BSC THESIS INDUSTRIAL ENGINEERING AND MANAGEMENT

IMPACT OF UNCERTAINTIES ON OPERATING ROOM SCHEDULING: A CASE STUDY AT HOSPITAL X

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March 2025

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VERSION
Final

STATUS
Final

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Preface

Dear reader,

I am delighted to present this bachelor thesis, titled "*Impact of Uncertainties on Operating Rooms Scheduling: A Case Study at Hospital X "* which represents the completion of my bachelor's degree in Industrial Engineering and Management at the University of Twente. During my journey of writing this paper, there were times I had several challenges since I have not worked on a project of this scale. However, through hard work and the use of prior knowledge I gained throughout my studies, I have successfully finished my bachelor thesis.

First of all, I would like to express my deepest gratitude to my university supervisors, Dr. Sebastian Rachuba and Dr. Daniela Guericke for being there for me and guiding me through the whole process Their expertise, constructive feedback, and encouragement significantly contributed to the development and completion of this thesis. I am truly thankful for their mentorship and dedication. In addition I would like to thank Hospital X and the company supervisor for providing me with the hospital data and for offering me the opportunity to collaborate with them on this research. Finally, I would like to thank my famiily and friends for their extreme emotional support during times of discouragement and stress.

Thanks to everyone who was there for me throughout the whole process.

I hope you enjoy reading my thesis.

Sincerely,
Asli Guvenc

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February 2025

MANAGEMENT SUMMARY

This thesis investigates the impact of uncertainties on operating rooms (OR) and is conducted at Hospital X, a German university hospital with 51 ORs. . The main objective of this research is to analyze uncertain factors influencing OR scheduling and provide data-driven recommendations to enhance scheduling practices, minimize inefficiencies, and improve operational performance at Hospital X. The uncertainties are surgery duration variability, emergency patient arrivals, and late starts of first surgeries of the day significantly affect OR utilization, leading to underutilization, overtime, and scheduling inefficiencies. The following research question guides this study:

“How do stochastic effects such as surgery durations, patient no-shows, and randomly arriving emergency patients affect the execution of hospital operating room schedules, and how should these factors be accounted for when creating OR schedules?”

A significant issue identified was the high rate of late starts, with many surgeries beginning after the required latest start time of 8:30 AM. These late starts lead subsequent procedures to delay, increasing the likelihood of overtime later in the day. This not only affects operational efficiency but also causes additional pressure on staff and decreases the quality of patient care.

Another key finding was the variability in surgery durations across different specialties. While it was not possible to determine whether surgeries exceeded their planned times, due to the absence of data on scheduled durations, the analysis revealed significant differences in how long procedures typically last. This inconsistency complicates scheduling, as the uncertain nature of surgery durations can lead to inefficient use of OR resources. Improving the estimation of surgery durations through data-driven models would allow the hospital to better anticipate variability and allocate resources more effectively, therefore reducing the risk of underutilization and overtime.

Additionally, while emergency patient arrivals are uncertain, the analysis identified patterns in their occurrence. Discovering these patterns would allow more flexible scheduling practices that can accommodate emergency cases without severely disrupting the elective surgery schedule.

Based on these findings, several recommendations were developed to help Hospital X optimize its OR scheduling. To better manage emergencies, a hybrid scheduling model should be implemented. In addition, late starts can be minimized by the introduction of automated reminder systems for surgical teams, alongside optimizing preoperative workflows to ensure all necessary preparations are completed on time.

Improving the accuracy of surgery duration predictions is also critical. By the use of historical data, the hospital can develop data-driven models that provide more reliable estimates for different types of procedures. This will allow for more accurate scheduling, reducing both underutilization and overtime.

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List of Abbreviations

OR = Operating Room
OT = Operating Theatre
MPSM = Managerial Problem Solving Method
HIS = Hospital Information Systems

1. INTRODUCTION

This section gives an introduction of this thesis, the organization, and the daily complexities that Hospital X faces when it comes to executing operating room (OR) schedules with the presence of emergency arrival, late start and surgery duration uncertainties. These uncertainties disrupt hospital workflows, leading to increased overtime, resource underutilization, and delays of scheduled surgeries. This research focuses on exploring the impact of various factors on the OR schedule flow at Hospital X, namely emergency patient arrivals, variations in surgery durations and late starts of the first surgeries of each day. We will do this by analyzing existing performed OR schedules to assess their impact on OR schedules and identify key characteristics, and pinpoint potential areas for scheduling improvements. In the subsequent sections of this chapter we define the scope and the methodology of the research.

1.1 Company Description

Hospital X is a tertiary care provider and a large university hospital located in Germany. It serves more than 50.000 patients each year with more than 2.500 employees across different medical fields, such as oncology, orthopedics, cardiology. The hospital focuses on delivering high quality care by a combination of state of the art technology and a team of highly skilled healthcare professionals. It delivers services including inpatient, ambulatory and preventative medical care.

The hospital is the largest healthcare institution in its region, and it has more than 20 medical departments. It provides 49 ORs which are used by these departments. As the hospital is the largest healthcare institution in the region, Hospital X manages a high volume of surgeries and diverse medical cases. Thus, with a large number of medical departments and ORs to manage and schedule, the hospital operates a complex network of ORs that requires efficient scheduling to ensure smooth operational flow. This is why Hospital X wants to deepen its understanding of these uncertainties occurring in the ORs and manage them more efficiently.

1.2 Motivation of Research

Operating Rooms (ORs) are among the most resource-intensive areas producing largest revenue and significant costs in a hospital, requiring efficient scheduling (Miao & Wang, 2021). The efficient management of ORs is essential for hospitals to ensure smooth operations, minimize delays and optimize resource utilization, especially for large organizations like Hospital X, which must continuously provide quality care with the presence of high demand.

OR scheduling involves assigning time slots for surgeries, determining when each patient will be operated and when the operation will end (Cardoen et al., 2010). Scheduling operations is a complex task, often influenced by multiple uncertain, maybe stochastic factors. Uncertainty refers to the lack of complete knowledge about future events, making it difficult to predict surgery durations or emergency arrivals. Stochastic factors, on the other hand, involve randomness and variability, such as the distribution of surgery durations or fluctuations in emergency cases. These factors consist **of arrival of emergency patients with different urgency levels**, **surgery duration variability**, **number of surgeries performed each day, surgeries that start later than required time**, and **overtime risk**. They directly affect the outcomes of OR scheduling, leading to gaps between scheduled and performed surgeries. These gaps arise because planned schedules do not always account for sudden disruptions, such as emergency cases requiring immediate attention, or prolonged surgeries exceeding their expected duration. As a result, subsequent procedures may be delayed, rescheduled, or even canceled, further impacting overall hospital efficiency.

Understanding how these elements influence OR scheduling is essential for two main reasons. Firstly, it allows hospitals to allocate resources such as staff and ORs more efficiently by taking into account the known effects of the uncertain factors. Efficient resource allocation helps ensure that medical staff, including surgeons, anesthesiologists, and nurses, are utilized effectively, reducing periods of idle time or excessive workloads. The idle periods can lead to frustration and decreased job satisfaction, and excessive workloads can result in stress, and burnout. Secondly, it helps minimize delays and disruptions, ultimately improving operational workflow due to less uncertainty.

The existing methods utilized by hospital X often struggle to integrate these uncertain events into scheduling effectively, leading to potential inefficiencies. For example, emergency surgeries take priority over scheduled procedures according to their urgency, causing delays or reschedules for elective surgeries. In addition, variability in surgery durations makes it challenging to predict room availability accurately, causing either underutilization leading to idle OR time and staff, or overutilization leading to overtime and rescheduling costs (Fügener et al., 2017).

The objective of this study is to first identify the nature and potential impacts of these effects, and then, quantify their impacts in terms of operational efficiency metrics for Hospital X. By the end of this research, we aim to provide recommendations on how to mitigate the impacts of the uncertainty. After conducting an analysis of the data from Hospital X, we will identify which factors create the most significant disruptions and bottlenecks within OR operations and develop insights of disruptions, such as correlations between certain patient categories (e.g., surgical specialties or emergency cases) and delays, overtime, or underutilization. The insights gathered from analysis will help in understanding which factors should be prioritized while scheduling surgeries. This study will add to the collection of knowledge on healthcare operations management for Hospital X.

1.3 Problem Identification

The hospital faces challenges in executing the planned operating room schedules due to various uncertain or stochastic factors. The surgeries follow a predetermined schedule, and some influences and their interactions are thought to affect the daily schedule and hinder the ability of the hospital to perform the schedules as planned. All factors affecting OR scheduling that are mentioned in the "Research Motivation" section are initially uncertain, as their behaviors are not fully understood. However, through data analysis, some of these factors will be discovered to be stochastic.

Through analyzing and discussing the impacts of these uncertainties, the hospital can gain deeper insights into why certain scheduling disruptions occur and develop strategies to mitigate them. We aim to quantify the impact of the factors that are discussed earlier, analyze their interactions, and determine how they should be accounted for when creating OR schedules.

1.3.1 Identification of action problem

The situation in the hospital leads to action problems, which can be identified as the difference between the norm (desired situation) and reality (actual situation) (Heerkens & van Winden, 2017). These problems are directly linked to uncertainties in the operating theatre (OT) and should be measurable through hospital data. The action problems we will focus on should be observable through the data provided by the hospital. By analyzing hospital data, we can determine how frequently these issues occur and how they influence daily scheduling.

We identify three action problems for this study. The surgery duration variability leads to either underutilization of ORs, or overtime, which means some surgeries are operated outside the regular hours. Some ORs remain idle while others are overutilized, leading to overtime. Furthermore, some emergency cases require immediate attention, often disrupting the elective surgeries. Considering these issues, we identify the action problems as **" Underutilization"**, **"Overtime"**, and **"Disruptions"**, which ultimately challenge the hospital in creating efficient OR schedules. Disruptions occur if emergency cases require immediate attention and interfere with elective surgeries. These disruptions can lead to rescheduling or even cancellations, directly affecting the hospital's ability to follow the planned schedules and reducing overall efficiency. However, due to limitations in the available data, it is not possible to analyze disruptions accurately. That is why, we will not be able to analyze the disruptions.t

As discussed during meetings with hospital management, Hospital X prioritizes performing as many surgeries as possible within its available resources to meet high patient demand and ensure efficient use of its operating room capacity. That is why underutilization caused by various factors are not acceptable for the hospital. In addition, overtime is both costly and leads to staff exhaustion, which are not desired for Hospital X. There is also a connection between underutilization and overtime. Periods of underutilization such as Gaps in the schedule or idle

ORs can cause surgeries to be pushed later into the day. The gaps may arise from surgeries that finished earlier than planned or the surgeries that took longer than planned and lead to the next surgeries to be postponed or cancelled. When these delays accumulate, especially if surgeries take longer than planned or emergencies arise, the likelihood of overtime increases. By understanding these action problems and their causes, the hospital can develop targeted strategies to mitigate their impact and improve the efficiency of OR schedules. The goal of this research is not to achieve 100% utilization, which could overwhelm hospital resources and staff. Instead, this study aims give recommendations to the hospital that will decrease the underutilization and overtime.

1.3.2 Problem cluster and motivation of core problem

A structured approach is essential to fully understand the problems in OR scheduling and their root causes. For this research we define a core problem. In order to identify key problem areas, analyze their impact, and develop solutions, we can visualize the relationships through the use of a problem cluster. Problem clusters are a structured tool to map the problems and their consequences by providing their connections, which helps to identify the core problem in research. (Heerkens et al., 2017). It allows us to distinguish between the core problem, which is the underlying cause, and the action problems, which are the observable issues that stem from it.

Mapping these relationships will allow the hospital to better understand the connections between different factors, and develop targeted solutions. By prioritizing the most important problems, the hospital can create more efficient OR schedules. This structured approach also ensures that recommendations address the root cause rather than just treating the symptoms of inefficiencies.

Figure 1 shows the connections between the action problem, the core problem, and the associated problems.

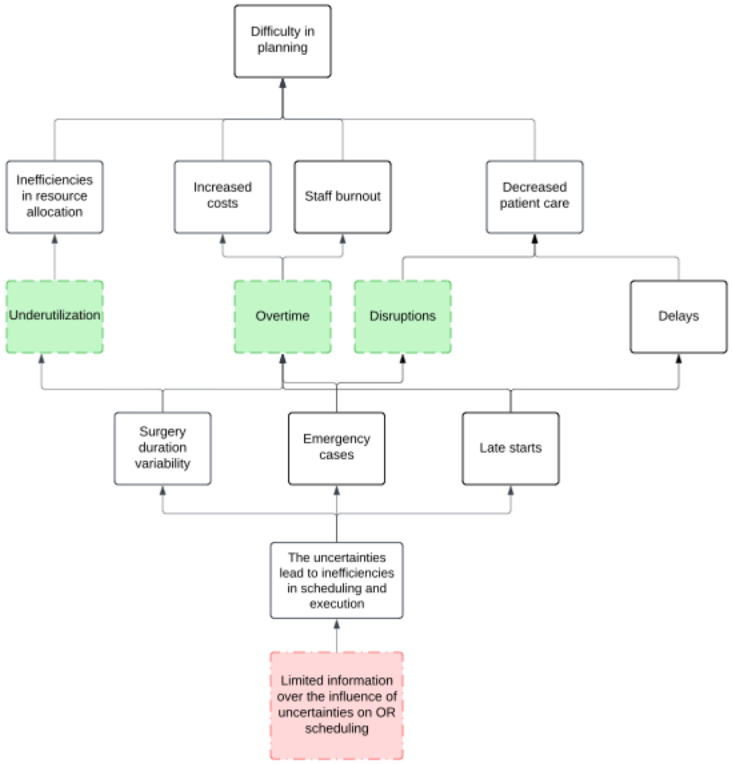


Figure 1:Problem Cluster

Identifying each problem and the connections between them will help us focus on the core problem which is the main problem of the case, and solve the problems faster. Since all the action problems stem from the uncertainty of some factors, the core problem for this research is stated as “Having limited information over the influence of uncertainties on OR scheduling”. This root issue prevents the hospital from executing the daily schedules of ORs as planned and leads to inefficiencies.

This problem regarding the execution of the plan is connected to three main factors: surgery durations variability, emergency cases and late starts. Surgery duration variability may cause underutilization due to surgeries taking shorter than planned, or overtime due to the surgeries taking longer than planned. Consequently, as shown in the problem cluster, the resources (OR time, staff, operation equipment) won’t be used efficiently if the ORs are underutilized, and the hospital will have more costs and staff burnout in the case of overtime. If the hospital knows which surgeries or specialties have larger or lower variability, it will be easier to create more stable and efficient schedules. We observe similar problems with emergency patients. The emergency patients mean unscheduled surgeries and may be prioritized over the scheduled patients according to their urgency levels. Thus, the arrival of emergency patients disrupts the daily operation schedule or even may lead to overtime of some. Lastly, some of the surgeries start later than their required start time. For hospital X, the first surgeries of the day are required to start before 8 AM. Delays for those surgeries may lead to overtime or delay of the subsequent surgeries. As shown in the problem cluster, delays and disruptions lead to decreased patient care. The decrease in patient care indicates that the patients in need of treatment may experience delays or might even need to be rescheduled. A significant consequence of all the problems is that the hospital has difficulties in scheduling operations efficiently. The ability to anticipate and incorporate these uncertainties into scheduling decisions will ultimately help the hospital in managing these factors betters and in creating more efficinet schedules.

1.4 Research Questions & Problem-Solving Approach

1.4.1 Problem-solving approach

The objective of this research is to analyze the impact of uncertain factors on OR scheduling and propose data-driven recommendations to the hospital on how to mitigate the negative influences of uncertain factors. In order to conduct the research, we will follow a systematic approach. We will use the Managerial Problem Solving Method (MPSM) while conducting the research. The reason to use MPSM is because it is a systematic and creative approach that is a general method and applies to many areas and can guide to a tailored solution. (Heerkens et al., 2017)

MPSM consists of seven phases that we will follow sequentially. Each phase is specified to the research context as follows:

Initially, we identified the action problems and associated problems previously in Section 1.3.1. For the first phase of the MPSM which is **"problem identification"**, we developed the problem cluster in Chapter 1 that helped us in identifying the core problem. The second phase of MPSM, **"problem approach"**, is also presented in Chapter 1 by determining the research design. We will conduct the research by understanding the problem and how it is managed currently in the hospital first, then do a literature to explore methods and analyze the provided data and make recommendations according to the analysis and literature review.

In Chapter 2, "Current Management Analysis", we will discuss how the schedules are determined and how responsive is the planned schedule to the uncertainties. This step corresponds to the third phase of MPSM, which is **"problem analysis"**.

In Chapter 3, "Literature Review", we will explore what are the impacts of the factors we discussed before and how to mitigate their effects, how should these factors be accounted for when scheduling and what analysis methods should be used for the analysis part. This chapter contributes to the fourth phase of MPSM, which is "**solution generation**", by providing the theoretical foundation and evidence-based insights to provide practical recommendations later in the research.

In Chapter 4, “Data Management”, we will conduct the analysis. In this chapter, we aim to present how each factor impacts the schedule, for example which factors are stochastic, do the late starts lead to overtime, which specialties have high variability, and the interaction between the factors These steps correspond to phase five and six of MPSM, **“decision making”** and **“implementation”**.

The last phase of MPSM consist of **“evaluation”**, however the thesis is limited to 10 weeks, thus evaluation won’t be possible since it requires time to see the impact of implementation.

1.4.2 Research Questions

In order to solve the action and core problems, we formulate several research questions that are centered on the uncertain or stochastic effects and their influence on the daily surgery schedules. The research questions are used to break down a problem statement into smaller, more manageable components, making it easier to understand and address. Throughout this research, we will answer one research question which clearly presents the objective of the study and seven sub-research questions to make the main question more manageable. The main objective of this study is to investigate the influences of uncertain or stochastic effects on the surgery scheduling. We need to explore nature of the factors, possible methods to analyze those, and current management of the hospital, so we can formulate the main research question and sub-research questions as follows:

Main Research Question:

“How do the uncertain or stochastic factors influence the Hospital X’s OR scheduling, and how should these factors be accounted for in the scheduling process?”

This main research question is derived from the core problem and aims to solve the core problem stated in the problem cluster “Having limited information over the influence of uncertainties on OR scheduling”. This research question requires to analyze each factor individually and to investigate the relationship between them. Answering this question will provide insights into how uncertainty and stochastic effects influence OR scheduling and determine how hospitals can account for these factors in their scheduling decisions to mitigate inefficiencies.

Sub Research Questions:

The sub-research questions are presented below. Table 1 indicates in which chapter each question will be addressed.

Chapter 2: Current Management
1. How are the uncertain or stochastic factors currently managed in the hospital?
Chapter 3: Literature Review
2. What statistical methods can be used to analyze and model these factors? 3. What are the key characteristics that makes these factors uncertain or stochastic?
Chapter 4: Data Analysis
4. How do these factors influence the OR scheduling and how can these factors be integrated into scheduling practices? 5. What are the interactions between these factors? 6. What are the potential implications of these interactions for daily surgery planning?

Table 1: Sub-Research Questions

1.4.3 Deliverables

This research will provide:

1. **Identification of impact of each factor and relationships between them:** The analysis will reveal the effects of uncertainties on different days or hours, such as the frequency and timing of emergency patient arrivals, typical variability in surgery durations, and the occurrence of late starts. Understanding these behaviours will help identify how these factors interact and influence operational efficiency.

2. **Recommendations to the hospital on what factors should be accounted when scheduling:** Based on the analysis, the research will provide actionable strategies for integrating these factors into the scheduling process. For example, it will suggest how to allocate time buffers for high-variability surgeries.

3. **Focused report of findings and recommended solutions:** The final report will summarize the research outcomes, including data-driven insights, analysis results, and

tailored recommendations for Hospital X. These solutions will aim to improve scheduling efficiency, reduce overtime and underutilization, and enhance overall operational performance.

1.5 Research Design

This research on investigating the influence of uncertainty on daily surgery scheduling in a hospital setting will adopt a mixed approach, a combination of descriptive and exploratory methods, mainly to ensure that our findings are not only statistically valid but also operationally relevant. The exploratory parts consist of the literature review, while the descriptive parts cover the analysis of the data from the hospital that will help us identify the impacts and measure the extent of inefficiencies. Throughout this research, we will explore the methods we can use to analyze the influences of uncertainties, and with the findings, we will look for ways to improve the daily scheduling and provide the hospital with recommendations The data will be provided by the hospital, which is collected from a real-life setting, thus we will be able to draw correct and valid conclusions. The detailed research design of this study is presented in Table A (Appendix A) .

1.5.1 Limitations of research

In this section, we will discuss the scope and limitations of the research. We observe some limitations within the research that may affect the process and outcome of the study. There are three main limitations that we need to mention:

Absence of Planned Schedule Data

The analysis is based only on performed surgeries, without access to originally planned schedules. As a result, direct comparisons between planned and actual schedules are not possible. That is why, we are not able to measure the disruptions caused by emergencies or delays caused by late starts.

Focus on Selected Stochastic Factors

The research examines specific factors (surgery duration variability, emergency arrivals, and late starts) while excluding other potential factors such as staffing shortages, equipment failures, or external hospital-wide disruptions due to lack of the related data. We will not conduct an analysis on those factors but will mention briefly in the lierature review. However, we will not give any quantitative recommendations regarding those factors.

Data privacy

When conducting the research, ethical considerations should be taken into account. Since the privacy of the patients should be considered for the shared data, both the hospital and we should pay attention to eliminate all the names and indications to avoid violating a patient's privacy.

It is important to discuss reliability and validity to ensure that the findings of this research are credible, reproducible, and applicable to hospital decision-making. The discussion on reliability and validity of this study is presented in Appendix B.

2. CURRENT SCHEDULING STRATEGIES AND CHALLENGES

The second chapter of this research focuses on how the OR scheduling is done in Hospital X currently. The goal of this chapter is to answer the first sub-research question ***"How are the uncertain or stochastic factors currently managed in the hospital?"***. **Section 2.1** discusses the details within OT and how scheduling decisions are made. In addition, hospital requirements and stakeholders involved are discussed in this chapter. By analyzing these procedures, we can better understand the structure in place and pinpoint areas where uncertainties may create inefficiencies. In **Section 2.2**, we discuss the limitations regarding OR scheduling for Hospital X. Identifying the limitations in the hospital's scheduling system is crucial for recognizing areas that need improvement. Limitations such as the impact of emergency cases, inflexible scheduling adjustments, and estimation inaccuracies in surgery durations can lead to inefficiencies in OR utilization. Examining these aspects will help determine potential areas for improvement and optimizing OR efficiency. Finally, **Section 2.3** concludes the chapter.

2.1 Hospital X Scheduling Strategy

The hospital is using its hospital information system (HIS) application, which is an IT application used to manage hospital operations, allowing precise planning of OR usage and resource allocation. Here the ORs are planned individually and the schedules are generated daily or weekly. As confirmed by the hospital, there are no fixed blocks for specialties, the hospital's objective is to perform as many surgeries as they can. However, a specific process is followed to ensure that all scheduling information is submitted, providing clarity and structure to the scheduling workflow. All head physicians are required to submit the schedule and estimated durations for their specialty for the next day into the HIS application before 1 PM. After 1 PM, the schedule is locked and only the OR coordinator can make changes on the schedule. Next to that, every day at 2 PM, surgical doctors, the OR coordinator, and OR management team meet to finalize the schedule for the following day. These meetings ensure collaborative work to handle potential conflicts, rescheduling needs, and resource availability.

Regular OR hours run from 8 AM to 4 PM, with all elective patients scheduled within this timeframe. On weekends or outside the regular hours, there are no scheduled surgeries. The hospital requires to start the first surgeries of the day before 8:30 AM. The surgeries starting after that time are assumed to be late starts.

The duration of the surgeries is estimated by the specialists from each department. The estimations of the durations are determined based on the operation type and activities needed to be completed during the operation, and the surgeons' level of training and experience. These estimations are crucial for efficient scheduling, enabling the hospital to maximize OR utilization without exceeding available time or resources. Additionally, if a specific patient has undergone the same type of surgery before or has critical health conditions, extra time is reserved for that patient within the schedule.

The staff and resource allocations are managed by different stakeholders. For example, the anesthesia department determines the number of staff needed for the planned surgeries, and OR management team determines the nursing staff and the essential medical equipment, in collaboration with the OR coordinator. Moreover, the hospital checks if there is availability in the intensive care unit (ICU). If there is no availability in ICU, the surgeries that require ICU are canceled for that day.

Furthermore, the hospital also receives emergency patients. The elective and non-elective patients share some ORs, so the emergency operations are mostly integrated into the OR schedule. Each specialty has specific ORs that can use but most of the ORs are used commonly by many specialties. The hospital manage emergency patients with a classification system, but it still causes schedule disruptions, indicating a need for a better approach.The emergency patients are classified and operated according to their urgency (N0 to N4). N0 requires immediate surgery, possibly at the patient's current location. N1 requires surgery on the next available OR, regardless of the specialty. N2 requires surgery in the next available OR within the same specialty. N3 requires surgery at the end of the elective program and doesn't disrupt the schedule. N4 is scheduled into the following day's OR program. This classification allows OR coordinators to make effective decisions based on the urgencies, preventing unnecessarily interrupting the schedule while prioritizing critical cases.

During regular hours, the emergency cases are performed according to availability of ORs and staff. After 4PM, two dedicated emergency teams are available to handle emergency cases that arrive or are planned to be operated after regular hours. This arrangement minimizes the impact on the following day's elective schedule, as after-hours emergencies can be managed without disrupting planned surgeries. However, if an emergency case needs to be scheduled for the following day and the schedule is already full, the hospital will contact the scheduled patients for a possibility of rescheduling or swapping times.

2.2 Operational Challenges in OR Scheduling

Hospital X faces several challenges that hinder its ability to maintain an efficient and adaptable scheduling system. These challenges arise from fixed scheduling structures, variable surgery duration, emergency patient arrivals, and inefficient resource allocation. The inability to accommodate unexpected changes, such as extended surgeries or emergency cases, often leads to delays, elective surgery cancellations, and underutilization of OR capacity.

This section examines the key problems affecting OR scheduling efficiency, including limited flexibility in adjusting schedules, uncertain surgery durations, lack of buffer times for surgeries, and bottlenecks in decision-making. Understanding these challenges is essential for identifying areas of improvement and optimizing OR scheduling.

Impact of Emergency Patients on Scheduled Patients

While Hospital X has a structured classification for emergency patients (N0 to N4) and dedicated teams to handle emergencies after 4 PM, the integration of elective and non-elective cases in the same ORs can still disrupt the schedule. The reliance on elective ORs to accommodate emergency cases, especially during regular hours, increases the risk of delays and cancellations. Additionally, the hospital must reschedule elective surgeries if an emergency case needs to be scheduled for the next day and all available slots are already taken. This process can lead to last-minute changes and thus patient dissatisfaction, indicating a lack of flexibility in accommodating emergencies without affecting planned surgeries.

Limited Flexibility for Uncertainties

The OR schedule is locked at 1:00 PM a day before the surgeries, allowing only the OR coordinator to make adjustments. While this lock-in increases stability, it limits the ability of head physicians to adapt to unforeseen changes, such as last-minute cancellations or emergency cases. This restriction may lead to inefficiencies, as any adjustments must go through a single coordinator, likely to create bottlenecks in decision-making.

Estimation of Surgery Durations

The duration of the surgeries is estimated by the specialists according to the surgery type, surgeon experience and procedures involved, however these durations are not estimated considering the possible complications during the surgeries or patient-specific factors. This uncertainty in actual surgery times can lead to overruns if there is not enough buffer time for the surgeries or idle time, affecting OR efficiency and delaying following cases. Adopting data-driven models, such as historical analysis, to estimate surgery durations more accurately could reduce the impact of variability and improve scheduling efficiency. By analyzing past data on surgery types, patient conditions, and specialty specific characteristics, the hospital could develop a model that better predicts actual surgery times, reducing overruns and idle times in the OR.

2.3 Conclusion

This section provides the current management analysis of Hospital X, aiming to answer the sub-research question "How *are the uncertain or stochastic factors currently managed in the hospital?"* Hospital X currently manages uncertainty through predefined scheduling rules, specialist estimations for surgery durations, and a structured classification system for emergency patients. However, these approaches do not fully account for the uncertain nature of surgery durations, emergency arrivals, or scheduling bottlenecks.

To better understand how uncertainty affects OR scheduling and whether these uncertain factors exhibit stochasticity, the following chapter will review relevant literature on uncertainty in OR scheduling, variability in surgery durations, emergency patient arrivals, and statistical methods used to analyze these factors.

3. LITERATURE REVIEW

Conducting a comprehensive literature review is important to gain an understanding of the existing knowledge, methodologies, and theoretical frameworks relevant to the research topic. This literature review ensures that the research builds on previous works, identifies gaps in the current knowledge, and guides the selection of appropriate models and statistical approaches. The literature review helps shape the research questions and supports the study's approach by looking at past research and strengthens the overall validity and reliability of the research outcomes. This chapter focuses on the previous research on OR scheduling under uncertainty, how this uncertainty is managed and the influence of the stochastic effects on OR scheduling. Through the literature review we will answer the following sub-research questions**: "How do these factors influence the OR scheduling and how can these factors be integrated into scheduling practices?"**, **"What are the interactions between these factors?"**, **"What are the potential implications of these interactions for daily surgery planning?"**. In **Section 3.1**, we discuss what are the uncertainties in OR scheduling and why do they exist. In **Section 3.2**, we discover the nature of these uncertainties, whether they follow probabilistic characteristics or not in order to determine the suitable analysis methods. In **Section 3.3**, we review the statistical techniques commonly used to study uncertainty in OR scheduling which will determine the anlaytical approach of this study. Finally, in **Section 3.4**, we conclude this chapter

3.1 Understanding Uncertainty in OR Scheduling

For most hospitals, operating rooms are a large source of both cost and profit. According to Gökalp et al., surgeries generate 40% of the overall revenue in hospitals (Gökalp et al., 2023). Therefore, effective planning and scheduling of the ORs is crucial for hospitals to reduce costs and generate revenue, while providing high-quality care (Jebali et al., 2006). However, achieving efficient OR schedules is challenging with the presence of several uncertain factors. To build a foundation for discussing factors that affect OR scheduling, it is crucial to first define uncertainty and explain its role in influencing scheduling efficiency.

3.1.1 Definition of Uncertainty in OR Setting

As defined by Tumeo, uncertainty refers to the state of lacking certainty or confidence about a specific value or outcome, where the exact result cannot be predicted completely due to incomplete information (Tumeo, 1994). In OR scheduling, uncertainty can arise at different decision-making levels, each influencing the hospital's ability to allocate resources efficiently and maintain smooth surgical workflows.

Before examining how uncertainty occurs at different levels of OR scheduling, it is important to distinguish between planning and scheduling. Distinguishing between planning and scheduling is particularly important in the context of this research because this thesis focuses on scheduling rather than planning. OR planning refers to a broader process and includes coordinating supply and demand for ORs. OR scheduling involves assigning time slots for surgeries, determining when each patient will be operated and when the operation will end (Cardoen et al., 2010). Since scheduling is more directly affected by real-time uncertainties, this research primarily examines how these factors influence OR scheduling and what methods can be used to mitigate their effects.

OR scheduling is typically decided in three levels: strategic, tactical, and operational, each with its own set of challenges and uncertainties (Zhang et al., 2020). Strategic level focuses on long term scheduling and deals with the distributing blocks or periods among specialties, tactical level focuses on mid-term scheduling and contructing schedules that optimize the efficiency of surgeries, and operational level deals with the day-to-day scheduling of individual surgeries, determining their precise sequence within a given day (Beaulieu et al., 2012). Understanding how uncertainty arises at different scheduling levels is crucial for identifying the key factors that disrupt OR workflows. The following section explores specific uncertain factors affecting OR scheduling.

3.1.2 Uncertain Factors in OR Scheduling

Certain factors in OR scheduling exhibit inherent uncertainty, which can disrupt the planned workflow and impact the efficiency of hospital operations. Recognizing and understanding these uncertain factors is essential to improving scheduling practices, resource utilization, and patient care outcomes. In this section, we explore key factors that are inherently uncertain in OR scheduling, focusing on surgery duration variability, emergency patient arrivals and late starts of surgeries.

The surgery duration refers to the total time a patient spends in the OR (Babayoff et al., 2022). However, as the data in hand only presents the start and end times of the procedures, we assume the surgery durations as the time between the cut and seam. The surgery duration itself is uncertain and introduces challenges to OR scheduling. Surgery durations vary significantly depending on the type of procedure, the surgeon’s experience, patient conditions, and similar clinical factors that are sources of variability (ShahabiKargar et al., 2014). Accurate estimation of the surgery durations is crucial since the surgeries that take longer than predicted may cause the subsequent surgery to postpone, or conversely, the surgeries that take shorter than planned may cause lower utilization of ORs (Kayis et al., 2012). However, even if the surgery durations are predicted accurately based on the clinical factors, non-clinical factors also have influence on the actual duration. For example, according to Wang et al., the surgeons’ workload also impact the surgery durations, and the surgery duration increases as the surgeons’ workload increases (Wang et al., 2018).

While the focus is mostly on the uncertainty of surgery duration estimations, the variability of surgery durations introduces additional complexities in OR scheduling. High variance in surgery durations, even when average times are accurately estimated, can disrupt schedules due to unexpected deviations. Schultz and Claudio emphasize that scheduling decisions based only on average durations without considering variability can lead to significant inefficiencies (Schultz & Claudio, 2014). Their research suggests that surgeries with high variability should be scheduled ideally earlier in the day, but not necessarily as the first case. The goal is to allow sufficient buffer time to absorb potential overruns without causing significant delays for subsequent surgeries. On the other hand, low-variability surgeries are more suitable to start the day because their predictability helps establish a stable schedule and reduces the risk of causing delays. Grouping surgeries based on their variability levels and sequencing them thoughtfully can help manage uncertainty, ensuring that potential overruns do not adversely affect the entire schedule.

The surgery duration uncertainty is an issue for two decision levels. In tactical level, the surgery durations are determined and operational level includes sequencing the surgeries considering the estimations (Erdogan & Denton, 2011). Since these estimates directly influence the scheduling process, inaccuracies at this level can have cascading effects, significantly impacting OR efficiency. Poor estimations and sequencing may result in either underutilization of resources or overtime, both leading to financial and operational consequences.

In addition to the variability in surgery durations, another significant source of uncertainty in OR scheduling arises from the emergency patient arrivals, which introduces its own set of challenges and complexities.

As stated by Tancrez et al., emergency patients, whose surgeries are not planned, disrupt the schedule (Tancrez et al., 2009). They arrive randomly and need immediate attention according to their urgency (Lamiri et al., 2008). Both their arrival and the required time for processing is uncertain. The uncertainty associated with emergency patient arrivals affects not only the allocation of ORs but also resource planning for surgical teams, anesthesia staff, and postoperative care units. Managing this uncertainty involves decisions at both the tactical and operational levels. At the tactical level, hospitals decide whether to dedicate specific ORs exclusively for emergencies or adopt flexible scheduling policies where ORs are shared between elective and emergency cases. This decision shapes the hospital's long-term capacity to handle emergency demand without severely affecting elective surgeries. In contrast, decisions at the operational level involve real-time management of emergency cases as they occur. This includes determining which OR will accommodate the emergency, reallocating scheduled elective surgeries if necessary, and adjusting staff assignments based on urgency and resource availability. There are several approaches to address these uncertainties.

Jung et al. (2019) conducted a simulation study comparing partially flexible and fully flexible OR policies. In a partially flexible policy, all ORs are shared between elective and emergency patients, providing greater adaptability when emergency cases arise. Conversely, in a fully flexible policy some ORs are shared by both emergeceny and elective cases while others are dedicated to only emergencies or electives. The study found that partially flexible policies offer more benefits, reducing delays for both emergency and elective surgeries due to the efficient reallocation of resources when emergencies occur (Jung et al., 2019). Similarly, in a study, it is observed that adopting partial flexibility poses improvements on patient waiting times and overtime than complete flexible and complete dedicated policies (Ferrand et al., 2014).

In addition, according to Wullink et al., dedicated ORs for only emergency patients (fully flexible) lead to longer waiting times and lower efficiency of OR utilization than the shared ORs (Wullink et al., 2007). However, for the shared ORs, the hospital needs to be more flexible, meaning, the emergency patients will have to be integrated into on of the ORs, according to the urgency, and the planned surgeries in that OR will have to be performed in another OR or treated later than the planned time. Ultimately, the choice of scheduling policy depends on hospital-specific factors, including emergency case volume, resource availability, and institutional priorities.

While emergency patient arrivals pose challenges due to their uncertainty, another critical source of uncertainty in OR scheduling arises from late starts of surgeries. Delays in starting the first surgery of the day are common in German hospitals, with over 70% of cases experiencing delays (Schuster et al., 2013). As stated by Dexter et al., the first surgeries starting even a few minutes of delay leads to the subsequent surgeries to run late (Dexter et al., 2009). This delay may lead to overtime and also decrease the number of surgeries performed (Fezza & Palermo, 2011).

In a study, it is proved that 1 minute reduction in delay of the first surgeries of the day results in approximately 1.1 minutes in labor costs (Dexter & Epstein, 2009). Apart from less costs, this also means less delays result in less staff burnout.

There are various casuses of late start, often stemming from a combination of administrative, logistical, and clinical factors. Common reasons include delays in patient preparation, unavailability of surgical staff, prolonged anesthesia induction, equipment setup issues, or incomplete preoperative assessments (Schuster et al., 2013).

Effectively managing late starts requires a combination of proactive planning and real-time problem-solving. For example, in a hospital, it is observed that only 30% of the surgeons arrived on time for the first surgeries of the day leading to on start rate of 31%, and when the hospital started to send reminder emails to the surgeons who have the first surgeries of the day, an increase in on-time start rate observed (Fezza & Palermo, 2011). This demonstrates how even simple interventions can lead to significant improvements in OR efficiency.

Certain factors in OR scheduling, such as surgery duration variability, emergency patient arrivals, and late starts of surgeries, exhibit uncertainty that can significantly disrupt the planned workflow and affect hospital efficiency. Understanding these uncertainties is crucial for improving scheduling practices, minimizing delays, optimizing resource utilization, and enhancing patient care outcomes. In the next section, we will discuss the nature of these uncertainties, exploring whether they are purely random or if they are stochastic that can be modeled and managed more effectively.

3.2 Determining Whether These Uncertain Factors Are Stochastic

Uncertainty in OR scheduling arises from various factors, each with distinct characteristics that influence how they impact hospital operations. Understanding the nature of these uncertainties is critical for developing effective strategies to mitigate their effects. Since stochastic behavior can be analyzed using statistical models, identifying which factors exhibit stochastic properties helps determine which uncertainties can be effectively analyzed through data. This distinction is essential for developing targeted strategies to improve OR scheduling efficiency.

A stochastic process refers to any process in which the progression or outcome can be effectively analyzed using probability (Doob, 1942). It describes events that involve randomness but follow identifiable probabilistic distributions, allowing for statistical modeling and prediction.

In this section, we examine whether these uncertainties are stochastic, following identifiable probabilistic distributions, or more random, influenced by several external factors.

Surgery durations exhibit stochastic nature (Tancrez et al., 2009). This means their variability can be modeled using probability distributions based on historical data. Factors such as the type of procedure, the surgeon's experience, and patient-specific conditions contribute to this variability (Choi & Wilhelm, 2012). Research shows that surgery durations frequently follow distributions like log-normal or normal (Stepaniak et al., 2009). Similarly, Choi and Wilhelm and Gökalp states that log-normal distribution is a good fit for surgery durations due to their right-skeweness (Choi & Wilhelm, 2012) (Gökalp, 2017). This stochastic behavior allows for predictive modeling, helping hospitals estimate expected durations and allocate resources more effectively

Emergency patient arrivals and length of emergency surgeries also demonstrate a stochastic nature, meaning they involve randomness and cannot be predicted fully (Lamiri et al., 2008) (Tancrez et al., 2009). Poisson processes are commonly used to model emergency arrivals (Tancrez et al., 2009). This allows hospitals to estimate the average number of emergency cases expected within specific time frames, helping in resource planning and OR allocation.

Unlike emergency surgeries and surgery duration variability, late starting first surgeries of the day are not necessarily stochastic. While late starts can be explained by stochastic models partially, they do not fullyfollow probabilistic distributions. They are many operational and patient related influences that lead to late starts. Therefore late starts are more random and less predictable due to those infleunces.

Understanding the nature of these uncertainties is essential for selecting appropriate management and analytical strategies. While surgery durations and emergency patient arrivals exhibit stochastic properties that allow for probabilistic modeling, late starts are more random and influenced by various operational factors. Discovering these differences helps hospitals improve their scheduling practices and resource allocation to mitigate disruptions effectively.

In the next section, we will explore the statistical approaches and models used to analyze these uncertainties, focusing on how different techniques can help quantify variability, predict behaviours, and improve OR scheduling efficiency.

3.3 Statistical Methods for Analyzing Uncertainty and Stochastic Effects

Effective OR scheduling relies on analyzing uncertainty and stochastic factors through statistical methods. In this section, we explore descriptive statistics, distributions, and regression models used in OR scheduling research to quantify variability, model uncertainty, and identify key relationships.

Descriptive statistics serve as the foundation point for any data analysis by summarizing and highlighting key features of the data, providing a clear baseline for further exploration. Descriptive statistics involve summarizing and characterizing data sets by computing metrics that highlight key features of the data (Ferson et al., 2007). This includes measures of central tendency such as the mean and median, which indicate the typical values within a dataset, and measures of dispersion such as variance and interquartile range, which reflect the spread or variability of the data.

These metrics help identify variations in surgery durations, such as specialties with high variability, and pinpoint frequent late starts or peak times for emergency surgeries. Visualization tools like box plots, histograms, and scatter plots enhance the understanding of these characteristicss.

While descriptive statistics effectively summarize individual factors, understanding relationships between variables requires more advanced techniques. Linear regression is used discover if there is a relationship between two variables (Twomey & Kroll, 2008). It is particularly useful in OR scheduling for quantifying how factors like late starts or the number of surgeries influence overtime. By deriving a mathematical formula using linear regression we will predict the dependent variable based on the independent variable. Using linear regression allows for predictions based on historical data, providing actionable insights for resource allocation and schedule optimization

The use of statistical methods in analyzing uncertainty and stochastic effects in OR scheduling is crucial for enhancing efficiency. Descriptive statistics provide insights into data insights while regression models reveal key relationships between scheduling variables. Together, these methods enable data-driven decisions that improve resource allocation, minimize delays, and enhance operational performance in hospital ORs.

3.4 Conclusion

This chapter reviewed key uncertainties in OR scheduling, their stochastic nature, and statistical methods for analysis. Surgery duration variability, emergency arrivals, and late starts were identified as major sources of inefficiency, contributing to underutilization, overtime, and schedule disruptions. Several research suggest strategies such as optimized sequencing, buffer times, and flexible scheduling policies to mitigate these challenges.

Surgery durations and emergency arrivals exhibit stochasticity, allowing for probabilistic modeling, whereas late starts are more random and influenced by operational factors. Understanding this distinction is essential for selecting appropriate analytical methods.

Descriptive statistics help examine characteristics of scheduling inefficiencies, while regression models quantify relationships between uncertainty factors and delays. These methods form the foundation for this study’s analysis.

This review highlights research gaps, particularly in how these uncertainties interact and impact OR scheduling. The next chapters present the methodology and statistical techniques used to analyze these effects at Hospital X.

4. DATA MANAGEMENT

In **Section 4.1**, we provide the description of data used, and in **Section 4.2**, we present the details of the datasets. In **Section 4.3**, we describe the data cleaning procedures implemented to ensure reliability and validity. In **Section 4.4** we will present the analysis methods along with key findings. Finally in Section 4.5, we will conclude the chapter.

4.1 Description of Data

This study is based on 2 datasets that are provided directly by Hospital X. The datasets are acquired based on requirements set by considering the scope of this research. Specific values and sensitive information like patient details, hospital name or surgeon information have been anonymized or removed, to comply with the confidentiality requirements and privacy policies.

The data is stored in Excel sheet format, allowing for structured analysis of key variables such as surgery durations, delays, emergency case frequency, and other metrics that influence OR efficiency. The datasets present two different timelines, 30 days in September 2024, from 1st September till 30th September for performed surgeries, both emergency and elective surgeries, and from 1st January 2023 till 18th September 2024 for only emergency surgeries.

The datasets contain the details of surgeries that took place in 51 different ORs, the plan of these operations, and details of emergency patients. There are 17 specialties presented in the data. The surgery durations are derived from start and end times of the operations. The dataset excludes preoperative and postoperative activities, such as patient preparation, anesthesia induction, and recovery room durations, thus the surgery duration captures the time between incision and closure Consequently, the analysis focuses only on the intraoperative phase, which may not fully reflect the total OR occupancy time.

Limitations

The exclusion of pre and post-operative phases limits the ability to analyze factors related to anesthesia preparation times, patient turnover efficiency, and recovery delays. Additionally, any variations in anesthesia or preoperative procedures are not captured, which could influence overall OR scheduling outcomes.

In addition, since we don’t have access to the planned schedule, because it is overwritten by the performed schedule, we cannot perform any analysis or provide any recommendations on the surgery duration deviations. That is why, we will assess the variability of the surgery durations, and how this varibility affects the OR scheduling.

Lastly, for the first dataset, we could not make distinction between elective and emergency surgeries because they do not capture the same time intervals. The emergency surgery dataset, second dataset, captures the days between 1st January 2023 and 18th September 2024, while first dataset captures the September 2024. The two datasets only overlap for 18 days instead of a whole month which prevents us to separate the elective and emergency patients.

4.2 Data Exploration

In the first dataset which provides information about the operations that took place, there are 3 sheets available: “Zeiten Doku” which includes the number of documented surgeries at each stage throughout September, “Erster Schnitt” which provides the average times on each stage of surgeries for each day, and “ Ubersicht” which presents the details of first and last operations for each day. In this dataset, there are both elective and emegency surgeries presented, however not all of the emergency surgeries in the emergency patient dataset are present in the first dataset.

Operating Area	Number of counters	Number of patient retrievals (date)	Number of patient arrivals (date)	Number of Release Anaesthesia Release (Date)	Number of operations started (date)	Number of operations completed (date)
Operating Area 1	609				521	519
Operating Area 2	371				360	358
Operating Area 3	159	39	78	67	150	148
Operating Area 4	63	16	25	29	57	57
Operating Area 5	95	42	54	57	85	82
Operating Area 6	131	52	73	73	127	125
Operating Area 7	159	14	14	14	158	156
Operating Area 8	166	82	109	82	163	159
Operating Area 9	63	13	24	24	63	62
Operating Area 10	75	54	58	57	72	71
Operating Area 11	129	93	101	95	126	125
Operating Area 12	63	31	52	54	60	59
Operating Area 13	103	43	55	77	101	97
Operating Area 14	171	84	94	92	159	150
Operating Area 15	2				2	2
Operating Area 16	343	1	5	100	306	293
Operating Area 17	1				1	1
Operating Area 18	64	29	42	43	60	59
Operating Area 19	59	29	37	39	48	47
Operating Area 20	28	12	19	21	28	28
Operating Area 21	58	21	30	35	49	47
(blank)						
Grand Total	**2.912**	**655**	**870**	**959**	**2.696**	**2.645**

Figure 2: “Zeiten Doku” sheet in the first dataset

Figure 2 depicts the sheet “Zeiten Doku”, showing the number of documented calls for appointments, arriving patients, anesthesia procedures, operations and completed surgeries for twenty operating areas in Hospital X. Operating areas consist of several ORs. There are 45 ORs used by elective surgeries, which 2 of them are only used for elective surgeries and 43 of them are shared with emergency surgeries . As it can be seen from the figure, some rows are empty due to lack of documentation.This sheet shows which fields are actually filled out in the surgery module. Not all times are always entered into the system, so the numbers on the sheet represent total values that are recorded. In other words, for example we can see that 150 patients have been operated in “Operating Area 3” but only 78 times it was documented when the patient arrived the hospital. Through this sheet, we can see that the hospital does not document all the processes for all of the operations.

First cut	(Multiple Items)				
surgery date	**operating area**	**specialty**	**average arrival of patients**	**average release from anesthesia**	**average start time of surgery**
(blank)	**(blank)**	(blank)			
(blank) Total					
29/04/2024	**Operating Area 1**	HERZ	12:00:00 AM	12:00:00 AM	10:37:00 AM
	Operating Area 2		12:00:00 AM	12:00:00 AM	8:55:00 AM
	Operating Area 3	HERZ	7:20:33 AM	8:23:25 AM	8:50:13 AM
	Operating Area 4	ORTHO	7:40:00 AM	8:08:00 AM	8:26:00 AM
	Operating Area 5	UROL	12:00:00 AM	8:15:50 AM	8:29:19 AM
	Operating Area 6	UROL	12:00:00 AM	8:08:24 AM	8:23:05 AM
	Operating Area 7	UROL	12:00:00 AM	12:00:00 AM	9:18:19 AM
	Operating Area 8	UROL	12:00:00 AM	12:00:00 AM	9:59:35 AM
	Operating Area 9	EXTERN	12:00:00 AM	8:10:00 AM	8:25:00 AM
	Operating Area 10	PLAST	12:00:00 AM	12:00:00 AM	8:29:00 AM
	Operating Area 11	CHEN	12:00:00 AM	12:00:00 AM	8:40:30 AM
	Operating Area 12	UROL	8:03:00 AM	8:15:00 AM	8:52:00 AM
	Operating Area 13	NCH	12:00:00 AM	8:28:00 AM	9:15:00 AM
	Operating Area 14	PLAST	7:10:14 AM	8:08:23 AM	8:29:30 AM
	Operating Area 15	NCH	8:10:52 AM	12:00:00 AM	8:50:01 AM
	Operating Area 16	UNFA	7:35:00 AM	7:59:00 AM	8:53:00 AM
	Operating Area 17	CHIR	8:23:40 AM	8:40:51 AM	8:59:35 AM
	Operating Area 18	GEFÄß	12:00:00 AM	8:35:00 AM	8:51:08 AM
	Operating Area 19	CHIR	8:02:52 AM	12:00:00 AM	8:37:59 AM
	Operating Area 20	HAUT	12:00:00 AM	12:00:00 AM	8:39:23 AM
	Operating Area 21	HAUT	12:00:00 AM	12:00:00 AM	8:28:03 AM
	Operating Area 22	HNO	8:00:00 AM	12:00:00 AM	8:35:00 AM
	Operating Area 23	GYN	8:10:00 AM	8:25:32 AM	8:30:00 AM
	Operating Area 24	GEB	8:28:00 AM	8:42:19 AM	8:48:15 AM
	Operating Area 25	HNO	12:00:00 AM	12:00:00 AM	12:00:00 AM

Last seam	Letzte Naht			
surgery date	**operating room**	**specialty**	**average start time of surgery**	**average finish time of operation**
29/04/2024	**Operating Area 1**	HERZ	10:37:00 AM	12:00:00 AM
	Operating Area 2	ORTHO	10:42:00 AM	12:00:00 AM
	Operating Area 3	HERZ	9:27:00 AM	9:40:00 AM
	Operating Area 4	ORTHO	10:17:00 AM	12:00:00 AM
	Operating Area 5	UROL	8:29:19 AM	12:00:00 AM
	Operating Area 6	UROL	12:00:00 AM	12:00:00 AM
	Operating Area 7	UROL	9:18:19 AM	10:00:55 AM
	Operating Area 8	UROL	9:59:35 AM	10:38:41 AM
	Operating Area 9	EXTERN	12:00:00 AM	12:00:00 AM
	Operating Area 10	PLAST	9:33:00 AM	12:00:00 AM
	Operating Area 11	CHEN	10:33:17 AM	12:00:00 AM
	Operating Area 12	UROL	12:00:00 AM	12:00:00 AM
	Operating Area 13	NCH	12:00:00 AM	12:00:00 AM
	Operating Area 14	PLAST	12:00:00 AM	12:00:00 AM
	Operating Area 15	NCH	12:00:00 AM	12:00:00 AM
	Operating Area 16	UNFA	8:53:00 AM	12:00:00 AM
	Operating Area 17	CHIR	12:00:00 AM	12:00:00 AM
	Operating Area 18	GEFÄß	12:00:00 AM	12:00:00 AM
	Operating Area 19	CHIR	12:00:00 AM	12:00:00 AM
	Operating Area 20	AUGEN	10:38:39 AM	10:42:59 AM
	Operating Area 21	AUGEN	10:34:00 AM	10:38:09 AM
	Operating Area 22	AUGEN	10:25:00 AM	10:41:02 AM
	Operating Area 23	AUGEN	9:19:10 AM	10:49:58 AM
	Operating Area 24	HAUT	10:18:26 AM	10:45:31 AM
	Operating Area 25	HAUT	10:01:46 AM	10:17:15 AM
	Operating Area 26	HNO	9:48:54 AM	12:00:00 AM
	Operating Area 27	GYN	12:00:00 AM	12:00:00 AM

Figure 3:" Erster Schnitt" sheet in the first dataset

Figure 3 presents a part of the second sheet " Erster Schnitt", providing the information of the specialty of the surgeries in the ORs, the average of patient arrival time, anesthesia release and start of surgery for the first and last operations. The red cells indicate that the surgeries start after 8.30 AM on average, which is the required latest start time of the first operations for each room.

Operating Area	1. FAB	Arrival Patient	Release from Anesthesia	First cut	Letzte FAB	Final cut	Final seam	Notiz
Operating Area 1						3:24:10 PM	7:10:23 PM	
Operating Area 2		7:50:00 AM	8:10:00 AM	8:34:00 AM		2:38:00 PM	3:20:00 PM	
Operating Area 3		7:17:00 AM	8:00:00 AM	8:59:00 AM		2:09:00 PM	4:41:00 PM	
Operating Area 4		7:34:00 AM	8:15:00 AM	8:29:00 AM		1:57:00 PM	2:47:17 PM	
Operating Area 5								
Operating Area 6		8:10:00 AM	8:20:00 AM	8:40:46 AM		2:39:17 PM	3:08:43 PM	
Operating Area 7		7:54:58 AM	8:10:00 AM	8:40:07 AM		1:41:00 PM	2:25:00 PM	
Operating Area 8						3:13:38 PM	4:20:00 PM	
Operating Area 9						3:19:14 PM	3:38:00 PM	
Operating Area 10		7:15:00 AM	8:10:00 AM	8:51:00 AM		1:23:01 PM	3:28:00 PM	
Operating Area 11		7:55:00 AM	8:30:00 AM	9:06:46 AM		2:04:31 PM	2:49:14 PM	
Operating Area 12			8:08:00 AM	8:27:00 AM		10:38:54 AM	3:26:15 PM	
Operating Area 13			8:13:00 AM	8:40:20 AM		2:02:00 PM	2:36:23 PM	
Operating Area 14						2:11:17 PM	3:20:43 PM	
Operating Area 15			8:08:00 AM	8:28:00 AM		12:07:00 PM	4:00:00 PM	
Operating Area 16			8:05:00 AM	8:22:54 AM				
Operating Area 17		7:20:45 AM	8:00:00 AM	8:40:00 AM		12:10:50 PM	4:50:00 PM	
Operating Area 18			8:10:00 AM	8:30:00 AM				
Operating Area 19				8:26:00 AM		1:09:54 PM	2:01:32 PM	
Operating Area 20				8:20:46 AM		3:27:00 PM	3:34:00 PM	
Operating Area 21				8:59:00 AM		12:34:13 PM	12:40:00 PM	
Operating Area 22				11:36:39 AM		11:36:39 AM	12:01:34 PM	
Operating Area 23		7:45:00 AM	7:56:00 AM	8:28:00 AM				

Figure 4: " Ubersicht" sheet in the first dataset

Figure 4 presents a part of the third sheet “Ubersicht”, which includes the times of first and last surgeries for each day. The red cells indicate the first surgeries started after 8:30 AM and the last surgeries that finished after 4:00 PM, which is the closing time of the ORs. The last surgeries finished after 4:00 PM lead to overtime.

The second dataset provides information about the emergency patients. The dataset contains the last 622 days’ information. We will be using the data of September 2024 when analyzing the emergency and elective surgeries together, and the complete time when we analyze the emergency surgeries on its own. The emergency surgeries dataset contains all the information regarding the surgeries, including patient details, date and time of arrival, date and time of surgery, urgency of the patients, diagnosis, procedures, the ORs that the surgeries performed in and specialties. In total there are 49 ORs used by emergency cases, 43 of them are shared with the electives and 6 of them are reserved only for emergencies.

4.3 Data Cleaning

When we receivced the data, we observed some errors and lack of documentation. Thus, we need to clean the data to get reliable results.

First of all, the datasets are presented in excel and all the cells are formatted correctly according to their values. Since Hospital X is a German hospital, the data was originally in German language. Therefore, for a proper analysis and presentation,we translated all the headings to English.

Secondly, as the hospital stated, the initial schedule is always overwritten by the performed operations. Therefore, some values and information are inconsistent or missing. We eliminated the operations that don’t have the essential information, like the missing date of operation, wrong surgery start and end times, etc. However, if the start date and time is recorded but the end date is missing, we still used those operations to calculate the surgery durations and other metrics since the missing end date values don’t affect the results. Moreover, there were invalid data points of surgery start and end time, and patient arrivals. Some surgeries are recorded as to be started or finished at 12.00 AM. When we discussed this with hospital, they mentioned that if there are staffing problems, some operations can only start at midday when on call duty begins. While this is the case, they also indicated that this might be a data error, so in order to eliminate any inconsistency and increase the reliability and accuracy of the study, we discarded all the surgeries that started or finished at 12:00 AM sharp. Also we saw surgeries with the same start and end times or surgery start times before the patient arrival time, we also eliminated those. Before data cleaning, we observed 2912 surgeries in the first dataset, and 8562 emergency surgeries in the second dataset. After cleaning the data we observed 2586 surgeries in the first dataset (elective surgeries and a part of emergency surgeries) and 6818 emergency surgeries in the second dataset.

5. DATA ANALYSIS

This chapter presents the data analysis conducted to investigate how uncertain or stochastic factors, namely surgery duration variability, emergency patient arrivals and late starts, influence Hospital X's OR scheduling. The analysis is made for each factor individually and the interaction of factors is also presented. From Section 3.1, we also know that these factors contribute to overtime. Thus we also included the analysis for overtime. The analysis aims to provide evidence to support the findings discussed in the literature review and data-driven recommendations to the hospital to address the main research question: *"How do the uncertain or stochastic factors influence Hospital X's OR scheduling, and how should these factors be accounted for in the scheduling process?"*

Additionally, the following sub-research questions will be answered in this section:

1. How do these factors influence OR scheduling, and how can they be integrated into scheduling practices?
2. What are the interactions between these factors?
3. What are the potential implications of these interactions for daily surgery planning?

In **Section 5.1,** we present the analysis methods along with key findings. In **Section 5.2,** we conclude the chapter.

5.1 Analyses and Key Findings

Emergency Surgeries

Our analysis begins with emergency surgeries as it brings stochastic uncertainty to OR schedules. Emergency surgeries mostly disrupt elective schedules due to their uncertain nature and urgency. We assessed the frequency, timing, and distribution of emergency cases, distinguishing between those treated on the day of arrival and those scheduled later.

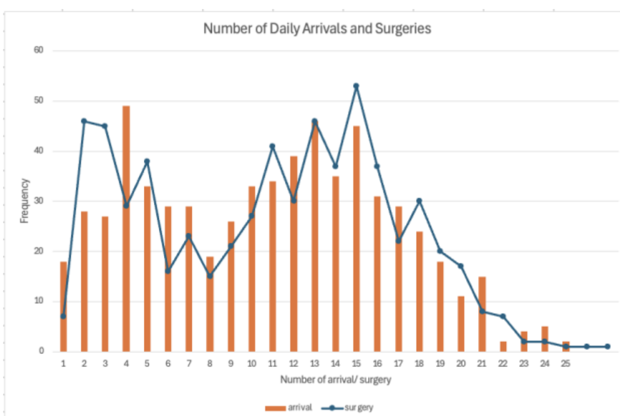


Figure 5: Frequency of the number of daily patient arrivals/ surgeries performed

To understand the relationship between emergency patient arrivals and emergency surgeries performed, we analyzed the frequency distribution of daily emergency arrivals and surgeries. Understanding this relationship is important because it provides insights into whether hospital capacity aligns with real-time emergency demand. In Figure 5, we see the frequency of the number of daily emergency patient arrivals (represented by orange bars) and emergency surgeries performed (represented by the blue line with dots) at Hospital X. The x-axis shows the number of emergency arrivals/surgeries per day, while the y-axis indicates the frequency, i.e., how often that specific number of emergency arrivals or surgeries occurred over the observed period.

The frequency of daily emergency arrival is at peak around 4–5 arrivals per day and 13–15 arrivals per day. This suggests that on most days, the hospital experiences a moderate number of emergency arrivals, with fewer days having very low (1–3) or very high (20+) arrivals.

The number of emergency surgeries per day shows a fluctuations with multiple peaks, notably around 2, 4, 11, 13, and 15 surgeries per day. After 15 surgeries per day, there's a sharp decline in frequency, indicating that performing more than 15 surgeries daily is relatively rare.

This analysis revealed variations in emergency case volumes, discovering peak times and potential bottlenecks. Understanding these characteristics is critical because emergency cases often lead to delays, cancellations, or rescheduling of elective surgeries, amplifying the scheduling challenges introduced by surgery duration variability.

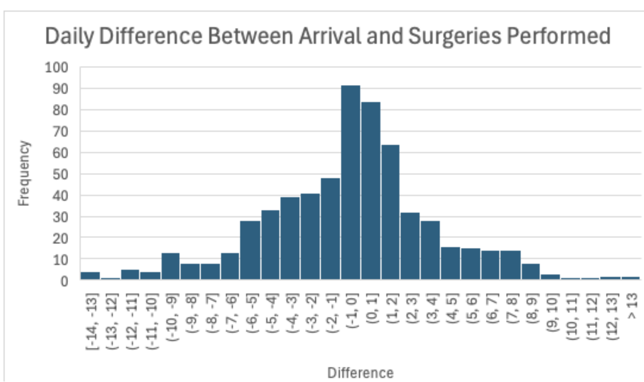


Figure 6: Frequency of daily difference between emergency arrival and surgeries performed

The gap between emergency arrivals and surgeries suggests that not all arrivals result in immediate surgery, pointing to potential backlogs, rescheduling, or prioritization of cases. The graph does not directly link the emergency arrivals and surgeries to the same days, which prevents a direct day-by-day comparison. Therefore, to fully understand the relationship between emergency arrivals and surgeries, we directly compare daily data instead of their frequency distributions. Figure 6 shows the frequency of daily difference between the number of emergency patient arrivals, and the number of emergency surgeries performed at Hospital X.

Positive values indicate more emergency arrivals than emergency surgeries (backlogs may form). Negative values indicate more surgeries than arrivals (clearing previous backlogs). Zero values indicate a balance between emergency arrivals and surgeries. The largest bars correspond to 0 and 1, suggesting that patient flow is mostly balanced. However, we still cannot know that if the emergency patients arrive are treated that day, we just know that the number of emergency arrivals and the surgeries performed are close or equal mostly. The points where emergency arrivals are higher than emergency surgeries are not a surprise to us since most of the emergency patients have urgency level P4 and P5, which indicates that the emergencies with those urgencies can also be treated the next day or can be scheduled as elective patients. Table 2 exhibits the number of emergency patients with P0, P4 and P5 urgencies.

urgency	Number of emergency cases
P0	1769
P4	4992
P5	57
Grand Total	**6818**

Table 2:Number of emergency cases based on urgency level

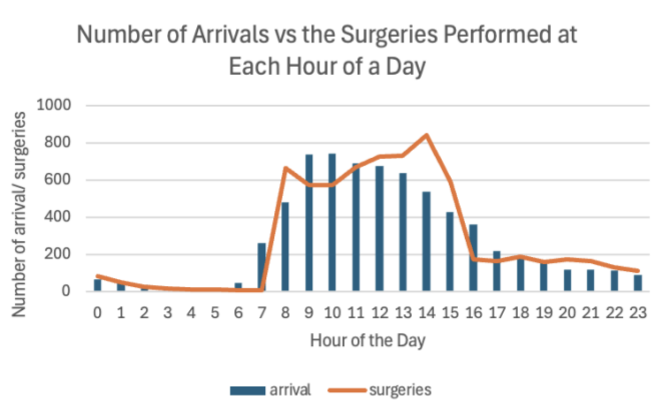


Figure 7: Number of daily emergency arrival and surgeries performed at each hour betweeen 1st January 2023 and 18th September 2024

After the analysis of daily arrivals and surgeries, we examined the distribution of emergency patient arrivals and surgeries performed by hour of the day. This analysis helps us understand how patient inflow aligns with surgical operations and resource demands throughout a typical day. Figure 7 presents the number of emergency arrivals and surgeries performed at each hour between 1st January 2023 and 18th September 2024. The numbers represent the sum of all days in that interval. The number of emergency arrivals increases sharply around 7-8 AM, peaking between 9 AM and 11 AM. This suggests that the hospital experiences the highest emergency caseload during standard working hours, which may strain resources shared with elective surgeries. Surgeries peak between 12 AM and 2 PM. Both arrivals and surgeries are minimal outside the regular hours (4 PM to 8 AM). This indicates that elective surgeries are mostly disrupted by emergency surgeries, potentially leading to delays in elective surgeries and maybe overtime. We will investigate this by analyzing the late start and overtime in the upcoming sections.

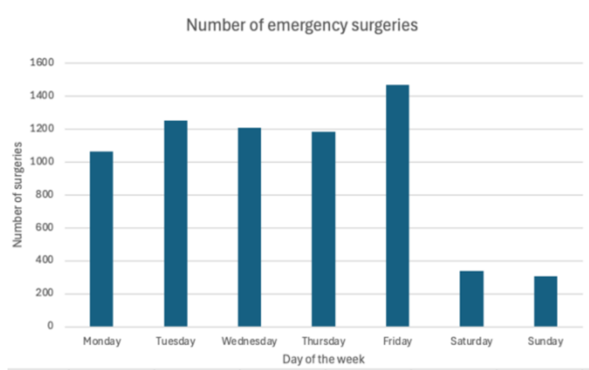


Figure 8: Number of daily emergency arrival and surgeries performed on each day of the week between 1st January 2023 and 18th September 2024

We perform further analysis on number of weekly surgeries. Figure 8 shows the number of emergency surgeries performed on each day of the week for 622 days, which shows that emergency surgeries are distributed nearly evenly throughout the weekdays, with a noticeable decline on weekends. However, the number of emergency surgeries performed on Fridays, slightly higher than the number of the surgeries on other days. This is actually more efficient than performing the surgeries on weekend due to limited OR operations and reduced staff availability.

Understanding emergency surgery durations is more than just quantifying time; it reveals the complexities of OR operations. The variability in durations reflects not only the diversity of medical conditions but also the uncertainty that hospitals must manage daily. This analysis helps hospitals anticipate the resource demands required for different types of emergencies, guiding decisions about OR allocation, staffing, and equipment readiness.

The uncertain nature of emergency surgeries means that even a single long-duration case can disrupt an entire day's schedule. Recognizing which specialties are prone to high variability allows for more reliable scheduling strategies, such as incorporating buffer times and maintaining flexible OR slots. Moreover, understanding the frequency of short-duration emergencies enables hospitals to optimize their schedules by clustering these cases, maximizing OR efficiency without compromising patient care.

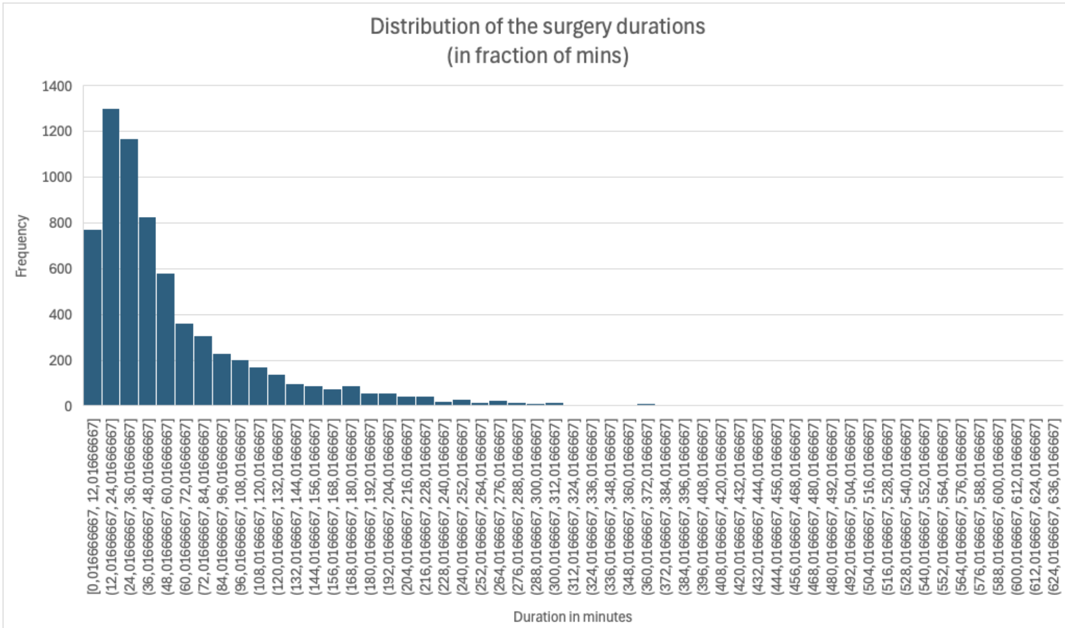


Figure 9: Distribution of emergency surgery durations

To gain deeper insights into the complexities of emergency cases, we analyzed the distribution of emergency surgery durations. Figure 9 shows the distribution of emergency surgery durations. The data reveals a right-skewed distribution, indicating that the majority of emergency surgeries are of short duration, with a sharp decline in frequency as the duration increases. Most surgeries are completed within 60 minutes, suggesting that many emergency procedures involve quick interventions and simple procedures. However, the long tail of the distribution highlights the presence of prolonged surgeries, extending beyond 400 minutes, representing highly complex or critical cases.

specialties	Average duration	StdDev	Count of surgeries
AUGEN	34,19685349	27,20811549	1017
CHEN	72,975	51,89668155	8
CHIR	85,39992658	82,81684606	454
GEB	27,07666667	15,16918416	10
GEFÄß	91,40151934	83,75088238	362
GYN	52,33756831	77,56858604	122
HAUT	16,50293785	12,77711443	295
HERZ	82,44035874	87,6256503	446
HNO	38,48261317	31,5260301	162
NCH	117,4455305	79,91807949	399
ORTHO	48,90733333	47,20413242	25
PLAST	62,99324713	71,33373949	812
THOR	90,4609127	59,89283661	84
UNFA	78,1209707	65,97586053	1092
UROL	32,35085707	30,83718077	1264
WSCHIR	78,31520913	53,71927377	263
ZOP	17,39444444	7,659731162	3
Grand Total	**60,93123594**	**65,79737819**	**6818**

Table 3: Average duration, standard deviation and number of emergency surgeries per specialty

Table 3 shows the average duration, standard deviation and number of emergency surgeries per specialty. When we anlayze the emergency surgery durations, we could observe significant variability. NCH and GEFÄß have the longest average durations (117.4 mins and 91.4 mins, respectively), with high standard deviations, reflecting the complexity of procedures in these fields. When we check the surgery times of those specialties, we see that those the treatment times of those specialties' emergency surgeries are at its peak between 8-10 PM. In contrast, specialty HAUT has much shorter average duration (16.5 mins), indicating quicker surgical procedures. In addition, AUGEN has a high number of cases (1,017 surgeries) with relatively short durations, suggesting frequent but less time-consuming emergency procedures. The surgery time of emergency AUGEN cases is at its peak between 3-4 PM. The number of emergency surgery performed per specialty at each hour is shown in Figure C.1 (Appendix C) . The histogram of the emergency surgeries with high average durations and high standard deviation, and emergency surgeries with low average durations and low standard deviation are shown in Figure C.2 (Appendix C).

Understanding surgery durations and specialty-specific variations naturally leads to an evaluation of how these cases are distributed across operating rooms, which plays a crucial role in resource allocation and efficiency.

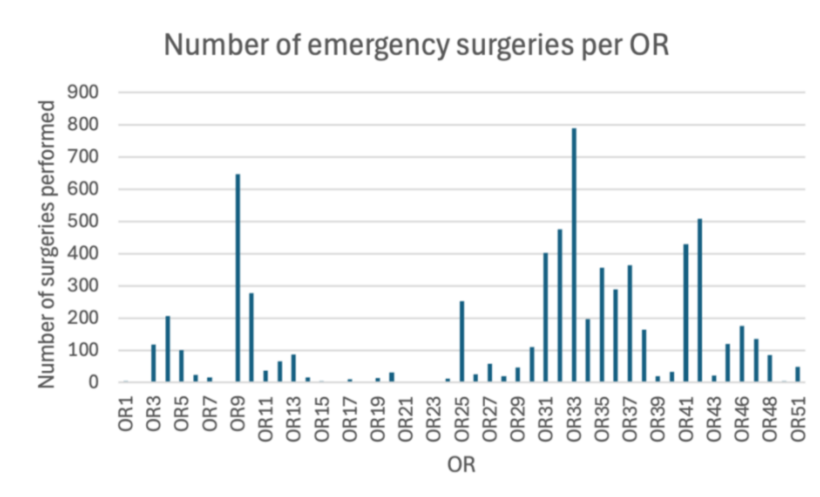


Figure 10: Number of emergency surgeries perfomed per OR

Figure 10 shows the number of emergency surgeries performed per OR between 1st January 2023 and 18th September 2024. ORs like OR33 and OR9 handle a significantly higher volume of emergency cases compared to others. Interestingly, while OR9 accommodates a large number of emergencies, these procedures tend to be shorter in duration, only UROL emergency surgeries with an avearge duration 32.3 minutes, suggesting it manages less complex cases with high turnover. In contrast, OR33 handles longer emergency procedures, emergency surgeries for mostly UNFA and WSCHIR, indicating its role in managing more complex surgeries requiring extended OR occupancy. The concentration of emergency surgeries in specific ORs suggests potential bottlenecks and imbalances in resource distribution. High dependence on a few ORs increases risk of delays, particularly during periods of peak demand.

Late Starts of the First Surgeries of the Day

While emergency surgeries present significant scheduling challenges due to their uncertain nature, another critical factor that contributes to delays and potential overtime is the late start of the first elective surgeries of the day. Beyond the impact of emergencies, late starts can cause the entire schedule to shift, leading to cascading delays and inefficiencies.

The late start analysis captures only one month, September 2024, since the available data only included that time period. When we analyze the impact of late starts of the elective surgeries, we excluded the weekends since there are no elective surgeries on weekends. That left us with 612 first elective surgeries of the day. We assume the first elective surgeries that start later than 8:30 AM as late starts since this is the required latest start time by the hospital. Considering that, we saw 459 first elective surgeries started later than 8:30 AM on weekdays out of 612 surgeries. In other words, the late start rate is 75%. An average of 21.85 surgeries start late daily out of an average of 29.14 first surgeries per OR, indicating that a significant proportion of the first surgeries experience delays. This tendency suggests systemic issues related to workflow, staffing, or preoperative processes.

Notably, in September, the highest number of late starts occurred on 4th September, with 26 delays out of 32 first surgeries. On this day, the average delay for all ORs was 1 hour and 42 minutes excluding non-delayed surgeries and 1 hour and 22 minutes including all surgeries. This indicates that delays can be substantial, significantly affecting the day's overall schedule. Analysis by day of the week shows that Mondays had the most late starts, with 106 delayed surgeries out of 139 first surgeries. This occurences may reflect operational challenges such as staff availability after weekends, patient preparation delays, or administrative inefficiencies specific to the start of the workweek.

Further, the OR33 recorded the highest number of late starts, with 21 delays out of 21 first surgeries. This 100% delay rate suggests persistent issues related to that specific OR, such as staffing constraints, equipment availability, or patient related factors.

Looking at the average delays across all ORs and specialties, the specialty GEB recorded the highest average delay at 149.28 minutes, though this was primarily driven by a single extreme case that began at 5:48 PM. This specific case cannot be counted as late start since it is beyond working hours. We assume that case is either emergency or planned that way. HNO had an average delay of 132 minutes, with most surgeries experiencing delays close to this average, indicating a more consistent occurences of late starts. Over the given period, 20 out of 28 first surgeries for HNO started late, demonstrating that this specialty is prone to delayed starts.

Additionally, HAUT and THOR had the highest late start rate at 100%, meaning that every recorded first surgery for these specialties started late. This consistency in delay highlights structural or operational inefficiencies that require further investigation.

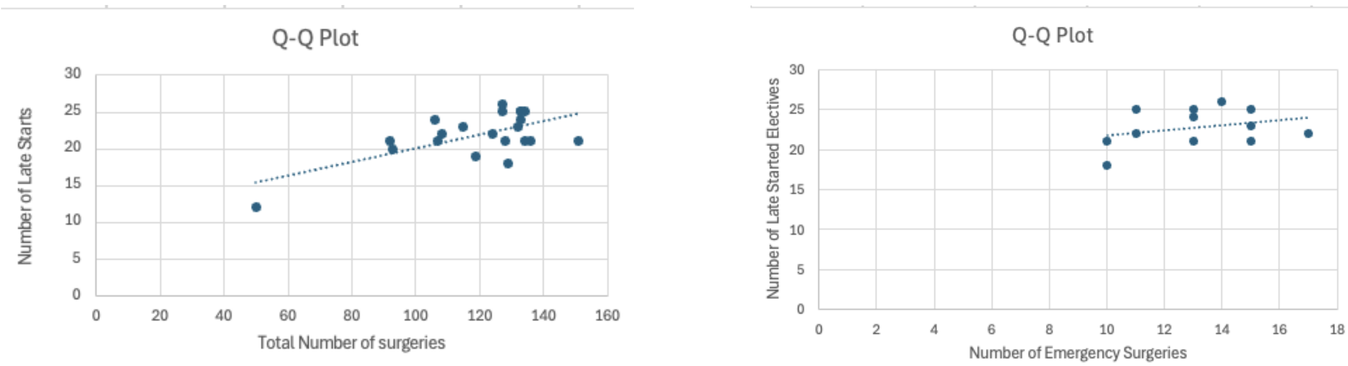


Figure 11:Scatter plots of number of emergency patients and number of late starts, and total number of surgeries performed and number of late starts

To understand the potential drivers of late starts, we examined their correlation with emergency surgeries. The scatter plots in Figure 11 show the number of emergency patients and number of late starts, and total number of surgeries performed and number of late starts, to visualize the correlations between two values. The correlation analysis using the built-in 'CORREL' function in Excel yielded a value of 0.3, indicating a positive but very weak relationship between the number of emergency surgeries and late starts. This suggests that while an increase in emergency surgeries is associated with more late starts, it is not the sole or primary cause. Other factors, such as staffing limitations, preparation delays, or general inefficiencies in scheduling, likely play a significant role.

Additionally, when analyzing the correlation between the total number of surgeries performed per day and late starts, we found a stronger positive correlation of 0.64. This implies that higher overall surgical volume on a given day is more closely linked to an increase in late starts, suggesting that resource strain, rather than emergency cases alone, contributes significantly to scheduling delays.

Overtime

While late starts significantly disrupt the planned surgery schedule, their impact extends beyond just delaying subsequent surgeries. One of the most critical consequences of late starts is their contribution to overtime, where surgeries extend beyond regular OR working hours. Overtime not only strains hospital resources, such as staff availability and equipment usage, but also leads to financial inefficiencies and burnout of surgical teams. In this section, we analyze how various factors, including late starts, number of surgeries, and emergency patient arrivals, contribute to overtime and explore insights that can help in optimizing scheduling practices.

If the surgeries are performed outside the regular working hours (8AM - 4PM), they are counted as overtime. When doing this analysis, we excluded the weekends, because on weekends there are no “regular hours”.

The analysis revealed that a portion of surgeries extended beyond regular working hours, leading to occurrences of overtime. By examining the distribution of overtime cases across different days, we identified key behaviours. Out of 2511 surgeries, 257 surgeries (10.2%) resulted in overtime. 140 of these surgeries started before 8 AM (and finished before 8 AM) or after 4 PM, meaning the majority were directly classified as overtime cases. 117 surgeries started during regular hours but extended beyond 4 PM, indicating inefficiencies in scheduling or unexpected procedural complications leading to longer than expected durations.

Examining the distribution of number of surgeries leading to overtime across different days of the week, Wednesdays had the highest number of surgeries both started outside regular working hours and surgeries started during regular hours, and ended outside the regular hours, in total 60, while Fridays had the least, with 45 surgeries. Tuesdays had the highest number of surgeries that started within regular hours but still ended in overtime, with 31 cases exceeding regular hours. This suggests that certain weekdays are more prone to late running surgeries, possibly due to heavier caseloads or staffing limitations.

Further analysis at the OR level identified OR51 as the most affected room, with 29 out of 77 surgeries resulting in overtime. Among these, only 3 surgeries started during regular hours, whereas 26 of the surgeries started before 8 AM (and finished before 8 AM) or after 4 PM. This highlights how specific ORs may be affected by overtime, potentially due to emergency surgeries or staffing constraints.

When considering specialty specific characteristics, PLAST had the highest number of overtime surgeries, with 39 out of 312 surgeries running late. Within these, 17 cases began during regular hours but extended past 4 PM, indicating that delays during procedures played a significant role in overtime for this specialty. Meanwhile, GEB had the highest relative overtime rate, with 34.48% of its surgeries resulting in overtime. Although this specialty had fewer total surgeries, the proportion of cases extending past scheduled hours was significantly high, further reinforcing the need for improved scheduling strategies in these areas.

When we filter the surgeries led to overtime and the ones started between 8 AM and 4 PM, we see that most of the surgeries start after 3 PM. The average duration of these surgeries was 2 hours and 13 minutes, making them highly likely to extend beyond regular working hours.

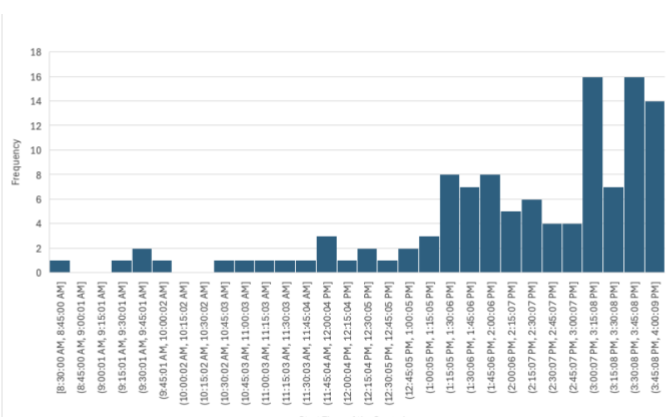


Figure 12: Frequency of surgeries according to their start time

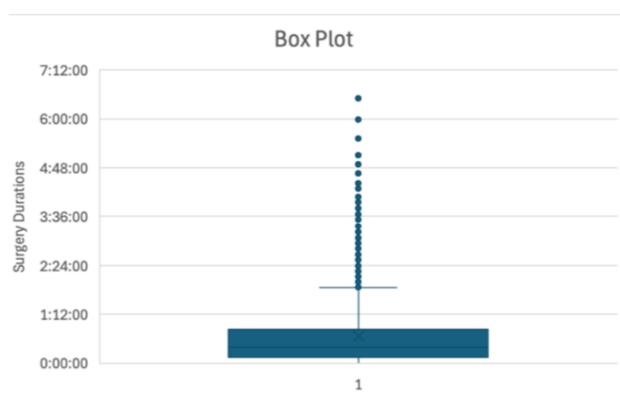


Figure 13: Box plot of the durations of the surgeries that started and finished during working hours.

To solve this problem, the surgeries that take longer than average and the surgeries with high variability may be performed earlier in the day, since overtime is costly and decreases the staff motivation and performance. We can see that this is what the hospital is also doing however sometimes the surgeries take longer than expected and lead to overtime. On the other hand, instead of performing the surgeries that last shorter in the afternoon, they can also be performed in the morning, which will lead to less surgeries being performed after working hours. Figure 12 shows the frequency of the start time of the surgeries that finished after working hours but started during working hours.

Furthermore, we also analyzed the surgeries that have not been performed outside working hours. We did this by filtering the surgeries with start and end times between 8 AM and 4PM. We saw that these were predominantly performed in the morning, and these procedures were generally shorter compared to those that extended beyond scheduled hours. This reinforces the idea that strategic allocation of surgery types throughout the day can significantly impact overall scheduling efficiency and staff workload. Figure 13 shows the boxplot of the durations of the surgeries that started and finished during working hours.

To extend the overtime analysis, it is crucial to examine broader behaviour in overtime occurrence. A key question is whether late starts and number of surgeries are directly correlated with increased overtime cases. We did this correlation analsysis through “CORREL” function in excel. Our investigation revealed a strong positive correlation of 0.61 between the number of late starts and the number of overtime cases per day. This means that on days when late starts are more frequent, overtime occurrences also tend to rise, suggesting that morning delays have a lasting impact on the overall surgical schedule.

Similarly, when analyzing the relationship between the total number of surgeries performed per day and overtime occurrences, we found moderate positive correlation of 0.58 . This indicates that as surgical volume increases, the likelihood of surgeries extending into overtime also rises. These findings highlight the importance of balancing daily caseloads effectively to mitigate the risk of prolonged working hours.

In contrast, when we examined the relationship between emergency surgeries and overtime, the correlation was much weaker. While emergency surgeries undoubtedly disrupt the schedule, they do not appear to be the primary driver of overtime occurrences statistically. This suggests that while emergency cases add uncertainty, the overall structure and sequencing of planned surgeries play a more significant role in determining whether overtime occurs.

To further quantify the effect of late starts and surgery volume on overtime occurrences, we conducted a linear regression analysis. In this analysis, overtime is the dependent variable, while the number of late starts and the total number of surgeries are the independent variables. The goal is to determine how much variance in overtime can be explained by these factors and assess their statistical significance.

Linear regression is an appropriate method for this analysis because it allows us to establish a quantitative relationship between independent and dependent variables, providing insight into how changes in late starts and number of surgeries influence overtime occurrences. The assumption of linearity is reasonable given that we expect increases in late starts and total surgeries to be associated with proportional increases in overtime. Furthermore, regression analysis provides key statistical outputs, such as coefficients, p-values, and R^2 values, which allow us to measure both the strength and reliability of these relationships. We used the built-in regression in analysis tools of excel for this analysis.

The regression results indicate that for every additional late start, the number of overtime cases increases by approximately 0.8. The p-value of 0.002 confirms that this relationship is statistically significant, meaning that late starts are a key predictor of overtime. The regression equation derived from the analysis is:

$$Number\ of\ Overtime\ Occurences = -5.29845 + 0.80223 \times (Number\ of\ Late\ Starts)$$

The negative intercept suggests that there are other factors influencing overtime occurrences that are not captured within this model. Additionally, the R^2 value of 37.9% indicates that while late starts explain a moderate proportion of overtime variability, other contributing factors exist.
Similarly, the regression analysis for the total number of surgeries reveals that for every additional surgery performed, the number of overtime cases increases by approximately 0.11. The relationship is statistically significant, as indicated by the p-value of 0.005. The corresponding regression equation is:

$$Number\ of\ Overtime\ Occurences = -0.929888 + 0.11012 \times (Number\ of\ Surgeries)$$

The R^2 value of 34.3% suggests that while the number of surgeries performed influences overtime, it does not fully account for its variability. This aligns with previous findings, reinforcing that factors such as surgery duration variability, emergency arrivals, and operational delays also play critical roles.

The regression analysis confirms that both late starts and the total number of surgeries are statistically significant predictors of overtime. However, additional factors contribute to the complexity of overtime occurrences. These insights emphasize the importance of improving scheduling efficiency, reducing late starts, and managing daily surgery volume to minimize excessive overtime.

Surgery Durations and Number of Surgeries

Another key factor influencing OR scheduling is the variability in surgery durations and the overall number of surgeries performed daily. Understanding how these factors contribute to scheduling challenges is essential for optimizing resource allocation and reducing disruptions.

The analysis of surgery durations reveals a right-skewed distribution, where most surgeries are relatively short, but a small number extend significantly beyond the average. The mean surgery duration is 45.93 minutes, with a standard deviation of 59.1 minutes, highlighting considerable variation. The median duration is 26.06 minutes, confirming that a majority of surgeries are shorter than the mean.

specialty	median	average	std
AUGEN	5	13,0627486	15,3838371
CHEN	54,35	69,3328283	46,7387955
CHIR	59,2916667	81,561747	69,9351544
EXTERN	27,0416667	33,5818452	16,745364
GEB	31,4	30,1124378	10,9066256
GEFÄß	66,5	89,4597436	73,9962239
GYN	37,7333333	56,3505089	73,1647385
HAUT	25,9666667	35,4281316	31,7627665
HERZ	58,9833333	99,9228986	93,8660489
HNO	23,5666667	39,6783489	41,133502
NCH	76,9833333	95,6424479	73,4371483
ORTHO	49,9416667	52,6527778	26,8977539
PLAST	40,3333333	64,3935135	71,6699919
THOR	81,8583333	102,577083	60,0154455
UNFA	50,1166667	67,5421642	61,0467075
UROL	28,3166667	50,3879346	64,9085293
WSCHIR	78,2416667	103,827778	68,7860404

Table 4:Median, average and standard deviation of the duration of surgeries per specialty

Among specialties, HERZ exhibits the highest variability, indicating significant inconsistency in procedure durations, whereas GEFAB has the lowest variability, suggesting that these surgeries are more predictable in length. Most specialties also follow a right-skewed distribution, meaning that while most surgeries are completed quickly, occasional long duration procedures create challenges in scheduling predictability. Table 4 shows the median duration, average duration and standard deviation for all specialties.

OR	MEDIAN	MEAN	STD
OR1	24	23,5	7,47663026
OR3	138,35	131,923718	107,429355
OR4	30,5	35,4830247	23,3205274
OR5	156,5	151,79127	88,25976
OR6	51,7333333	52,2103604	26,8068849
OR7	124,258333	131,745833	66,9662261
OR8	16	23,6	21,1730961
OR9	24,85	33,2245791	26,3199878
OR10	21,7416667	28,0333333	19,092363
OR11	72,2666667	87,5761905	55,7583192
OR12	24	26,6284553	14,1494961
OR13	19,5	25,2089286	20,8280835
OR14	24	24	#DIV/0!
OR15	18,5	15,8444444	8,95050174
OR17	20	18,3333333	2,88675135
OR20	20,9166667	20,9166667	#DIV/0!
OR21	32,4083333	32,4083333	10,4769655
OR24	29,1583333	36,2047222	20,6107251
OR25	51,6333333	65,0089372	62,9448044
OR26	30	27,6135417	18,6603503
OR27	24,1333333	26,6676768	16,4604481
OR28	48,5	59,9719298	47,9333919
OR29	40,5333333	55,432971	47,1564336
OR30	122,491667	139,559333	113,912551
OR31	76,3	102,143711	77,9296459
OR32	54,0833333	90,8772152	85,8938573
OR33	58,1166667	75,9549242	61,3041798
OR34	48,4583333	59,85	48,480192
OR35	70,625	88,5161111	73,7347058
OR36	65,85	88,5914583	76,697544
OR37	69,5	89,2541026	73,3590509
OR38	60,4166667	88,5951515	68,2944178
OR39	4,03333333	5,90509499	4,01931192
OR40	4,03333333	4,55579955	1,69678303
OR41	21,0916667	26,729594	20,0370306
OR42	17,6083333	22,3259058	16,9237058
OR43	8	22,6133333	25,3447984
OR44	20	20	#DIV/0!
OR45	26,65	35,2977912	31,3069703
OR46	24,1166667	35,5743243	32,4798958
OR47	26,6333333	44,1080645	43,5902853
OR48	41,2	63,3911765	83,6580063
OR49	11,5	12,7166667	9,02582714
OR50	67,5	67,5	17,6776695
OR51	26,0416667	25,6225926	12,6348045

Table 5: Median, average and standard devaition of the durations of surgeries per OR

Table 5 shows the median, average and standard deviation of the durations of the surgeries per OR. When we analyze the surgeries per OR, we see that OR30 has the highest average surgery durations, with a median of 122.49 minutes and a high standard deviation 113.9 minutes, suggesting a need for greater scheduling flexibility. In contrast OR40 has the lowest average and median. The median is very close to average so we can say that the durations of surgeries are concentrated more around the average, as standard deviation is also small, with a few outliers. All the surgeries performed in this OR are AUGEN surgeries.

Majority of the surgeries last less than 1,5 hours. The longest specialty belongs to specialty GYN and is performed in OR48 with 10 hours 40 minutes. Specialty HERZ and OR OR5 have the highest number of outliers. All the surgeries in that OR belong to the specialty HERZ. The distribution graphs of all specialties are shown in Figure C.4 (Appendix C).

Moreover, the distribution of surgeries across the week provides valuable insights into the efficiency and strain on hospital resources. The data reveals that Mondays, Tuesdays, and Wednesdays consistently have the highest number of surgeries, while Thursdays see the lowest volume outside of weekends. This concentration of surgeries at the beginning of the week shows an effort to complete surgeries early, possibly to ensure post-surgical recovery time before the weekend. However, these high numbers in the first half of the week can create scheduling bottlenecks, leading to increased delays, late starts, and potential overtime.

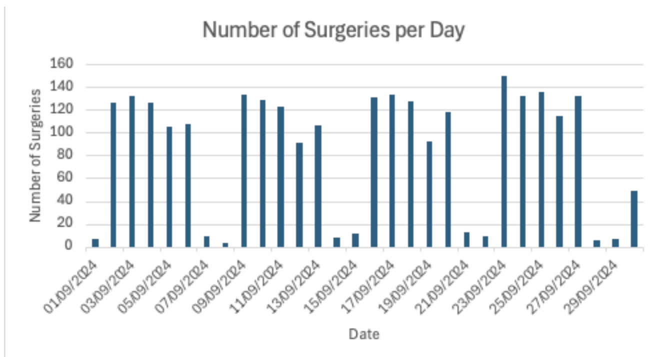


Figure 14: Number of surgeries per day

Conversely, the relatively low volume of surgeries on Thursdays presents an opportunity for redistributing workload. Shifting some procedures from high-volume days to Thursdays could balance OR utilization and reduce the likelihood of cascading scheduling disruptions. Figure 14 shows the distribution of the surgeries across days. The days are not present in the graph but the dates with highest number of surgeries correspond to Mondays, Tuesdays and Wednesdays.

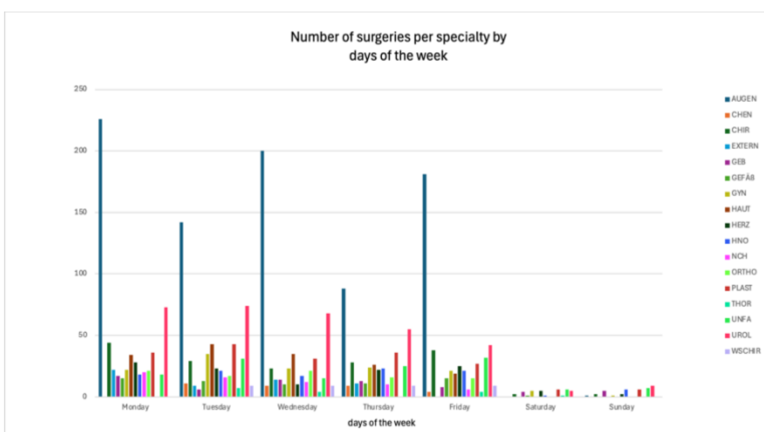
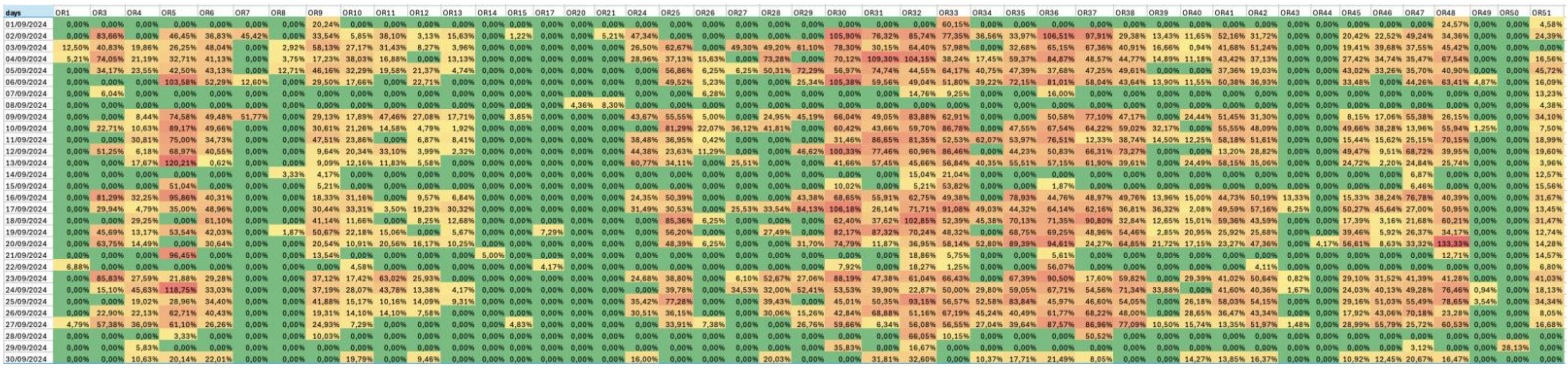


Figure 15: Number of surgeries per specialty by the days of week

Figure 15 shows the number of surgeries per specialty by the days of week. At the specialty level, AUGEN has the highest number of surgeries daily, while THOR has the lowest volume. This contrast can be attributed to the nature of procedures performed. AUGEN surgeries tend to be shorter and more routine, allowing for a higher number of cases per day, whereas THOR surgeries are generally longer and more complex, requiring extensive OR time and specialized resources.

This analysis suggests that scheduling strategies should account for both overall surgery volume variations and specialty specific needs. High-volume specialties with shorter procedures may benefit from being scheduled strategically throughout the day to maximize efficiency, while specialties with high variability or longer procedures may require dedicated OR slots with buffer time to accommodate uncertain durations.



days	OR1	OR3	OR4	OR5	OR6	OR7	OR8	OR9	OR10	OR11	OR12	OR13
01/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	20,24%	0,00%	0,00%	0,00%	0,00%
02/09/2024	0,00%	83,66%	0,00%	46,45%	36,83%	45,42%	0,00%	33,54%	5,85%	38,10%	3,13%	15,63%
03/09/2024	12,50%	40,83%	19,86%	26,25%	48,04%	0,00%	2,92%	58,13%	27,17%	31,43%	8,27%	3,96%
04/09/2024	5,21%	74,05%	21,19%	32,71%	41,13%	0,00%	3,75%	17,23%	38,03%	16,88%	0,00%	13,13%
05/09/2024	0,00%	34,17%	23,55%	42,50%	43,13%	0,00%	12,71%	46,16%	32,29%	19,58%	21,37%	4,74%
06/09/2024	0,00%	0,00%	0,00%	103,58%	52,29%	12,60%	0,00%	29,50%	17,66%	0,00%	22,71%	0,00%
07/09/2024	0,00%	6,04%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
08/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
09/09/2024	0,00%	0,00%	8,44%	74,58%	49,48%	51,77%	0,00%	29,13%	17,89%	47,46%	27,08%	17,71%
10/09/2024	0,00%	22,71%	10,63%	89,17%	49,66%	0,00%	0,00%	30,61%	21,26%	14,58%	4,79%	1,92%
11/09/2024	0,00%	0,00%	30,81%	75,00%	34,73%	0,00%	0,00%	47,51%	23,86%	0,00%	6,87%	8,41%
12/09/2024	0,00%	51,25%	6,18%	68,97%	40,55%	0,00%	0,00%	9,64%	20,34%	33,10%	3,99%	2,32%
13/09/2024	0,00%	0,00%	17,67%	120,21%	0,62%	0,00%	0,00%	9,09%	12,16%	11,83%	5,58%	0,00%
14/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	3,33%	4,17%	0,00%	0,00%	0,00%	0,00%
15/09/2024	0,00%	0,00%	0,00%	51,04%	0,00%	0,00%	0,00%	5,21%	0,00%	0,00%	0,00%	0,00%
16/09/2024	0,00%	81,29%	32,25%	95,86%	40,31%	0,00%	0,00%	18,33%	31,16%	0,00%	9,57%	6,84%
17/09/2024	0,00%	29,94%	4,79%	35,00%	48,96%	0,00%	0,00%	30,44%	33,31%	3,50%	19,23%	30,32%
18/09/2024	0,00%	0,00%	29,25%	0,00%	61,10%	0,00%	0,00%	41,14%	11,66%	0,00%	8,25%	12,68%
19/09/2024	0,00%	45,69%	13,17%	53,54%	42,03%	0,00%	1,87%	50,67%	22,18%	15,06%	0,00%	5,67%
20/09/2024	0,00%	63,75%	14,49%	0,00%	30,64%	0,00%	0,00%	20,54%	10,91%	20,56%	16,17%	10,25%
21/09/2024	0,00%	0,00%	0,00%	96,45%	0,00%	0,00%	0,00%	13,54%	0,00%	0,00%	0,00%	0,00%
22/09/2024	6,88%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	4,58%	0,00%	0,00%	0,00%
23/09/2024	0,00%	85,83%	27,59%	21,88%	29,28%	0,00%	0,00%	37,12%	17,42%	63,02%	25,93%	0,00%
24/09/2024	0,00%	15,10%	45,63%	118,75%	33,03%	0,00%	0,00%	37,19%	28,07%	43,78%	13,38%	4,17%
25/09/2024	0,00%	0,00%	19,02%	28,96%	34,40%	0,00%	0,00%	41,88%	15,17%	10,16%	14,09%	9,31%
26/09/2024	0,00%	22,90%	22,13%	62,71%	40,43%	0,00%	0,00%	19,31%	14,10%	14,10%	7,58%	0,00%
27/09/2024	4,79%	57,38%	36,09%	61,10%	26,26%	0,00%	0,00%	24,93%	7,29%	0,00%	0,00%	0,00%
28/09/2024	0,00%	0,00%	0,00%	3,33%	0,00%	0,00%	0,00%	10,03%	0,00%	0,00%	0,00%	0,00%
29/09/2024	0,00%	0,00%	5,83%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
30/09/2024	0,00%	0,00%	10,63%	20,14%	22,01%	0,00%	0,00%	0,00%	19,79%	0,00%	9,46%	0,00%

days	OR14	OR15	OR17	OR20	OR21	OR24	OR25	OR26	OR27	OR28	OR29
01/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
02/09/2024	0,00%	1,22%	0,00%	0,00%	5,21%	47,34%	0,00%	0,00%	0,00%	0,00%	0,00%
03/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	26,50%	62,67%	0,00%	49,30%	49,20%	61,10%
04/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	28,96%	37,13%	15,63%	0,00%	73,28%	0,00%
05/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	56,86%	6,25%	6,25%	50,31%	72,29%
06/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	49,52%	5,23%	0,00%	0,00%	25,34%
07/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	6,28%	0,00%	0,00%	0,00%
08/09/2024	0,00%	0,00%	0,00%	4,36%	8,30%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
09/09/2024	0,00%	3,85%	0,00%	0,00%	0,00%	43,67%	55,55%	5,00%	0,00%	24,95%	45,19%
10/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	81,29%	22,07%	36,12%	41,81%	0,00%
11/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	38,48%	36,95%	0,42%	0,00%	0,00%	0,00%
12/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	44,38%	23,63%	11,29%	0,00%	0,00%	46,62%
13/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	60,77%	34,11%	0,00%	25,51%	0,00%	0,00%
14/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
15/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
16/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	24,35%	50,39%	0,00%	0,00%	0,00%	43,38%
17/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	31,49%	30,53%	0,00%	25,53%	33,54%	84,13%
18/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	85,36%	6,25%	0,00%	0,00%	0,00%
19/09/2024	0,00%	0,00%	7,29%	0,00%	0,00%	0,00%	56,20%	0,00%	0,00%	27,49%	0,00%
20/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	48,39%	6,25%	0,00%	0,00%	31,70%
21/09/2024	5,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
22/09/2024	0,00%	0,00%	4,17%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
23/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	24,68%	38,80%	0,00%	6,10%	52,67%	27,06%
24/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	39,78%	0,00%	34,53%	32,00%	52,41%
25/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	35,42%	77,28%	0,00%	0,00%	39,43%	0,00%
26/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	30,51%	36,15%	0,00%	0,00%	30,06%	15,26%
27/09/2024	0,00%	4,83%	0,00%	0,00%	0,00%	0,00%	33,91%	7,38%	0,00%	0,00%	26,76%
28/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
29/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
30/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	16,00%	0,00%	0,00%	0,00%	20,03%	0,00%

days	OR30	OR31	OR32	OR33	OR34	OR35	OR36	OR37	OR38	OR39	OR40
01/09/2024	0,00%	0,00%	0,00%	60,15%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
02/09/2024	105,90%	76,32%	85,74%	77,35%	38,56%	33,97%	106,51%	97,91%	29,38%	13,43%	11,65%
03/09/2024	78,30%	30,15%	64,40%	57,98%	0,00%	32,68%	65,15%	67,36%	40,91%	16,66%	0,94%
04/09/2024	70,12%	109,30%	104,15%	38,24%	17,45%	59,37%	84,87%	48,57%	44,77%	14,89%	11,18%
05/09/2024	56,97%	74,74%	44,55%	64,17%	40,75%	47,39%	37,68%	47,25%	49,61%	0,00%	0,00%
06/09/2024	105,38%	59,56%	49,04%	51,80%	39,22%	72,15%	81,01%	58,04%	43,64%	13,90%	11,55%
07/09/2024	0,00%	0,00%	14,76%	9,25%	0,00%	0,00%	16,00%	0,00%	0,00%	0,00%	0,00%
08/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
09/09/2024	66,04%	49,05%	83,88%	62,91%	0,00%	0,00%	50,58%	77,10%	47,17%	0,00%	24,44%
10/09/2024	60,42%	43,66%	59,70%	86,78%	0,00%	47,55%	67,54%	64,22%	59,02%	32,17%	0,00%
11/09/2024	31,46%	86,65%	81,35%	52,53%	62,07%	53,97%	76,51%	12,33%	38,74%	14,50%	12,25%
12/09/2024	100,33%	77,46%	60,96%	86,46%	0,00%	44,23%	50,83%	66,31%	73,27%	0,00%	0,00%
13/09/2024	41,66%	57,45%	45,66%	56,84%	40,35%	55,51%	57,15%	61,90%	39,61%	0,00%	24,49%
14/09/2024	0,00%	0,00%	15,04%	21,04%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
15/09/2024	10,02%	0,00%	5,21%	53,82%	0,00%	0,00%	1,87%	0,00%	0,00%	0,00%	0,00%
16/09/2024	68,65%	55,91%	62,75%	49,38%	0,00%	78,93%	44,76%	48,97%	49,76%	13,96%	15,00%
17/09/2024	106,18%	26,14%	71,71%	91,08%	49,03%	44,32%	64,14%	62,16%	36,81%	36,32%	2,08%
18/09/2024	62,40%	37,62%	102,85%	52,39%	45,38%	70,13%	71,35%	90,80%	32,84%	12,65%	15,01%
19/09/2024	82,17%	87,32%	70,24%	48,32%	0,00%	68,75%	69,25%	48,96%	54,46%	2,85%	20,95%
20/09/2024	74,79%	11,87%	36,95%	58,14%	52,80%	89,39%	94,61%	24,27%	64,85%	21,72%	17,15%
21/09/2024	0,00%	0,00%	18,86%	5,75%	0,00%	0,00%	5,61%	0,00%	0,00%	0,00%	0,00%
22/09/2024	7,92%	0,00%	18,27%	1,25%	0,00%	0,00%	56,07%	0,00%	0,00%	0,00%	0,00%
23/09/2024	88,19%	47,38%	61,04%	66,43%	0,00%	67,39%	90,50%	17,60%	59,82%	0,00%	29,39%
24/09/2024	53,53%	39,90%	22,87%	50,00%	29,80%	59,05%	67,71%	54,56%	71,34%	33,88%	0,00%
25/09/2024	45,01%	50,35%	93,15%	56,57%	52,58%	83,84%	45,97%	46,60%	54,05%	0,00%	26,18%
26/09/2024	42,84%	68,88%	51,16%	67,19%	45,24%	40,49%	61,77%	68,22%	48,00%	0,00%	28,65%
27/09/2024	59,66%	6,34%	56,08%	56,55%	27,04%	39,64%	87,57%	86,96%	77,09%	10,50%	15,74%
28/09/2024	0,00%	0,00%	66,05%	10,15%	0,00%	0,00%	0,00%	50,52%	0,00%	0,00%	0,00%
29/09/2024	35,83%	0,00%	16,67%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
30/09/2024	0,00%	31,81%	32,60%	0,00%	10,37%	17,71%	21,49%	8,05%	0,00%	0,00%	14,27%

days	OR41	OR42	OR43	OR44	OR45	OR46	OR47	OR48	OR49	OR50	OR51
01/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	24,57%	0,00%	0,00%	4,58%
02/09/2024	52,16%	31,72%	0,00%	0,00%	20,42%	22,52%	49,24%	34,36%	0,00%	0,00%	24,39%
03/09/2024	41,68%	51,24%	0,00%	0,00%	19,41%	39,68%	37,55%	45,42%	0,00%	0,00%	0,00%
04/09/2024	43,42%	37,13%	0,00%	0,00%	27,42%	34,74%	35,47%	67,54%	0,00%	0,00%	16,56%
05/09/2024	37,36%	19,03%	0,00%	0,00%	43,02%	33,26%	35,70%	40,90%	0,00%	0,00%	45,72%
06/09/2024	50,38%	36,93%	0,00%	0,00%	33,48%	0,00%	44,26%	63,41%	4,87%	0,00%	16,09%
07/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	13,23%
08/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	4,38%
09/09/2024	51,45%	31,30%	0,00%	0,00%	8,15%	17,06%	55,38%	26,15%	0,00%	0,00%	34,10%
10/09/2024	55,55%	48,09%	0,00%	0,00%	49,66%	38,28%	13,96%	55,94%	1,25%	0,00%	7,50%
11/09/2024	58,18%	51,61%	0,00%	0,00%	15,44%	15,62%	25,15%	70,15%	0,00%	0,00%	18,99%
12/09/2024	13,20%	28,82%	0,00%	0,00%	49,47%	9,51%	68,72%	39,95%	0,00%	0,00%	19,60%
13/09/2024	58,15%	35,06%	0,00%	0,00%	24,72%	2,20%	24,84%	25,74%	0,00%	0,00%	3,96%
14/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	6,87%	0,00%	0,00%	0,00%	12,57%
15/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	6,46%	0,00%	0,00%	0,00%	15,56%
16/09/2024	44,73%	50,19%	13,33%	0,00%	15,33%	38,24%	76,78%	40,39%	0,00%	0,00%	31,67%
17/09/2024	49,59%	57,16%	6,25%	0,00%	50,27%	45,64%	27,00%	50,95%	0,00%	0,00%	13,45%
18/09/2024	59,36%	43,59%	0,00%	0,00%	17,39%	3,16%	21,68%	60,21%	0,00%	0,00%	31,47%
19/09/2024	25,92%	25,68%	0,00%	0,00%	39,46%	5,92%	26,37%	34,17%	0,00%	0,00%	12,74%
20/09/2024	23,27%	47,36%	0,00%	4,17%	56,61%	8,63%	33,32%	133,33%	0,00%	0,00%	14,28%
21/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	12,71%	0,00%	0,00%	14,57%
22/09/2024	0,00%	4,11%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	6,80%
23/09/2024	41,02%	50,64%	0,82%	0,00%	29,10%	31,52%	41,39%	41,28%	0,00%	0,00%	41,03%
24/09/2024	41,60%	40,36%	1,67%	0,00%	24,03%	40,13%	49,28%	76,46%	0,94%	0,00%	18,13%
25/09/2024	58,03%	54,15%	0,00%	0,00%	29,16%	51,03%	55,49%	78,65%	3,54%	0,00%	34,34%
26/09/2024	36,47%	43,34%	0,00%	0,00%	17,92%	43,06%	70,18%	23,28%	0,00%	0,00%	8,05%
27/09/2024	13,35%	51,97%	1,48%	0,00%	28,99%	55,79%	25,72%	60,53%	0,00%	0,00%	16,68%
28/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
29/09/2024	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	3,12%	0,00%	0,00%	28,13%	0,00%
30/09/2024	13,85%	16,37%	0,00%	0,00%	10,92%	12,45%	20,67%	16,47%	0,00%	0,00%	0,00%

Figure 16: Utilization heatmap for ORs on each day

Lastly, we also analyzed the utilization per OR. We did this though a heatmap. Figure 16 displays the utilization heatmap of ORs on each day. The heatmap visualization provides a comprehensive overview of OR utilization across different dates and operating rooms. The color-coded representation allows us to identify the ORs with of no utilization (green), low utilization (yellow), moderate utilization (orange) and high or overutilization (red).The data shows that some ORs experience consistent high utilization (red areas), while others remain underutilized (green and yellow areas) on several days. This suggests an imbalance in how ORs are assigned and scheduled, potentially leading to inefficiencies in resource allocation.

ORs such as OR30, OR32, and OR36 appear frequently in red zones, indicating frequent overutilization. These ORs may be handling a high numbers of complex or emergency cases, leading to scheduling bottlenecks and increased likelihood of overtime. Conversely, several ORs, such as OR1 and OR50, display frequent periods of low utilization. This raises questions about whether these ORs are underused due to specialty constraints, scheduling inefficiencies, or lower demand on certain days. Overutilized ORs may experience delays and higher overtime occurrences, reinforcing the scheduling inefficiencies observed in previous analyses.Underutilized ORs could be optimized by reallocating surgeries from overused ORs, ensuring a more balanced workload and better resource utilization.

5.2 Conclusion

In the fifth chapter, we analyzed the data provided by the hospital with the goal of answering three sub research questions:

1. *How do these factors influence OR scheduling, and how can they be integrated into scheduling practices?*
2. *What are the interactions between these factors?*
3. *What are the potential implications of these interactions for daily surgery planning?*

We designed the data analysis in a way that we can answer these questions which will eventually help us to answer the main research question:

- *How do the uncertain or stochastic factors influence the Hospital X's OR scheduling, and how should these factors be accounted for in the scheduling process?*

The comprehensive analysis of surgery scheduling at Hospital X has revealed critical insights into the stochastic and uncertain factors influencing OR efficiency. Emergency surgeries, late starts, and surgery duration variability significantly impact scheduling outcomes, often leading to overtime and resource strain. Our findings highlight the necessity for strategic planning to accommodate emergency cases, optimize elective surgery scheduling, and manage late starts effectively. By addressing these challenges with data-driven strategies, Hospital X can enhance scheduling efficiency, reduce overtime, and optimize OR utilization.

6. RECOMMENDATIONS

In this chapter we will provide actionable recommendations for Hospital X based on the findings from the data analysis and insights from the literature review. The analysis highlighted key challenges faced by Hospital X in executing its daily operating room (OR) schedules, including disruptions caused by emergency patient arrivals, frequent late starts of first surgeries, and variability in surgery durations.

The recommendations provided in this chapter aim to mitigate these challenges by improving OR scheduling practices, increasing resource allocation, and ensuring a smoother operational flow within the hospital. Looking at both data-driven insights and practices in healthcare operations management, the proposed solutions are adapted to the unique needs and operational environment of Hospital X. Implementing these recommendations is expected to optimize OR utilization, reduce operational costs, and improve overall patient care outcomes. The following sections present specific strategies for managing emergency surgeries, reducing late starts, minimizing overtime, and understanding the nature of surgery durations.

The findings of this research highlight several inefficiencies in OR scheduling at Hospital X. These issues have lead to disruptions to elective surgeries, overtime, and underutilization of OR capacity. To address these challenges, we propose a set of recommendations aimed at improving scheduling accuracy, increasing flexibility in OR utilization, and optimizing resource allocation.

A critical issue identified in this study is the disruption caused by emergency surgeries, which frequently disrupt the elective surgery schedules. While emergency cases are uncertain, their integration into the hospital's scheduling system can be improved by adopting a more flexible OR allocation model. The hospital has already dedicated rooms for emergency cases and shared room for emergency and elective cases. However the emergency cases can be distributed to ORs more efficiently. Performing emergency surgeries according to their specialty in dedicated ORs, by looking at which specialties have high average and variability will help the Hospital X to run smoother operations.This ensures that emergency cases with high average and variability won't have major impact on the elective surgery schedule. Additionally, a prioritization algorithm can be implemented to dynamically adjust elective surgery slots in real time based on emergency case arrivals, which will minimize last minute disruptions. Given that emergency surgeries peak in the afternoon hours, an expansion of the afternoon emergency OR teams could further increase the hospital's ability to manage unexpected cases without decreasing the efficiency of the elective schedule.

Next to emergency case management, addressing late starts of the first surgeries of the day is crucial for improving OR utilization. The analysis reveals that a significant proportion of first surgeries start later than the required 8:30 AM start time, often leading to cascading delays throughout the day. To mitigate this issue, we recommend introducing an automated reminder system for surgical staff, ensuring that all key staff, including surgeons, anesthesiologists, and nurses, are alerted in advance about their scheduled start times. Optimizing preoperative workflows can also benefit alongside the alerts, where parallel processing methods are introduced to reduce patient preparation time. For instance, instead of sequentially performing anesthesia induction after patient arrival in the OR, preoperative procedures can be conducted in a designated area beforehand, allowing for a smooth transition into the surgical phase. Additionally, implementing dynamic buffering in the schedule where extra time is allocated to specilaties that have historically frequent delays can help absorb schedule variability and prevent disruptions.

Another major challenge identified in this research is the occurrence of surgeries extending beyond regular OR hours, resulting in overtime. The findings suggest that late starts and high surgical volumes are correlated with the number of overtime cases. To reduce the impact of this, we propose restructuring the daily surgical schedule to ensure that long and high-variability surgeries are prioritized earlier in the day, not necessariliy scheduling them as the first surgeries, while low-variability procedures are scheduled later in the afternoon. This way, if surgeries with high duration variability take longer than expected, the other low variability surgeries can be treated in other ORs, so that most of the surgeries can be performed within regular working hours.

This approach would minimize the likelihood of surgeries exceeding the allocated OR time. Additionally, the implementation of an overtime threshold monitoring system can help OR managers proactively identify surgeries that are likely to overrun and allow for real-time schedule adjustments.

Furthermore, the research findings highlight that variability in surgery durations remains a key contributor to scheduling inefficiencies. Since the surgeries that take longer than average are minority, the hospital may consider allocating ORs for surgeries that take longer so that the other surgeries that take shorter can be performed in other ORs smoothly. This may increase the use of ORs. In addition, while surgical durations are currently estimated based on specialist input, a transition to a data-driven prediction model would significantly increase accuracy. Machine learning algorithms trained on historical surgery data can be employed to improve estimations and reduce scheduling challenges.

Finally, a significant limitation in the hospital's scheduling process is that the planned schedule is overwritten by the performed surgeries. This prevents us, or the hospital, from comparing the initial plan with actual surgery execution. Thus we cannot determine how the actual surgeries durations deviate from the estimated surgery durations, or how the emergency surgeries or late starts cause delays or disruptions. Taking these into account, we advise the hospital to keep the planned schedule separately and compare how the schedule deviated from initial plan periodically. This will help the hospital to detect the inefficinecies and mitigate them better.

By integrating these recommendations, Hospital X can improve its scheduling efficiency, minimize disruptions caused by emergency arrivals, and optimize its use of OR resources. The implementation of a hybrid OR allocation model, alongside real-time scheduling adjustments, will ensure that emrgency surgeries are managed more effectively without displacing elective cases. Addressing late starts through preoperative workflow improvements and schedule buffering will help create a more stable daily schedule. Furthermore, strategic sequencing of surgeries, supported with an advanced monitoring system, will reduce overtime occurrences and enhance overall hospital efficiency. Finally, developing data-driven models for surgery duration predictions will enable more precise scheduling, reducing uncertainty and improving resource utilization. Collectively, these measures will allow Hospital X to enhance its OR scheduling framework, leading to improved patient care, cost savings, and better utilization of medical staff.

7. CONCLUSION

This thesis explored the impact of uncertain factors such as emergency patient arrivals, surgery duration variability, and late starts on the OR schedules at Hospital X. Through comprehensive data analysis and literature review, we found that these uncertainties significantly affect hospital efficiency, leading to overtime, underutilization, and scheduling disruptions.

The analysis demonstrated that late start rate is high and has a cascading effect on daily schedules, often resulting in overtime. Emergency surgeries, while uncertain, follow identifiable characteristics that can be managed with flexible scheduling strategies. Surgery durations exhibit considerable variability, highlighting the need for data-driven prediction models and scheduling policies in line with the variability

The findings emphasize the importance of integrating stochastic analysis into OR scheduling practices. Recommendations provided in this thesis offer actionable solutions for Hospital X to enhance operational efficiency, optimize resource utilization, and improve patient care.

This study contributes to the field of healthcare operations management by providing insights into managing uncertainty in OR scheduling and offering practical solutions for improving hospital operations.

Limitations

Despite the valuable insights generated by this research, we faced several limitations. First, the dataset we used lacked information on planned surgery schedules, making it impossible to analyze scheduling disruptions, specifically how emergency surgeries impact elective surgeries. Additionally, the data did not distinguish between elective and emergency surgeries within the performed schedule, which limited the ability to assess the full impact of emergency arrivals on schedule disruptions.

In addition, while the statistical analyses conducted offer valuable insights, the complexity of the stochastic factors involved suggests that more advanced models such as machine learning algorithms could provide deeper predictive insights, which were beyond the scope of this study.

Quality of Findings

Despite these limitations, the findings are robust within the context of the available data. Characteristics of emergency arrivals, variability in surgery durations, and late starts of the first surgeries of the day were all identified using established statistical methods, providing a solid foundation for practical recommendations. However, the absence of detailed scheduling data and elective-emergency categorization in the first dataset means that some results should be interpreted carefully and may benefit from further validation through future research or more comprehensive datasets.

Future Research

While this study has provided valuable insights into the stochastic factors affecting OR scheduling, there are opportunities for future research to expand on these findings. Future studies could explore real-time scheduling algorithms that adapt dynamically to unforeseen changes, such as emergency arrivals or prolonged surgeries. Additionally, integrating machine learning techniques to predict surgery durations and optimize scheduling decisions could further enhance hospital operations. Research on the impact of other stochastic factors, such as staff availability, equipment failures, or patient specific risks, could also provide a more comprehensive understanding of OR scheduling challenges. Lastly, conducting similar analyses in different hospital settings could validate the applicability of these findings and recommendations across diverse healthcare environments.

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APPENDICES

Appendix A

Research Question	Type of Research	Research Population	Research Subjects	Data Gathering Method	Data Analysis Method
SRQ1: How are the uncertain or stochastic factors currently managed in the hospital?	Descriptive	Hospital	Hospital Management Team	Meeting with hospital management	Qualitative
SRQ2: What statistical methods can be used to analyze and model these factors?	Exploratory	Literature	Statistical Approaches	Literature review	Qualitative
SRQ3: What are the key characteristics that makes these factors uncertain or stochastic?	Descriptive	Literature	Uncertainty and Stochasticity	Literature review	Qualitative
SRQ4: How do these factors influence the OR scheduling and how can these factors be integrated into scheduling practices?	Descriptive & Exploratory	Hospital & Literature	Hospital Data	Data Analysis	Quantitative
SRQ5: What are the interactions between these factors?	Descriptive & Exploratory	Hospital & Literature	Hospital Data	Data Analysis	Quantitative
SRQ6: What are the potential implications of these interactions for daily surgery planning?	Descriptive & Exploratory	Hospital & Literature	Hospital Data	Data Analysis & Literature Review	Qualitative & Quantitative

Appendix B

Assessment of Validity and Reliability of Measurement

Research can be determined as scientific by its validity and reliability. (Heerkens et al., 2017) That is why our objective is to achieve validity and reliability in our research. Validity in research ensures that the results are true, and a measure accomplishes its claim. (Cooper & Schindler, 2014) We divide the validity into two as internal and external validity. Since our purpose for this research is to measure how strong the impact of uncertainties are and the relationship between them, it is important to do the measurements correctly and to be able to apply them to other populations. Internal validity ensures that we choose the appropriate measuring tools and apply them correctly, so it is important that methods of analysis are suitable for the data and measure correctly. External validity ensures that we will be able to apply our findings outside Hospital X, thus, even though the research is conducted on Hospital X specifically, it is important to understand the influences of stochastic effects and generalize their applicability to other settings, at different times. The literature review plays a crucial role in establishing the theoretical foundation for this study by examining existing research, identifying relevant methodologies, and providing insights that complement the data analysis. This ensures that the study's findings are grounded in established knowledge and can be meaningfully applied in different healthcare environments.

Reliability of a research indicates that the results are reliable and stable, and we don't reach the findings by coincidence. (Heerkens et al., 2017) To make sure that our research is reliable, we make sure that the results are the same if the measurements are repeated. That is why we will conduct the research systematically. For systematic research, we will adopt a theoretical framework to measure the strength of stochastic effects and their relationship. In conclusion, by adopting a suitable theoretical framework and sticking to the systematic approach of the research, I aim to achieve reliability and validity of the research.

Appendix C

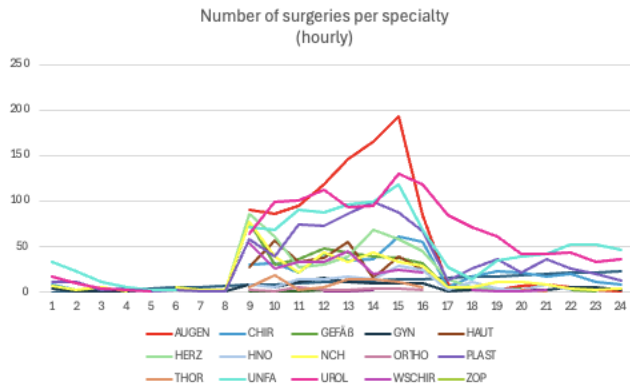


Figure C.17: Number of surgeries per specialty at each hour (emergency surgeries)

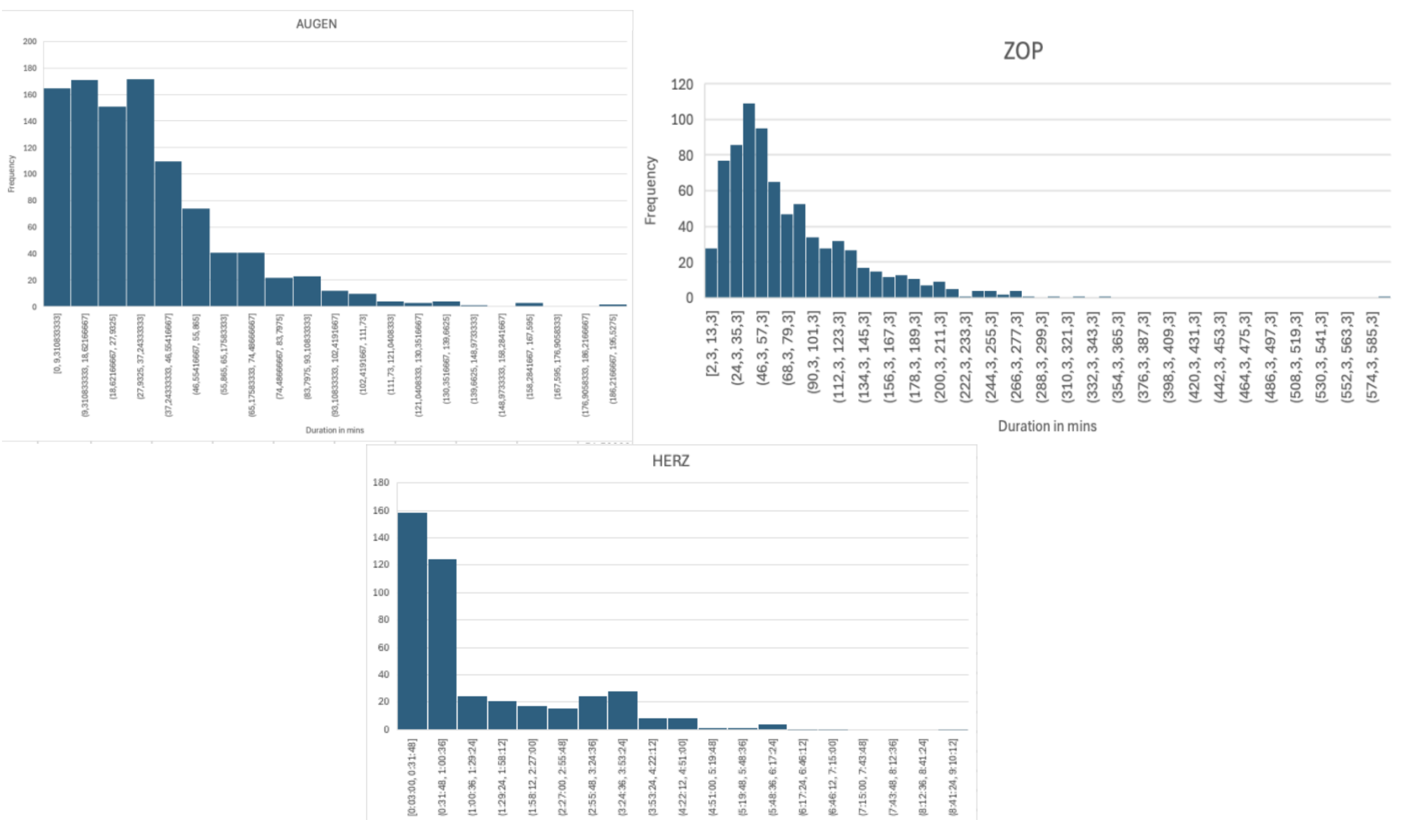


Figure C.18: The histograms of the emergency surgeries with high average durations and high standard deviation, and emergency surgeries with low average durations and low standard deviation

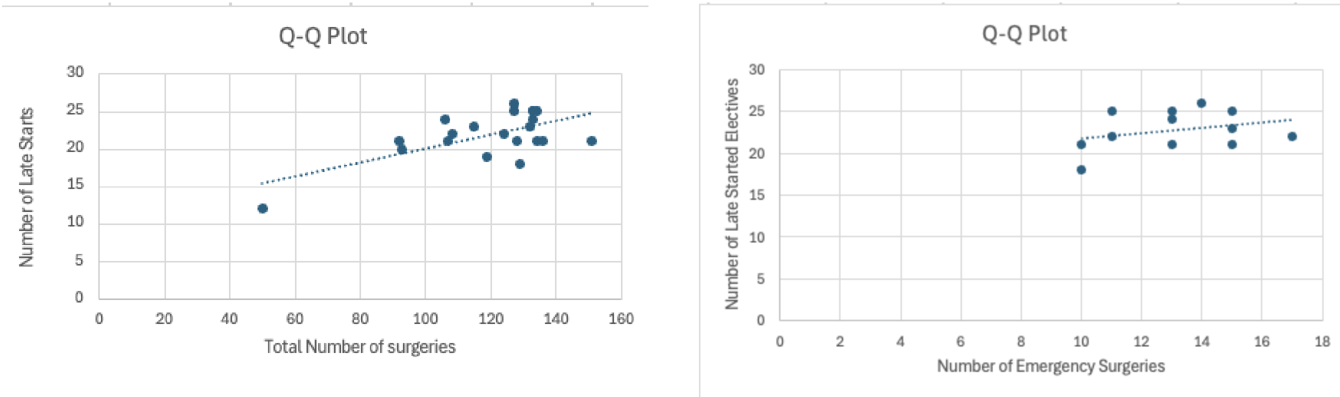
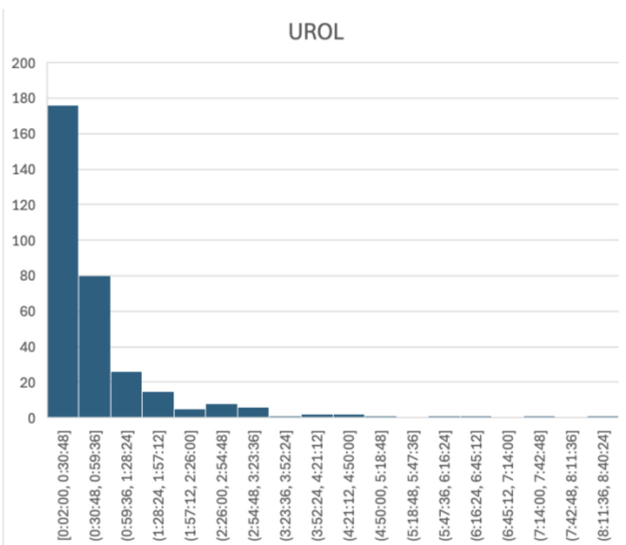
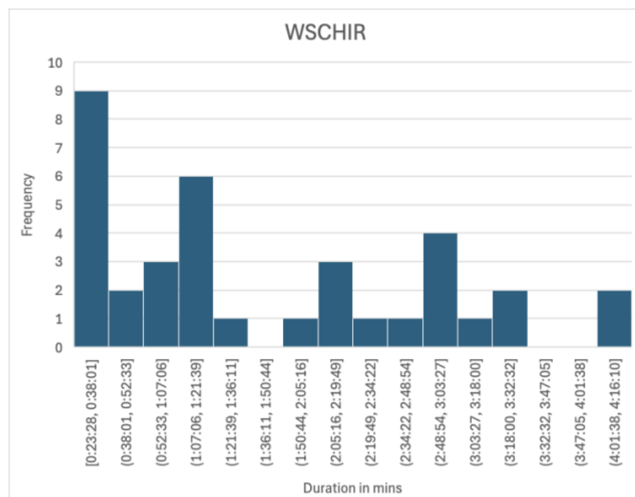
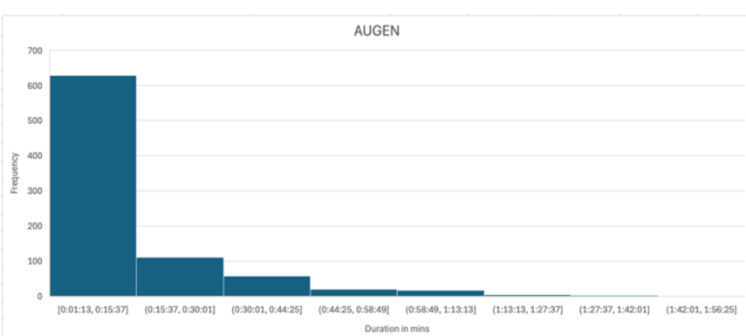
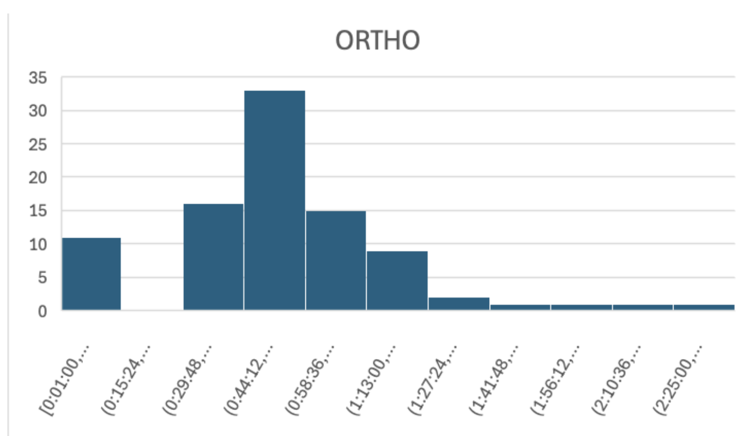


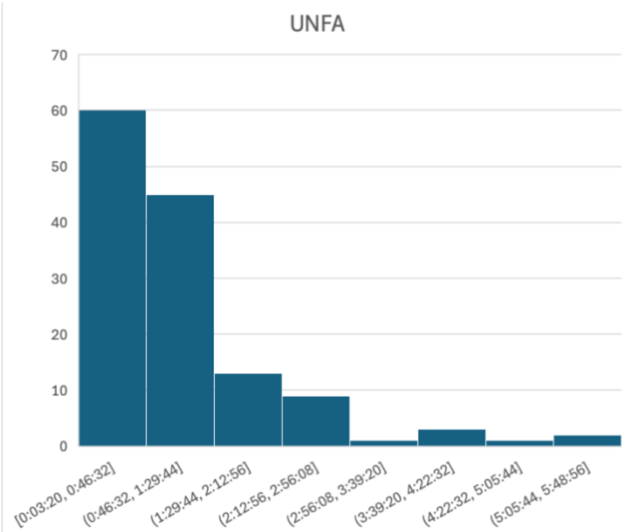
Figure C.19: q-q plots of number of emergency patients and number of late starts, and total number of surgeries performed and number of late starts,







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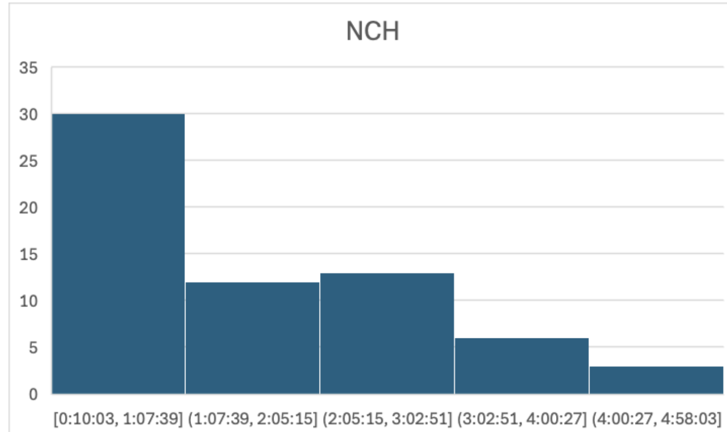
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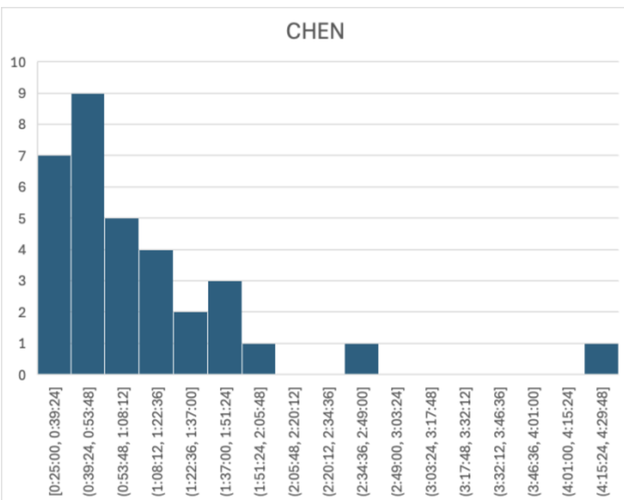
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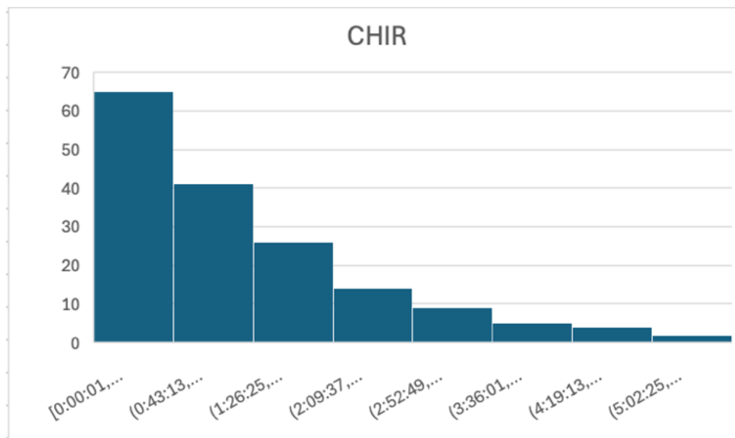
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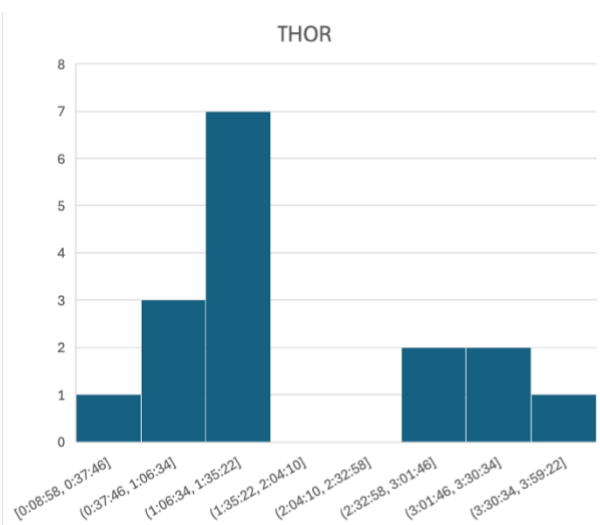
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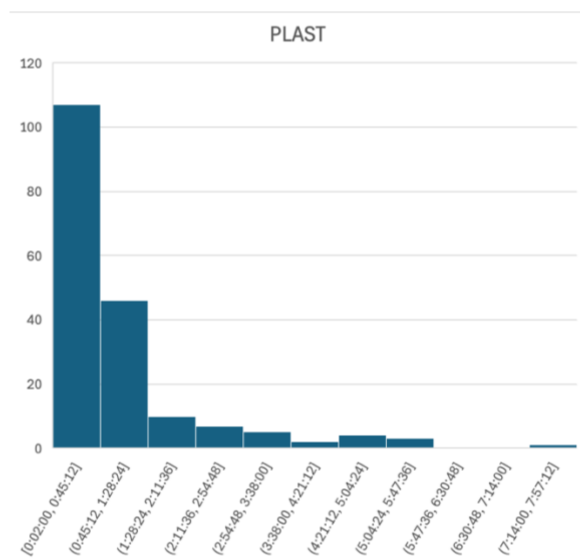
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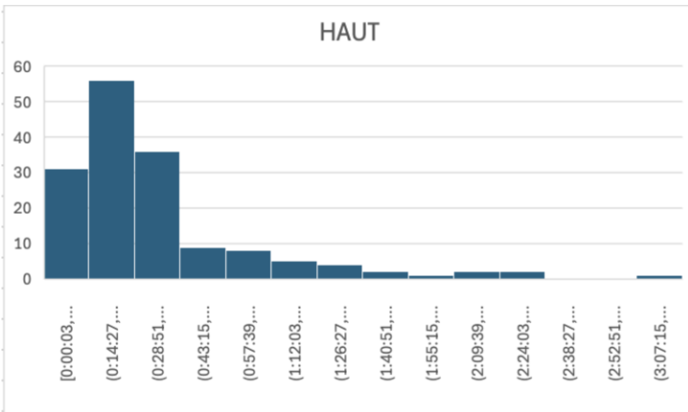
80
60
40
20
0
[0:02:00, 0:45:12]
(0:45:12, 1:28:24]
(1:28:24, 2:11:36]
(2:11:36, 2:54:48]
(2:54:48, 3:38:00]
(3:38:00, 4:21:12]
(4:21:12, 5:04:24]
(5:04:24, 5:47:36]
(5:47:36, 6:30:48]
(6:30:48, 7:14:00]
(7:14:00, 7:57:12]


HAUT
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50
40
30
20
10
0
[0:00:03,...
(0:14:27,...
(0:28:51,...
(0:43:15,...
(0:57:39,...
(1:12:03,...
(1:26:27,...
(1:40:51,...
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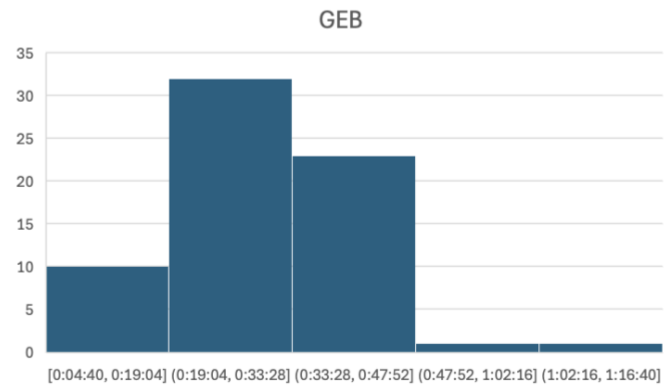
(2:09:39,...
(2:24:03,...
(2:38:27,...
(2:52:51,...
(3:07:15,...


GEB
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25
20
15
10
5
0
[0:04:40, 0:19:04]
(0:19:04, 0:33:28]
(0:33:28, 0:47:52]
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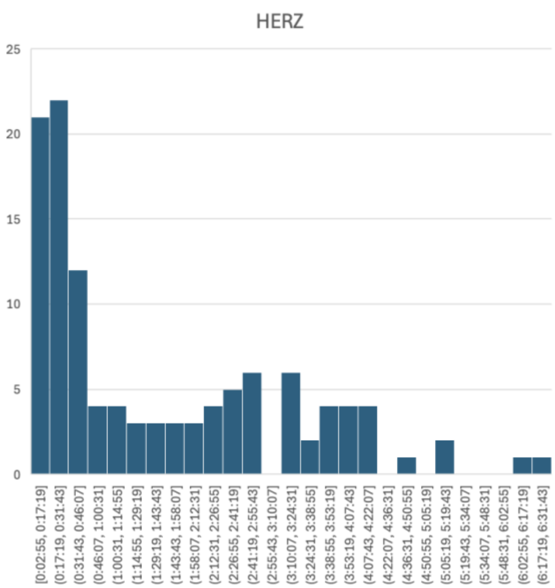
(1:02:16, 1:16:40]


HERZ
25
20
15
10
5
0
[0:02:55, 0:17:19]
(0:17:19, 0:31:43]
(0:31:43, 0:46:07]
(0:46:07, 1:00:31]
(1:00:31, 1:14:55]
(1:14:55, 1:29:19]
(1:29:19, 1:43:43]
(1:43:43, 1:58:07]
(1:58:07, 2:12:31]
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(2:41:19, 2:55:43]
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(3:10:07, 3:24:31]
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(3:38:55, 3:53:19]
(3:53:19, 4:07:43]
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(5:05:19, 5:19:43]
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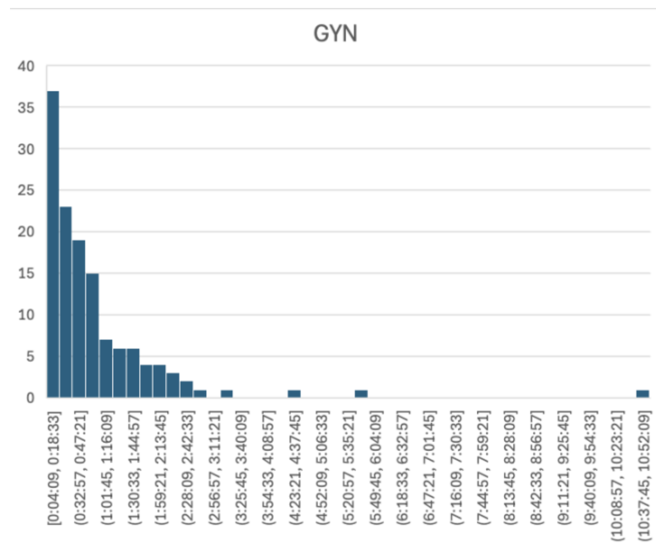
(6:17:19, 6:31:43]


GYN
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5
0
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(1:01:45, 1:16:09]
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(2:28:09, 2:42:33]
(2:56:57, 3:11:21]
(3:25:45, 3:40:09]
(3:54:33, 4:08:57]
(4:23:21, 4:37:45]
(4:52:09, 5:06:33]
(5:20:57, 5:35:21]
(5:49:45, 6:04:09]
(6:18:33, 6:32:57]
(6:47:21, 7:01:45]
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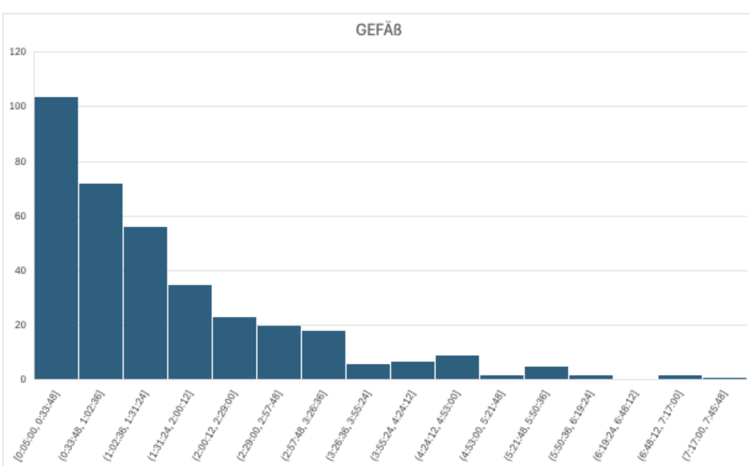
(8:13:45, 8:28:09]
(8:42:33, 8:56:57]
(9:11:21, 9:25:45]
(9:40:09, 9:54:33]
(10:08:57, 10:23:21]
(10:37:45, 10:52:09]


GEFÄß
120
100
80
60
40
20
0
[0:05:00, 0:33:48]
(0:33:48, 1:02:36]
(1:02:36, 1:31:24]
(1:31:24, 2:00:12]
(2:00:12, 2:29:00]
(2:29:00, 2:57:48]
(2:57:48, 3:26:36]
(3:26:36, 3:55:24]
(3:55:24, 4:24:12]
(4:24:12, 4:53:00]
(4:53:00, 5:21:48]
(5:21:48, 5:50:36]
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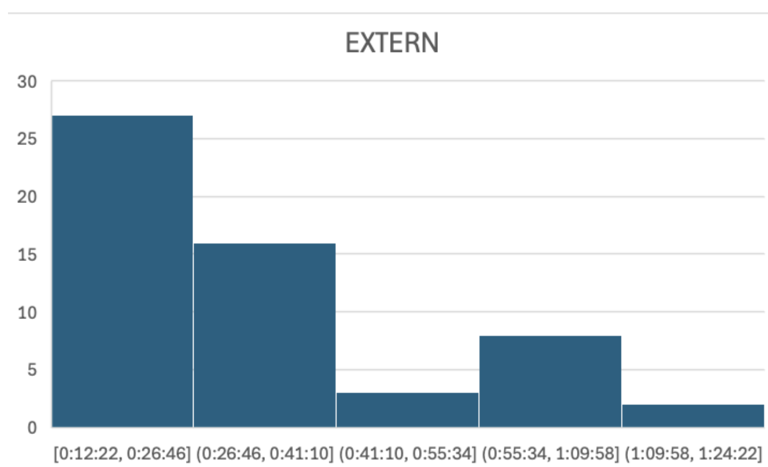
(6:19:24, 6:48:12]
(6:48:12, 7:17:00]
(7:17:00, 7:45:48]


EXTERN
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20
15
10
5
0
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(0:26:46, 0:41:10]
(0:41:10, 0:55:34]
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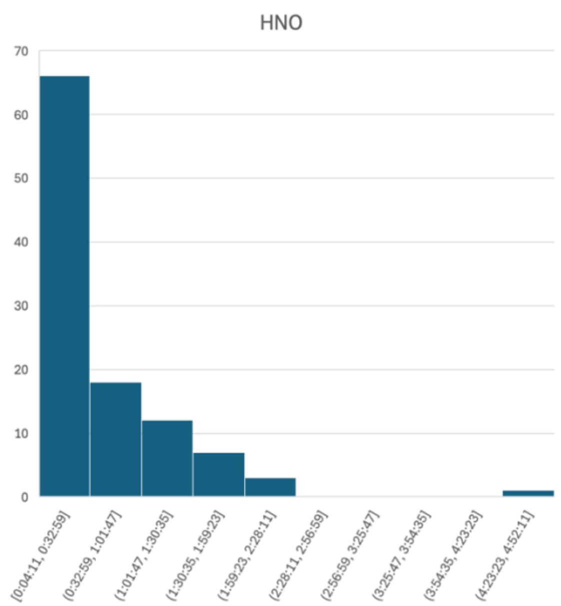
(1:09:58, 1:24:22]



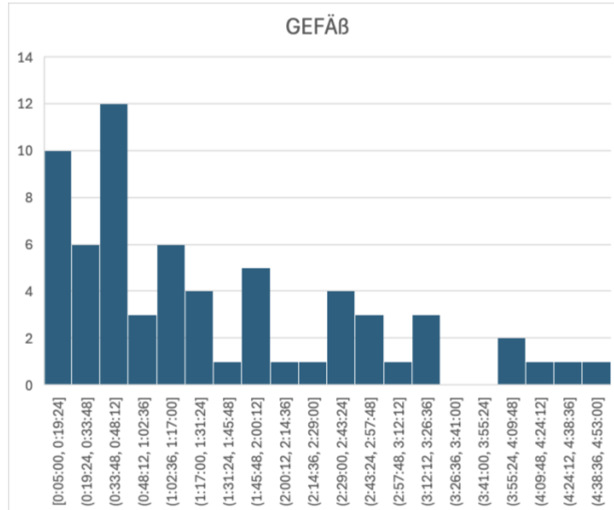


Figure C.20: The surgery duration histograms of all specialties