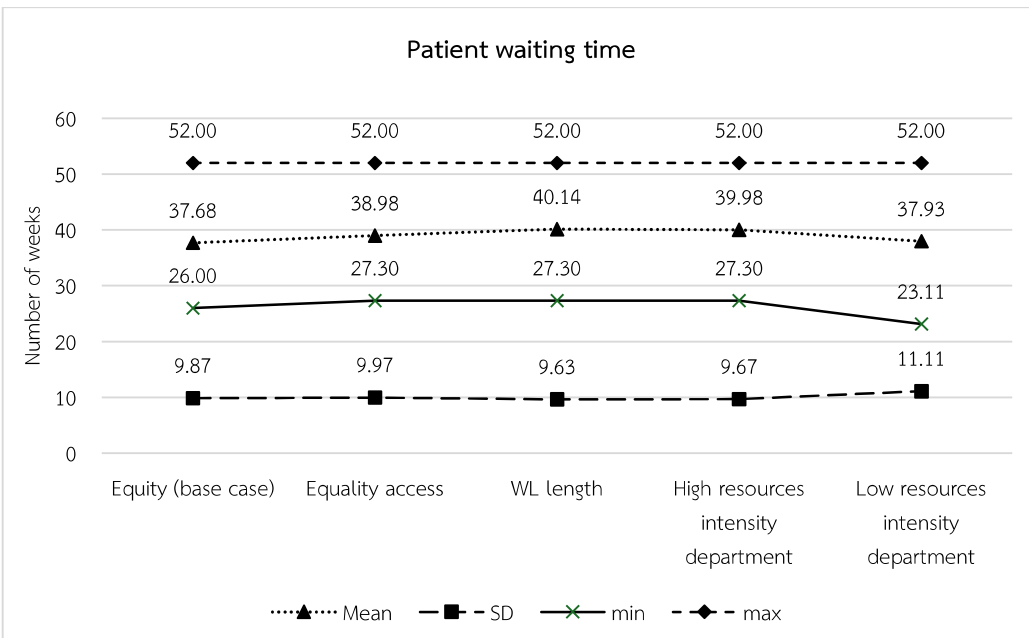

Figure. 4.1.4 Statistical analyses across scenarios

As shown in **Figure. 4.1.4**, there is no significant difference in patient waiting time in varying prioritization settings across different scenarios.

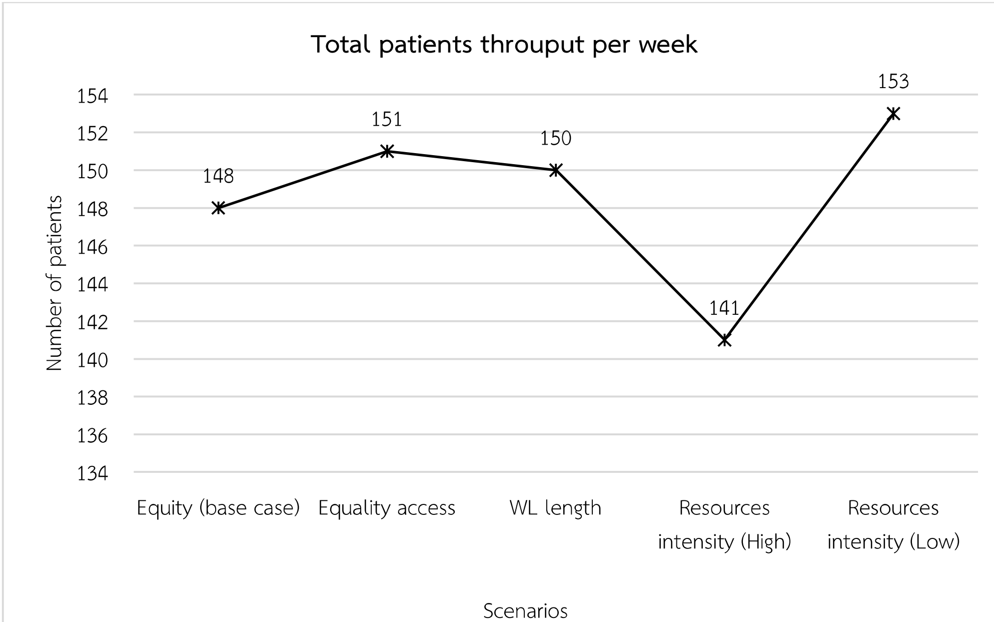

Figure 4.1.5. Patient throughput per week across scenarios

Figure 4.1.5 shows significant differences in total patient throughput across various priority settings. Based case scenario can treat 148 patients per week while scenario 2 increases throughput to 151 patients per week. This highlights the tradeoff between equity access and equality access. Scenario 3 addresses long backlogs and results in a throughput of 150 patients per week. And scenario 4 and 5 prioritizing cases based on resource requirements leads to varying throughputs, with high-resource intensity departments focusing can treating 153 patients while low-resource intensity focus treating 141 patients per week.

Additionally, there is considerable variation in resource utilization among facilities across different scenarios. Equality access, backlog concern, and low-resource intensity scenarios exhibit high variation in utilization rates. In contrast, the equity access and high-resource intensity scenarios show minimal variation in resource utilization across facilities as shown in **Figure. 4.1.6**. These scenarios provide OR managers with valuable insights into informed decision-making. By characterizing each priority scheme into different scenarios, administrators can better understand the implications of various approaches for priority-setting within surgical departments.

These insights help align priority setting practices with institutional objectives and healthcare delivery models.

They offer a deeper understanding of the trade-offs and considerations involved in allocating limited OR resources effectively while striving to meet the needs of a diverse patient population and optimize resource efficiency.

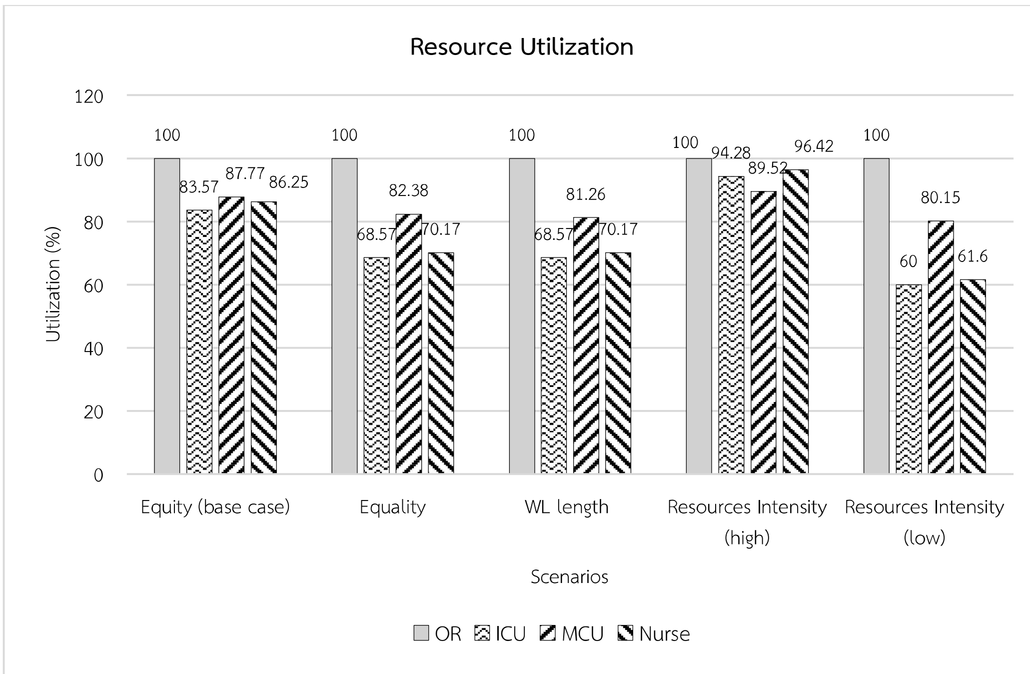

Figure 4.1.6. Resource utilization across different scenarios setting

In **Figure 4.1.7**, a notable observation arises regarding the impact of different overtime allowances on average waiting times. With a 10% increase in the overtime allowance for resources, there is a significant decrease in the average waiting time of approximately 9%, decreasing from 37.7 to 34.5 weeks. Further increases to 15% and 20% over time of the resources allowance result in smaller decreases from the base case, approximately 13.5% and 17.5%, respectively. Interestingly, when the overtime allowance is increased to 25%, there is no change in average waiting time compared to the 20% overtime allowance, which remains at approximately 1%.

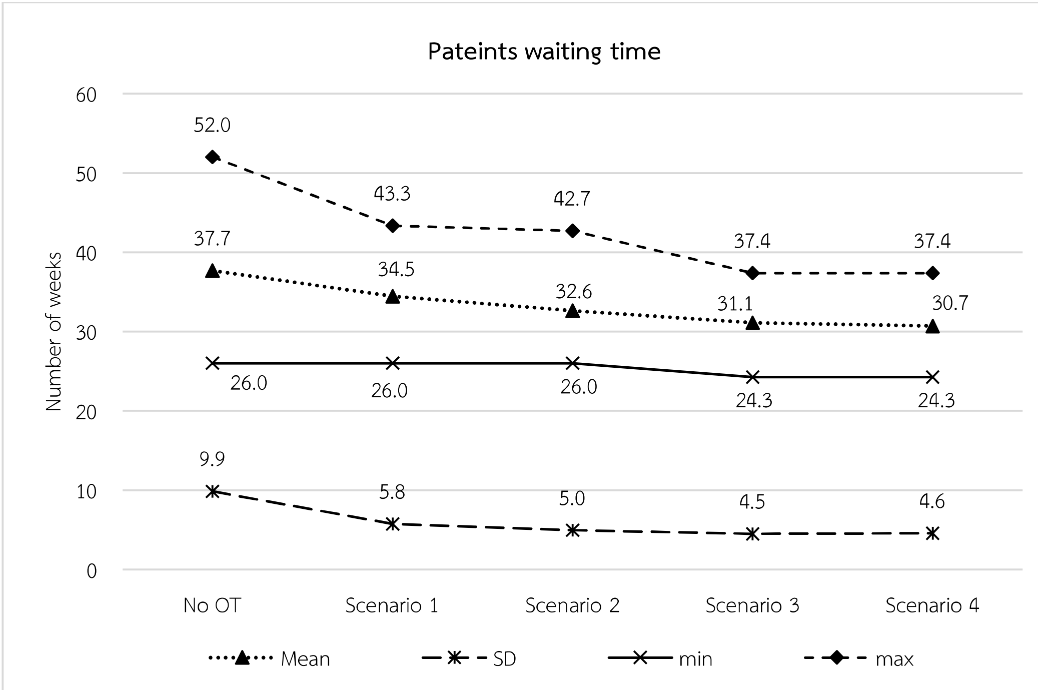

Figure. 4.1.7 Statistical analyses across scenarios

Table 2 presents the relationship between overtime allowances, waiting times, and incurred costs, emphasizing the importance of balancing resource allocation for efficient waiting list management with optimal overtime allowances. Hospital administrators can refer to this guideline to determine whether increasing operations overtime is necessary to reduce average patient waiting times. By carefully considering the trade-offs between resource utilization, waiting times, and incurred costs, administrators can make informed decisions to optimize patient care delivery while ensuring the efficient use of resources.

Table 4.2 Scenarios comparison

	No OT	*Scenario 1*	*Scenario 2*	*Scenario 3*	*Scenario 4*
Average WL clearance time (weeks)	37.7	34.5	32.6	31.1	30.7
% decrease from base case (%)	-	8.55%	13.38%	17.45%	18.50%
% increase overtime costs from 10%	-	-	136.2%	267.6%	304.4%

4.2 Stage 2: Multi Criteria Decision Making Patient Prioritization

Following the strategic allocation of operating room (OR) blocks to each surgical department in Phase 1, the second stage addresses operational-level decisions. In this phase, each department is responsible for selecting which patients from their waiting lists will be scheduled for surgery, based on the number of OR blocks allocated.

To support this decision-making process, a Multi-Criteria Decision Making (MCDM) approach is introduced. Unlike traditional first-come, first-served (FCFS) scheduling, MCDM enables a more equitable and clinically informed patient ranking by evaluating multiple criteria simultaneously. The prioritization criteria are derived from expert input and literature, incorporating both medical urgency and socio-personal factors to ensure fairness and effectiveness in scheduling decisions.

This section presents the MCDM process through a numerical case study involving ten elective surgical patients, using the TOPSIS method to illustrate how patients can be ranked objectively based on their comprehensive clinical and personal profiles.

4.2.1 Criteria Identification

To develop an effective and equitable patient prioritization framework for elective surgical services, this study adopted a structured set of criteria synthesized from established literature and existing healthcare prioritization practices. The analytical hierarchy for patient prioritization was constructed based on four overarching criteria categories: C1: Clinical and Functional Variables, C2: Expected Benefits, C3: Social Role Variables, and C4: Personal Characteristics, as proposed by Rahimi et al. (2016) and extended by Li et al. (2019), Srikunmar et al. (2018), and Silva et al. (2021).

Each of these main criteria encompasses specific sub-criteria that reflect the complexity and multifactorial nature of surgical prioritization. The sub-criteria were selected to ensure a balance between clinical necessity, potential outcome benefits, and broader socioeconomic considerations. The hierarchical structure used in this study is presented in **Figure 4.1.8**.

Clinical and Functional Variables (C1) include:

1) C11: Disease severity
2) C12: Pain
3) C13: Rate of disease progression
4) C14: Difficulty in performing daily activities

Expected Benefits (C2) include:

1) C21: Probability and degree of expected health improvement
2) C22: Risk of comorbidity development without surgery
3) Social Role Variables (C3) cover:
4) C31: Limitation in caregiving responsibilities
5) C32: Dependency level
6) C33: Geographic accessibility
7) C34: Financial capacity to undergo surgery
8) C35: Overall life impact
9) C36: Urgency based on treatment delay consequences
10) C37: Limitation in work, education, or employment participation

Personal Characteristics (C4) include:

1) C41: Age
2) C42: Gender
3) C43: Diabetes status
4) C44: Anemia
5) C45: Hypertension
6) C46: Sleep disorders

These criteria collectively serve as the input parameters for the Analytic Hierarchy Process (AHP) model developed in this study to support the prioritization of general surgical patients as shown in **Figure 8. The** prioritization outcome reflects a combination of medical urgency, potential benefits, and socio-personal considerations, ensuring that limited healthcare resources are allocated in the most impactful and ethically grounded manner.

4.2.2 Weighting method

To determine the relative importance of each criterion, a weighting methodology was employed using expert judgment through pairwise comparisons. A panel of ten decision-makers—including clinicians, hospital administrators, and public health experts—evaluated each sub-criterion using a scale of 1 to 10. The mean scores were computed, and the AHP methodology was applied to derive the final weights (Wi) for both the main criteria and their sub-components.

Main Criteria Weight Distribution: The aggregated weights for the four main criteria were as follows:

C1: Clinical and Functional Variables – 32.85%

C2: Expected Benefits – 18.98%

C3: Social Role Variables – 27.52%

C4: Personal Characteristics – 20.64%

These results indicate that clinical and functional factors were deemed most significant, comprising nearly one-third of the overall decision weight. Social role and personal characteristics also held substantial influence, underscoring the importance of a holistic approach that goes beyond clinical metrics alone.

These weights served as foundational parameters for the subsequent prioritization phase, enabling a comprehensive and objective evaluation of patient cases as shown in Table 1.

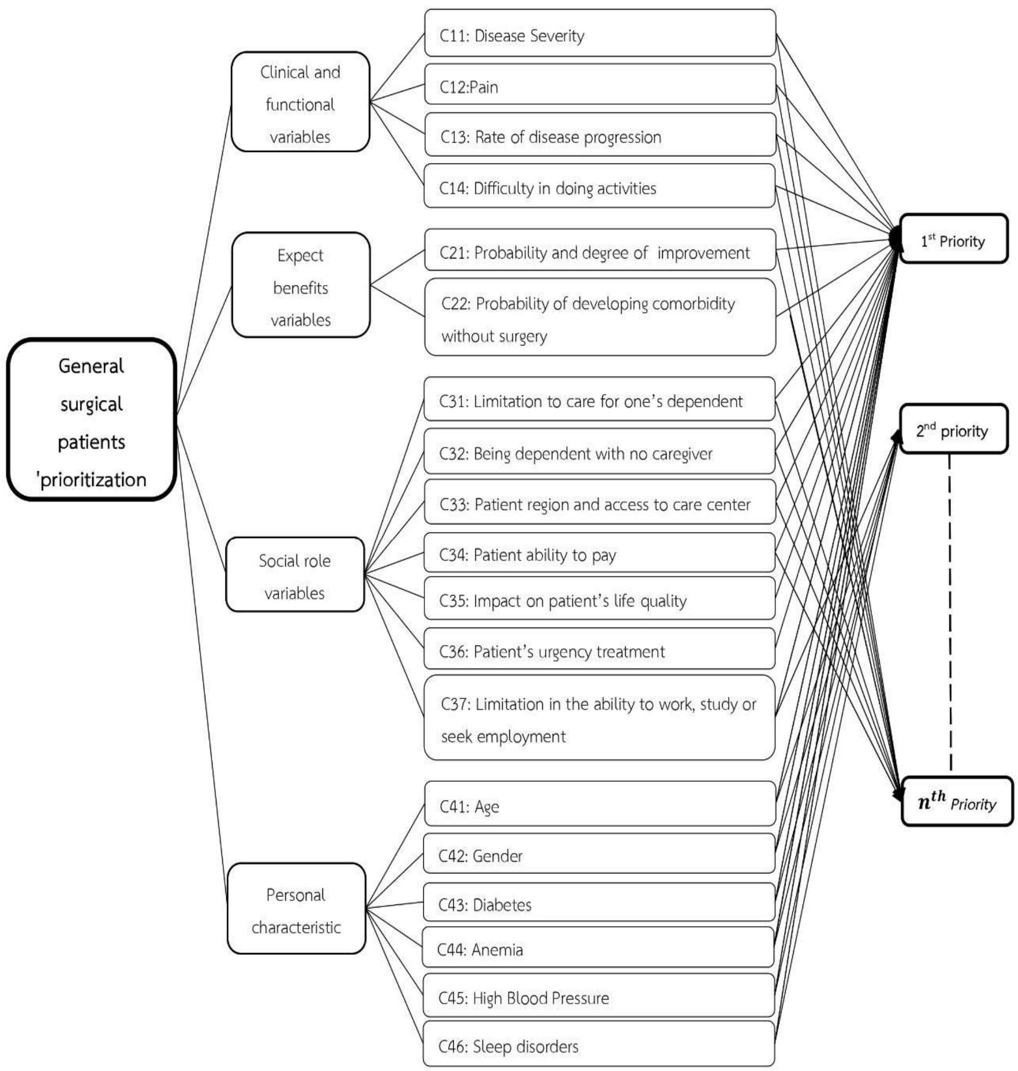

Figure 4.1.8: Analytic Hierarchy Process for General surgical patient prioritization

Table 4.3 Relevant scores assigned by 10 experts in related area to 19 criteria

Main Criteria	Criteria	1	2	3	4	5	6	7	8	9	10	Wi	Total (∑Wi)
C1: Clinical and Function	C11	10	9	8	10	8	10	10	9	9	9	0.1021	0.3285
	C12	9	8	8	8	8	8	9	8	8	7	0.0899	
	C13	8	5	5	7	8	6	8	5	7	5	0.0710	
	C14	6	7	5	5	7	7	5	6	6	5	0.0655	
C2: Expected Benefit	C21	10	9	8	10	10	7	9	10	9	9	0.1010	0.1898
	C22	7	7	7	10	7	9	9	7	10	7	0.0888	
C3: Social Role	C31	3	6	3	2	5	3	2	3	1	1	0.0322	0.2752
	C32	3	3	5	4	2	4	6	1	5	1	0.0377	
	C33	6	6	1	6	6	2	3	6	2	5	0.0477	
	C34	3	4	4	3	4	2	4	5	5	6	0.0444	
	C35	2	4	1	3	3	4	2	4	5	6	0.0377	
	C36	1	5	1	5	5	3	6	5	4	4	0.0433	
	C37	2	6	2	4	2	2	3	1	5	2	0.0322	
C4: Personal Characteristic	C41	3	5	2	3	3	1	5	2	2	5	0.0344	0.2064
	C42	5	3	3	5	4	4	2	1	2	1	0.0333	
	C43	2	4	2	3	4	2	3	4	5	2	0.0344	
	C44	5	5	5	2	5	5	4	5	4	5	0.0499	
	C45	4	1	1	1	1	5	1	3	4	3	0.0266	
	C46	5	2	4	1	1	1	1	2	5	3	0.0277	

4.2.3 TOPSIS Method for Patient Ranking

To generate the final prioritization of patients, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed. This method evaluates each alternative by measuring its Euclidean distance from both an ideal best and an ideal worst solution, thereby identifying the most suitable option through relative closeness to the ideal point.

Ten patient cases were evaluated using the sub-criteria identified and weighted in the previous phase. The raw clinical and demographic data for each patient are presented in Table 4.3.

Using the weighted normalized decision matrix shown in Table 4.5, the TOPSIS model calculated the Euclidean distance of each patient from the ideal best (d^{+}) and ideal worst (d^{-}) solutions. These distances were then used to compute the relative closeness (Rj) to the ideal solution, which determines the final patient ranking. Results are summarized in Table 4.4.

Table 4.4 Basic patient information and clinical evaluation

Patient No	C11	C12	C13	C14	C21	C22	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43	C44	C45	C46
1	4	2	5	5	7	68	1	0	1	0	1	0	0	30	0	1	0	1	1
2	4	3	1	2	86	86	1	1	1	1	1	1	1	21	1	1	1	1	0
3	1	4	3	5	87	46	1	1	1	0	0	1	0	41	0	1	1	0	1
4	3	3	1	5	35	99	0	0	1	0	0	0	0	75	0	1	0	1	0
5	2	0	5	1	14	26	0	1	0	0	0	1	1	69	1	1	1	0	1
6	5	1	1	4	13	21	0	1	1	0	0	1	0	47	1	1	1	1	0
7	2	4	1	3	47	40	1	1	1	1	0	1	1	44	0	1	1	1	1
8	2	1	2	1	58	54	1	1	1	0	0	1	1	19	1	0	1	0	0
9	4	1	1	1	32	72	1	0	1	1	1	0	0	76	0	0	1	0	1
10	3	2	2	2	55	54	1	0	0	1	1	0	1	70	1	0	1	0	1

Table 4.5 Weighted normalized matrix

Patient No	C11	C12	C13	C14	C21	C22	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43	C44	C45	C46
1	0.039	0.022	0.043	0.033	0.005	0.034	0.013	0.000	0.010	0.000	0.014	0.000	0.000	0.007	0.000	0.013	0.000	0.015	0.015
2	0.039	0.033	0.009	0.013	0.055	0.043	0.013	0.018	0.010	0.014	0.014	0.017	0.016	0.005	0.018	0.013	0.012	0.015	0.000
3	0.010	0.044	0.026	0.033	0.056	0.023	0.013	0.018	0.010	0.000	0.000	0.017	0.000	0.009	0.000	0.013	0.012	0.000	0.015
4	0.029	0.033	0.009	0.033	0.023	0.049	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.017	0.000	0.013	0.000	0.015	0.000
5	0.020	0.000	0.043	0.007	0.009	0.013	0.000	0.018	0.000	0.000	0.000	0.017	0.016	0.016	0.018	0.013	0.012	0.000	0.015
6	0.049	0.011	0.009	0.026	0.008	0.010	0.000	0.018	0.010	0.000	0.000	0.017	0.000	0.011	0.018	0.013	0.012	0.015	0.000
7	0.020	0.044	0.009	0.020	0.030	0.020	0.013	0.018	0.010	0.014	0.000	0.017	0.016	0.010	0.000	0.013	0.012	0.015	0.015
8	0.020	0.011	0.017	0.007	0.037	0.027	0.013	0.018	0.010	0.000	0.000	0.017	0.016	0.004	0.018	0.000	0.012	0.000	0.000
9	0.039	0.011	0.009	0.007	0.021	0.036	0.013	0.000	0.010	0.014	0.014	0.000	0.000	0.017	0.000	0.000	0.012	0.000	0.015
10	0.029	0.022	0.017	0.013	0.035	0.027	0.013	0.000	0.000	0.014	0.014	0.000	0.016	0.016	0.018	0.000	0.012	0.000	0.015

Table 4.6 Euclidean distance and relative closeness & rank

Patient No	d^{+}	d^{-}	Rj	Patient Rank
1	0.072	0.070	0.493	6
2	0.047	0.094	0.665	1
3	0.061	0.087	0.586	2
4	0.070	0.075	0.515	4
5	0.089	0.058	0.394	10
6	0.085	0.061	0.420	9
7	0.066	0.074	0.528	3
8	0.073	0.061	0.454	7
9	0.078	0.061	0.439	8
10	0.063	0.066	0.511	5

The results show a different prioritization order compared to the hospital's current first-come, first-served scheduling. For example, Patient No. 5 is ranked 10th by TOPSIS, while the hospital's traditional system prioritized them 5th. This discrepancy illustrates that using different decision-making frameworks—MCDM vs. staff judgment—may lead to inconsistencies.

The main advantage of the MCDM approach is its ability to interpret multiple criteria simultaneously, which human decision-makers may not easily process due to cognitive limitations. Staff may rely on experience and intuition, allowing for faster but potentially less systematic decisions.

The use of the TOPSIS method in a non-urgent healthcare service setting can improve patient satisfaction by enabling more objective and meaningful prioritization, potentially improving patients' preoperative conditions. However, integrating this framework into daily practice would require computational infrastructure and staff training, implying a need for investment and planning.

Overall, this study demonstrates that a systematic decision-making approach using TOPSIS can enhance elective surgical patient prioritization, particularly where detailed patient information is available, and the healthcare system aims to optimize resource allocation.

The ranking of the patient from the TOPSIS model was calculated based on the biopsychosocial aspects used in this study. While its rank was found to be different compared to the current first-come first-serve procedure from real case. For instance, TOPSIS ranked patient no.5 as the 10th order while the current procedure was given at the 5th order. The difference of results between two frameworks (MCDM and staff) implies that using different decision-making methods may lead to inconstancy in the decision process. Staff can make decisions more rapidly than using the MCDM model because they use their experience while MCDM must calculate based on the recorded data.

MCDM tends to provide the results more concisely because it can interpret the results based on multiple criteria in which staff cannot achieve this ability. The satisfaction of the patient may be increased due to the ability to make a proper prioritization which can improve the overall health of each patient before surgery. The MCDM framework required to be operated on a computing device which may lead to investment consideration in the future. However, the non-urgent healthcare service setting can be beneficial from incorporating MCDM framework for elective surgical patient prioritization in advance because the care service can gather the scheduled patient data to improve the planning of the resources utilization in the healthcare service setting more appropriately.

The main challenge in scheduling elective surgical patients is to manage patient prioritization based on multiple biopsychosocial criteria. This research demonstrates a decision-making framework, using both MCDM method and TOPSIS technique, to support elective surgical

patient prioritization based on multiple biopsychosocial criteria. A case study was presented to illustrate numerical examples of the framework based on the data in a non-urgent healthcare service setting. Results were presented to exemplify a consequence of the elective surgical patient prioritization framework in this study. The satisfaction of the patient is increased due to the ability in making a decisive prioritization which can improve overall health of each patient before surgery. The non-urgent healthcare service setting can gather the scheduled patient data to from the MCDM framework to improve the planning of the resources utilization in the healthcare service setting more appropriately.