CHAPTER II
LITERATURE REVIEWS

The study aims to incorporate the knowledge of medical informatics (Surgical Informatics), and Operation Research (OR) to study the integration of resource allocation and patient prioritization in Operating Theatre (OT).

2.1 Operating room planning and scheduling

The Operating room (OR) is one of the most expensive units and a central hub in the hospital system. The largest cost categories of a hospital are operating rooms and the downstream patient ward groups, averaging 33% and 31% of its total cost, respectively. It generates most of their funding, makes up most of their cost and strongly influences the use of various resources (Cardoen et al., 2010). Activities inside OR have a substantial impact in hospital system, since ORs are clearly connected with other downstream resources **(Figure 2.1.1)** for instance, the Post Anesthesia Care Unit (PACU), the Intensive Care Unit (ICU), the intermediate care unit (IMC) and general patient ward. As shown in Figure 1, after surgeries, in most cases patients are admitted to a ward. In more severe cases, patients are sent to the ICU. This is an inpatient in which patients can either be admitted to an ICU or a general ward. Patients in an ICU will be transferred to a ward before discharge. Alternatively, patients might be discharged without being sent to a ward (e.g., outpatient). Patients in the wards will be transferred to the ICU if their condition becomes unstable. Most patients leave the system only after recovering in a ward, but they might also leave the hospital directly from the ICU (e.g., if transferred to another hospital).

Hence, operating room (OR) management has remarkable impacts on the efficiency of not only OR departments themselves but also other functions of hospitals. For these reasons, the OR planning and scheduling attracted a lot of attention to managing and improving productivity.

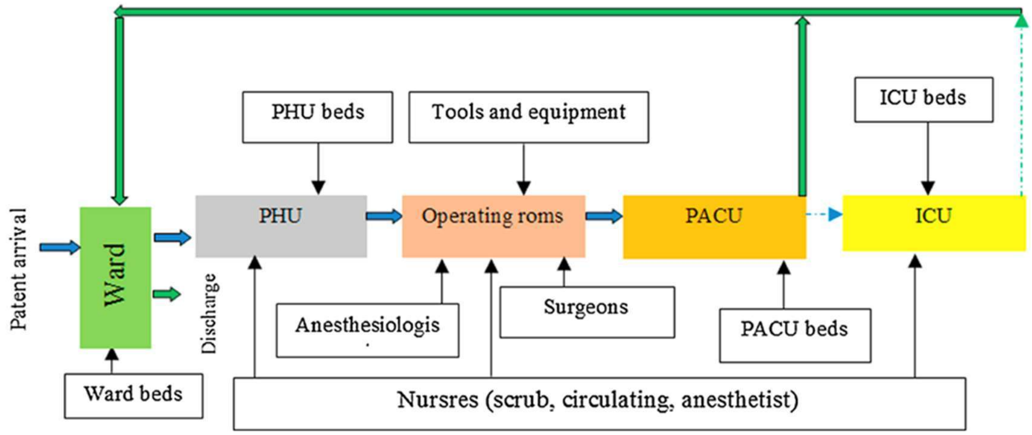


Figure 2.1.1 Operating room

2.1.1 Patients and OR suit characteristics

There are two types of classifications of patients in the OR planning and scheduling problems as shown **in Figure 2.1.2**, elective patients or non-elective patients, and inpatients or outpatients. An elective patient class stands for the patient with whom the surgery can be well planned and distinguish between inpatient and outpatient in which inpatient refer to hospitalized patients who must stay overnight, while outpatients typically enter and leave the hospital on the same day.

On the other hand, non-elective patient class groups for whom surgery is unexpected and hence need to be performed urgently and a distinction can be made between urgent and emergency surgery based on responsiveness to the patient’s arrival (i.e., the waiting time till start of surgery). Whereas the surgery of emergent patients (emergencies) must be performed as soon as possible, urgent patients (urgencies) refer to non-elective patients that are sufficiently stable so that their surgery can possibly be postponed for a short period.

In an OR suit there are three policies namely, dedicated, shared and hybrid policy. A dedicated policy: was defined as a reserving OR rooms for non-elective cases only; shared policy was defined as an OR having both non-elective and elective cases. Hybrid policy: was defined as an OR blood having a mix of both dedicated and shared rooms. Duma & Aringhieri. (2019) conducted an in-depth study on how dedicated, shared and hybrid policy perform in a wide range scenario. They concluded that, while dedicated and shared policies might be preferred in certain context (dedicated policies reduce elective cancellation and shared policies result in better resources use), hybrid policies are recommended because they are better addressing the inherent trade-off between elective and emergency patient metrics.

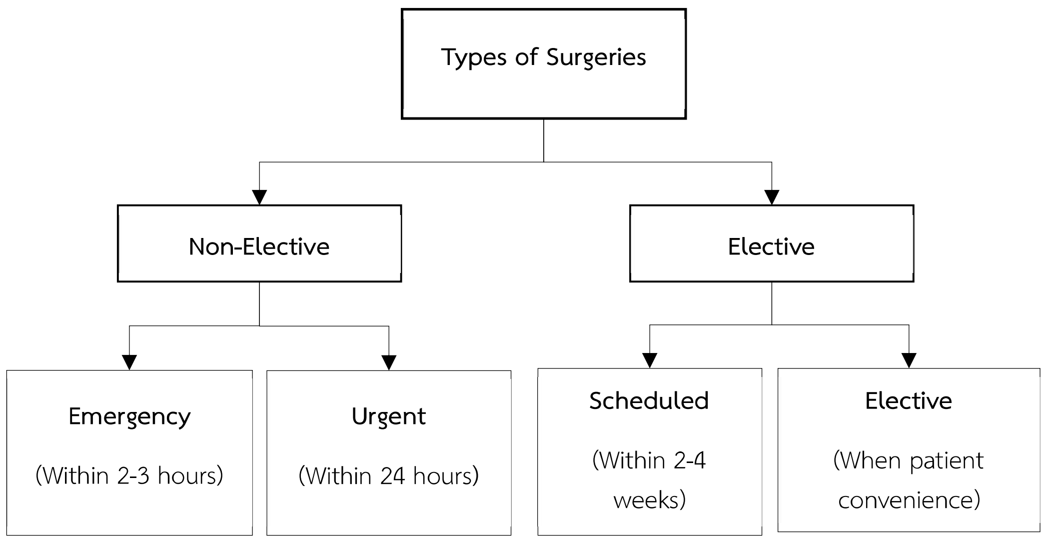


Figure 2.1.2 Patient categories

2.1.2 Decision hierarchy and Scheduling policy

OR planning and scheduling decisions can be structured into a **three-level hierarchy**: strategic, tactical, and operational (Hans et al., 2011; Beliën & Demeulemeester, 2007; Cardoen et al., 2010), as shown in **Figure 2.1.3.**

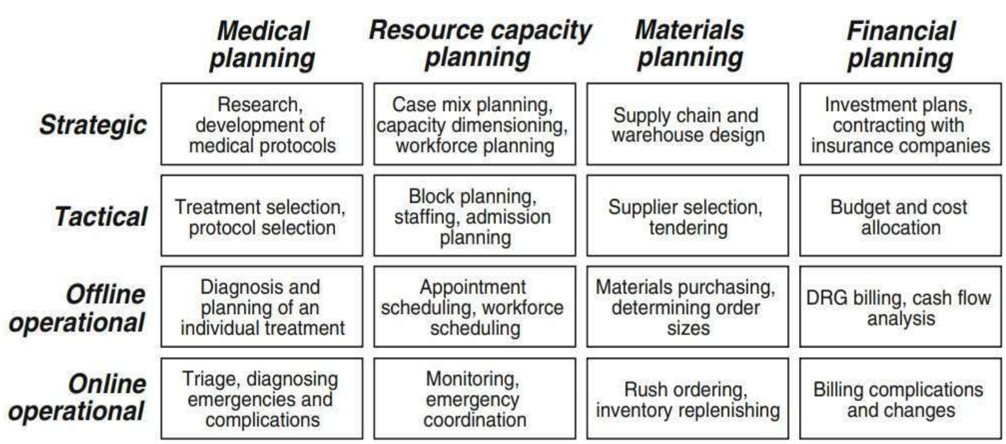
3.4.2.1 The strategic level involves long-term decisions about the healthcare system's direction, such as expanding resources (e.g., purchasing MRI machines), implementing new medical protocols, or forming partnerships with insurers. In OR management, this includes case mix planning (CMP)—deciding how to allocate total OR time among different specialties or surgical teams.

3.4.2.2 The tactical level addresses medium-term planning, particularly the development of a master surgery schedule (MSS). This schedule specifies how OR time is distributed across different departments over weeks or months.

3.4.2.3 The operational level focuses on short-term decisions, such as assigning individual surgeries to specific ORs on particular days (Jebali & Diabat, 2017). Due to upstream constraints, this level offers limited flexibility.

To operate these decisions, hospitals adopt one of three OR scheduling strategies:

1) **Block strategy**: OR time is pre-assigned in fixed blocks (e.g., 8:00–16:00) to specific departments or surgeons (Zhu et al., 2018).
2) **Open strategy**: all surgical cases compete for OR slots without pre-assigned times, promoting flexibility (Denton et al., 2007).
3) **Modified block strategy**: combines the above two to maintain managerial flexibility and efficient resource use (Zhu et al., 2018; Mullen et al., 2017).



	Medical planning	Resource capacity planning	Materials planning	Financial planning
Strategic	Research, development of medical protocols	Case mix planning, capacity dimensioning, workforce planning	Supply chain and warehouse design	Investment plans, contracting with insurance companies
Tactical	Treatment selection, protocol selection	Block planning, staffing, admission planning	Supplier selection, tendering	Budget and cost allocation
Offline operational	Diagnosis and planning of an individual treatment	Appointment scheduling, workforce scheduling	Materials purchasing, determining order sizes	DRG billing, cash flow analysis
Online operational	Triage, diagnosing emergencies and complications	Monitoring, emergency coordination	Rush ordering, inventory replenishing	Billing complications and changes

Figure 2.1.3. Decision hierarchy

Managing OR resources is inherently complex due to limited capacity, variable procedure durations, diverse patient needs, and the involvement of multiple stakeholders with often conflicting objectives (e.g., minimizing cost vs. maximizing patient satisfaction). Additionally, because elective cases account for up to 75% of surgeries (Hassanzadeh et al., 2022; Jebali & Diabat, 2017), careful integration of non-elective surgeries—often performed in dedicated units—is necessary to maintain efficiency (Cardoen et al., 2010; Min & Yih, 2010; Mullen et al., 2017; Neyshabouri & Berg, 2017). Ultimately, effective OR planning aims to reduce total costs and patient waiting times while maximizing resource utilization.

2.2 Patient waiting list management

Patient waiting list management is a critical component of healthcare delivery, especially in the context of surgical services where demand for services significantly exceeds supply. Ineffective and inefficient resource management in the OR department can consequently affect elective surgery waiting lists, leading to prolonged waiting times, negatively impacting patient health and satisfaction, and sometimes resulting in patients leaving before receiving treatment. Reducing patient waiting times is a critical performance indicator in healthcare systems and is crucial for patient satisfaction and loyalty to healthcare centers (Howlett & Wood, 2022). Therefore, various strategies have been employed by hospital managers to address elective patient surgical backlogs, such as increasing installed capacity, improving efficiency, and managing demand (Negash et al., 2022).

For instance, (VanBerkel & Blake, 2007) addressed waiting list problems by considering increasing installed capacity, aiming to optimize resources, and decreasing patient wait times in OR planning and scheduling procedures. They utilized discrete-event simulation to analyze the impact of changing bed capacity and OR time on throughput and waiting times. However, the option to increase capacity is limited by constraints such as budget, space, and human resources and is infeasible for some hospitals in some areas.

Comparatively, the option to improve the effectiveness and efficiency of OR management is generally more meaningful and feasible for hospitals (Abedini et al., 2016). A study by (Spratt & Kozan, 2016) considered improving efficiency by constructing a mixed-integer nonlinear programming (MINLP) approach to formulate the problem of generating MSS for managing the waiting list, adhering to staff and equipment restrictions, and ensuring timely treatment of patients.

Table 2.1 Summary of strategies in managing the waiting list

Study	Strategies	Methodology	Key findings
(VanBerkel & Blake, 2007)	Increasing Capacity	Discrete-event simulation	Increasing bed capacity and OR time can significantly impact throughput and reduce waiting times using discrete-event simulation
(Spratt & Kozan, 2016)	Improving Efficiency	Mixed-integer nonlinear programming (MINLP)	Ensured timely treatment of patients while managing resources
(Bowers, 2011)	Demand-Side Management	Model simulation	Estimated number of patients treated within target waiting time
(Powers et al., 2023)	Demand-Side Management	Dynamic priority scoring (DPS)	Focused on equitable ranking of patients
Our study	Considering all three strategies	Mathematical modeling (MINLP)	Allocate optimal resources, provide fair access time to surgical service across department, minimize total cost

Other than the above-mentioned approaches, demand-side management is critical when there is nothing much to do with the supply side. (Bowers, 2011) developed a model simulation of waiting list management that incorporated patient priority to explore the impact of seasonal variations in demand and supply on waiting times for elective surgical procedures in different specialties. The simulation estimated the number of patients who would be treated within the specified target waiting time. (Powers et al., 2023), on the other hand, proposed a dynamic priority scoring (DPS) system to rank elective surgery patients more equitably, based on a combination of waiting time and clinical factors. These two studies do not incorporate OR resource allocation into waiting list management and focus on individual patient priority settings rather than departmental as shown in **Table 2.1.**

Recently, waiting list management has received increased attention, particularly since the suspension of elective surgery due to COVID-19 pandemic. The extension of OR time has been used to reduce waiting lists by taking advantage of empty OR and existing surgical teams (Negash et al., 2022).

Unfortunately, during the peak of the pandemic, downstream resources such as ICU and MCU are redirected to use for COVID-19 patients resulting in unavailability to handle the patients flow from the OR. As a result, this led to a dramatically increased surgery backlog, and the volume of the surgery backlog accumulated from the cancellation of elective surgery remains unknown. Some studies integrated waiting list estimation and backlog clearance time projections using the simulation method. For instance, (Wang et al., 2020) estimated the backlog size in Ontario due to COVID-19 disruption and the time needed for backlog clearance utilizing forecasting and queuing models. (Oussedik et al., 2021) modeled the orthopedic pathway to estimate elective waiting list numbers and suggest recovery strategies. Furthermore, (Joshi et al., 2021) used machine learning for predictive analytics and offered real-time estimations on backlog clearance time and associated costs based on resource optimization. However, due to the ongoing pandemic, the exact size of elective surgery waiting lists remains unknown. (Abdullah et al., 2022) developed a 2-stage discrete event simulation framework to evaluate elective surgery cancellation and resumption strategies, considering the trade-offs between overutilization, extended wait times, and operational outcomes.

Efficient OR planning is critical for addressing the surgical waiting list (Barbagallo et al., 2015). As the pandemic transitions into an endemic phase, there is widespread recognition of the importance of effectively managing waiting lists and reallocating resources in OR planning. However, as reviewed summarized in **Table 2** a notable gap exists in the literature concerning the integration of elective surgery waiting list management with the allocation of OR resources. This study seeks to address this gap by examining three strategies in OR resource reallocation: increasing capacity, prioritizing surgical departments, and optimizing resource utilization within the OR system to enhance efficiency in order to minimize patient waiting time and total incurred costs.

Table 2.2 Summary of integration waiting list management and resource management

Study	Objectives	Methodology	Key findings
(Wang et al., 2020)	Estimate surgery backlog size and clearance time result from COVID-19	Forecasting and queuing models	Provided estimates for backlog size and project time for clearance, aiding in recovery planning
(Oussedik et al., 2021)	Model orthopedic pathway to estimate elective surgery waiting lists and suggest recovery strategies	Pathway modeling	Proposed strategies for managing orthopedic surgery waiting list and optimizing resources
(Joshi et al., 2021)	Use machine learning for predictive analysis to estimate backlog clearance time and associate costs	Machine learning algorithm	Offered real time estimations on clearance time and costs, facilitating resource optimization
Our study	Formulate mathematical model for managing resource and waiting list	Math modeling technique (MINLP)	Optimal resources allocation results in minimum average waiting time and costs

2.3 Performance measure

2.3.1 Patient waiting time

Long waiting lists are among the most heard complaints in general health care especially after the emergence of the COVID-19 pandemic. The concern justifies many studies aiming at decreasing the waiting times for patients (Cardoen et al., 2010). Patient throughput is another performance measure that is closely related to patient waiting time. The dependency between waiting time, and throughput on the one hand, is clearly stated in Little’s Law, i.e., the average inventory in a system equals the average cycle time (which includes the waiting time and the process time) multiplied by the average throughput. The studies classified under patient throughput focus on increasing the number of treated patients which obviously leads indirectly to shorter patient waiting times or shorter waiting list clearance time. Clearance times have been estimated using queuing models before. Like clearance times, our model estimated the time required to reach the BAU workload. In our case however, the DES model allows for estimation of the entire distribution of clearance times based on actual data across all surgical groups whereas the queuing models based on Little's Law primarily estimates mean clearance times.

For instance, VanBerkel & Blake. (2007) use discrete-event simulation to examine how a change in throughput triggers a decrease in waiting time. In particular, they affect throughput by changing the capacity of beds in the wards and by changing the amount of available operating room time. Wang et al. (2020) estimate the size of the nonemergent surgical backlog owing to COVID-19 in Ontario, and the time and resources required to clear this backlog. Time series forecasting, queuing models and probabilistic sensitivity analysis were used to estimate the size of the backlog and clearance time. Joshi et al. (2021) developed a predictive analytics tool that would help evaluate different scenarios and multiple variables for clearance of surgical patient backlog during the COVID-19 pandemic. They built mathematical models for identified (1) time to clear the case backlog, (2) utilization of personal protective equipment (PPE) and (3) assessment of overtime needs. Abdullah et al. (2022) developed a 2-stage discrete events simulation (DES) based framework for the evaluation of elective surgery cancellation strategies and resumption scenarios across multiple operational outcomes. stage 1: Evaluating the Surgery Reduction Patterns and stage 2: DES model for the Evaluation of Resumption Strategies. Their modelling framework accounts for the tradeoffs between over-utilization (that can lead to significant overtime), and extended patient wait times. It is noteworthy that, for multiple surgical specialties(SSs) in the hospital system that require the same resources, the focus on solely maximizing surgical patient throughput might result in unfair access to the surgical resources and left one another behind. Therefore, to ensure fair and equal access for multiple SSs in healthcare organizations, we introduce the term "deviation of waiting list clearance time". Our goal is to minimize the deviation of waiting list clearance time among multiple SSs.

2.3.2 Minimize total costs

In the context of budget cuts domestically and in many countries' responses to an economic downturn, how to invest and distribute public resources is a pressing issue (Daniels, 2016) and OR is one of the most expensive units and a central hub in the hospital system. The largest cost categories of a hospital are operating rooms and the downstream patient ward groups, averaging 33% and 31% of its total cost, respectively. According to Fügener et al. (2014) discussed with operating room managers and indicated that there are four cost components that drive downstream costs: fixed costs, overcapacity costs, staffing costs, and additional weekend staffing costs. Moreover, additional to downstream cost, which is commonly called hospital related cost, patient related cost is another cost involved in planning and scheduling the operating room as well. For instance, Rovers et al. (2022) investigated cost incur due to long waiting time for surgery (cost of waiting per week). There is a significant cost incurred when a patient waits too long for surgery as shown in **Figure 2.3.1**

In our study we consider overtime cost of surgical block per block, overcapacity downstream ICU and waiting time cost. The patient-related costs are incurred by the long waiting time for surgery (cost per week waiting). (Rovers et al., 2022). The extra healthcare expenditure due to waiting for surgery was determined by calculating the difference in healthcareexpenditure before and after surgery. Only costs from a healthcare perspective were included, for example, extra visits to the hospital, general practitioner, physiotherapist. Net monetary loss, which is defined as the total loss of waiting another week for surgery, expressed in monetary terms.The net monetary loss is calculated by multiplying the loss in quality of life due to waiting 1 week for surgery by a threshold value, and subsequently the extra costs of waiting another week for surgery are added

The hospital-related costs are incurred by overusing surgical blocks as well as exceeding the regular SICU capacity. A fixed cost of opening a surgical block is based primarily on the staff required to support OR itself (surgeons, nurses, anesthesia, etc.). There are assumed to be fixed cost since. ORs typically planned to be open for a full day or not at all (Denton et al., 2010). This cost is neglected; we assumed all specialties incur the same amount of fixed cost when opening a surgical block.

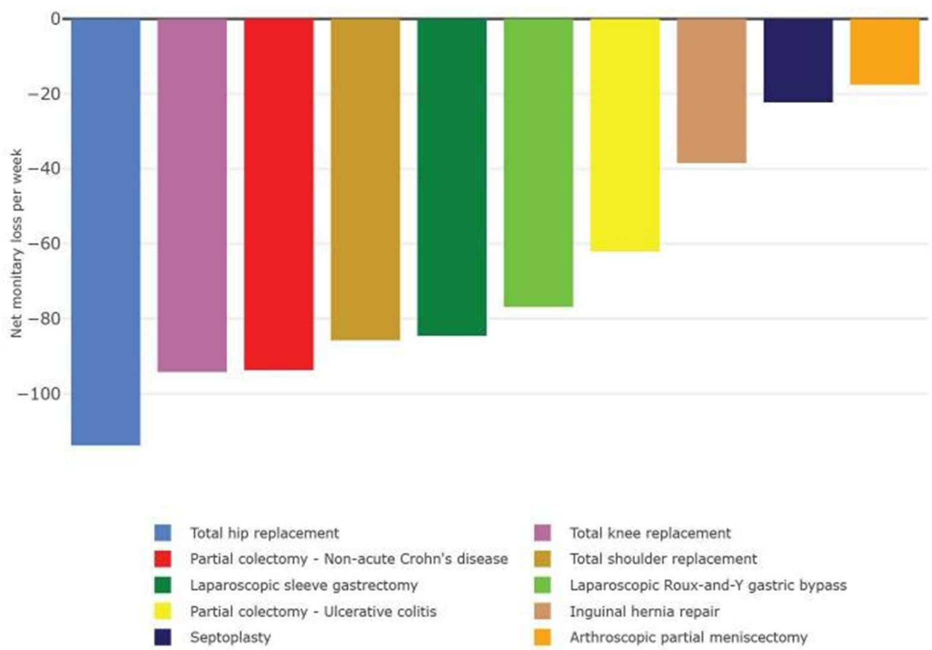


Figure 2.3.1 Surgery associated net monetary loss per week (Rovers et al., 2022).

As downstream resources (ICUs) are critically important, without an available ICU theoperation cannot be started or the existing patient in the ICU will be needed to discharge early to make available ICU bed for incoming patients. Overcapacity costs are costs that incur due to requiring capacity beyond capacity. This situation occurs, for example when patients must be transferred to ICUs in other hospital or wrong ICU as capacity limits (depending on service level(α^i). Hence, an exceeding capacity of ICU downstream will result in penalty cost (Fügener et al.,2014). The overcapacity costs depend on the service levels α^i. The higher the service level is, thelower the overcapacity costs are. Setting the appropriate service levels α^i should be done on a strategic level and is therefore outside the scope of this study.

2.4 Multi-objective optimization

Planning and scheduling processes in OR are recognized as highly complex tasks. This complexity stems from various constraints, occasionally conflicting with their objectives, as they aim to improve quality and satisfaction while simultaneously reducing costs and managing resources effectively. However, the diverse mix of surgery cases and the individual characteristics of each patient, along with the involvement of various stakeholders with conflicting interests, poses challenges in achieving multiple objectives (Barbagallo et al., 2015).

Hence, this is a multi-objective multi-constraints (MOMC) optimization problem. The objective of all resource allocation in healthcare organizations, from an optimization perspective, is to reduce total costs and patient waiting time while maximizing resource efficiency. Various studies incorporated hospital-related costs into OR planning and scheduling. Different cost components are considered in the literature. For instance, Fügener et al. (2014) identified four cost components—fixed costs, overcapacity costs, staffing costs, and additional weekend staffing costs characterized as downstream costs. These costs significantly contribute to overall expenses in the hospital. In contrast, Zhang et al. (2019) considered two types of costs, namely, patient-related costs and hospital costs. Hospital-related costs are incurred by opening and overusing surgical blocks, as well as exceeding regular ICU capacity, while patient-related costs are incurred by scheduling and postponing surgeries.

As mentioned above, various cost components are involved in the OR block allocation problem. Different studies have incorporated various types of cost components while addressing different objectives. For instance, Denton et al. (2010)

studied optimization models for planning and scheduling multiple ORs under uncertainty. They concentrated on decisions regarding surgery-to-OR assignments, aiming to create an assignment that balances two conflicting criteria: (1) the fixed cost of opening individual OR, and (2) the total cost of overtime across all OR. Their objectives were to minimize the weighted sum of the total cost of opening an OR and the total overtime cost resulting from OR overbooking. These studies focused on individual surgeries rather than surgical departments, overlooking upstream (intake) and downstream (recovery) resources. Moreover, the authors added upstream cost and downstream cost to the fixed cost of opening OR in the model.

Lin and Li (2021) focused on the OR scheduling problem in healthcare institutions, aiming to minimize operating costs while maximizing the utilization of OR and maintaining good quality care. Two main cost components were considered, namely, waste cost (the amount of unused time in the operating room, discouraging inefficiency) and overtime-operating cost (the cost incurred when the total operating time scheduled for an operating room exceeds its regular opening hours).

Fügener et al. (2014), on the other hand, discussed the tactical MSS problem in which the block OR time was assigned to different surgical specialties. They concentrated on the effect of the MSS on patient flow to downstream inpatient care units and proposed an approach for planning the MSS to minimize downstream costs by leveling bed demand and reducing weekend bed requests.

Furthermore, Fügener (2015) integrated strategic and tactical MSS problems using mixed-integer programming (MIP). This involved incorporating downstream resources such as ICU and regular patient ward into the model to maximize hospital revenues. The model's outcome determined the number of OR blocks allocated to each surgical specialty (SS).

Rather than integrating strategic and tactical levels, Shafaei and Mozdgir (2018) developed a mathematical model to construct an MSS based on the total number of OR blocks allocated to each SS at a medium-sized hospital in Iran. From the number of OR blocks allocated, the model then reallocated OR blocks to each SS aimed at minimizing OR spare time while considering the initial set of OR block allocation at the strategic level. The proposed model was solved using a lexicographic goal programming approach. Similarly,

Lu et al. (2019) developed a multiphase OR scheduling approach that addressed two different decision levels. The first phase mainly focused on an allocation of the number of OR blocks for each SS, with the objectives of maximizing profit and minimizing overtime costs. In the second phase, the MSS model was constructed to schedule surgeries in each SS to maximize the number of scheduled patients in all OR in a certain specialty, minimize underutilization and overtime costs, and balance OR according to a standard of OR working time, simultaneously. A multi-objective linear programming (MOLP) model was used to handle the problem. To reduce the complexity of the model, downstream resources (ICU and ward) and uncertainty in surgery duration were ignored.

Patrão et al. (2022) proposed two stages of OR planning and scheduling. They introduced an integer linear programming model (ILP) that is based on patient volume in CMP at a strategic level to assign the number of OR blocks to each SS and in the tactical level, MSS, the model aimed to determine which OR blocks should be allocated to any particular SS on any particular day.

The literature shows that there is a widespread focus on combining strategic and tactical levels in OR planning and scheduling. Optimization methods are widely used in the OR context (Abdalkareem et al., 2021). However, there is less attention in OR planning and scheduling in an optimization context that simultaneously focuses on reducing total incurred costs, patient waiting time, and maximizing resource efficiency. Moreover, concerning cost considerations, OR planning and scheduling predominantly incorporate hospital-related costs (e.g., overtime cost and overcapacity penalty cost), often neglecting patient-related costs (e.g., patient waiting costs), which play a crucial role in the planning and scheduling process.

The costs incurred due to prolonged waiting times for surgery, as highlighted by Rovers et al. (2022), present a significant financial burden known as patient waiting cost. This encompasses additional healthcare expenditures, medication costs, and a decline in the quality of life for patients awaiting procedures. Patient-related costs are quantified by the expenses attributed to prolonged waiting times for surgery on a per-patient, per-week basis within each surgical department. In parallel, hospital-related costs stem from unit capacity resources exceeding, such as those in the OR, ICU, MCU, and nursing time. For instance, an unavailable ICU and MCU bed may necessitate policies like premature discharge or the creation of temporary capacity, resulting in elevated costs compared to normal operations. Hence, our study incorporates multiple aspects of cost components, encompassing patient-related costs (cost associated with waiting times) and hospital-related costs (overtime of OR and nurses and overcapacity penalty costs of ICU and MCU) in OR block allocation. It is important to incorporate both of these costs together in OR planning, since it conflicts with each other whether the patient waiting time and cost should be reduced by adding more overtime resources. Therefore, this study aims to minimize total incurred costs while simultaneously reducing patient waiting times and optimizing resource utilization efficiency.

2.5 Multi-Criteria Decision Making in Healthcare

Multi-Criteria Decision Making (MCDM) refers to a set of methodologies designed to support decisions that involve evaluating multiple, often conflicting, criteria. These methods are particularly valuable in complex environments where decisions cannot rely on a single factor. In the healthcare sector, MCDM serves as a useful framework for structuring problems, assessing alternatives, and recommending actions to improve service delivery and patient outcomes.

In recent years, healthcare systems have increasingly incorporated MCDM approaches into various aspects of management and policymaking (Amaral & Costa, 2014; Zeng et al., 2013; Kuo et al., 2012; Li et al., 2019). For example, Kuo et al. (2012) applied the fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to rank healthcare failure modes in risk analysis. Zeng et al. (2013) modified the VIKOR method by introducing a data normalization approach tailored to medical datasets. Similarly, Amaral and Costa (2014) employed the PROMETHEE II method to assist decision-makers in resolving emergency department congestion.

The issue of patient prioritization is a critical concern in healthcare services, particularly for elective procedures were waiting lists are common. Li et al. (2019) emphasized that effective waiting list management requires acknowledging both the clinical urgency of patients and their broader social and personal contexts. This dual perspective underlines the importance of designing decision support systems that incorporate not only clinical guidelines but also insights from medical professionals to ensure that the most appropriate patients are scheduled for timely intervention.

Given the limitations of healthcare resources, prioritizing patients for treatment becomes a practical and ethical necessity. Several researchers have proposed frameworks using MCDM techniques to address this challenge. For instance, Rana et al. (2023) utilized fuzzy TOPSIS to develop a model for prioritizing patients awaiting elective surgeries in Chile, ensuring a more systematic and fair selection process. In another case, Solans et al. (2013) created a universal scoring system for elective surgery candidates in the Catalan public health system. Their model evaluates patients across three dimensions—clinical condition, potential benefit, and social function—through eight weighted criteria: severity of disease (23%), pain or primary symptoms (14%), rate of disease progression (15%), limitations in daily activities (14%), probability and magnitude of improvement (12%), lack of caregiving support (5%), caregiving responsibilities (8%), and limitations in work, education, or job-seeking ability (9%).

In a similar vein, Silva et al. (2021) proposed a decision support system that reflects both the clinical and social priorities of patients awaiting surgery, advocating for a comprehensive and balanced approach to prioritization. Meanwhile, Srikumar et al. (2018) introduced a general surgery prioritization framework implemented in New Zealand, aiming to enhance transparency, reliability, and fairness in surgical scheduling decisions. Their model aligns clinical judgment with equitable access, although ongoing evaluation is needed to ensure fairness in practical application.

These studies demonstrate the growing role of MCDM in supporting resource allocation and patient scheduling in healthcare. By integrating diverse factors—ranging from medical urgency to social vulnerability, MCDM tools can significantly improve the fairness and effectiveness of healthcare delivery.