Interim Report form

1. ***The interim report will be filled out by the student***
2. ***The student will forward the interim report to the project's academic supervisor for feedback, approval and signature.***
3. ***The student will upload the complete form to the submission box in the Moodle.***

The interim report is part of the final report and will be structured as follows:

1. *Abstract*
2. *Introduction- the background of the project, the problem is designed to address*
3. *Report on the work done from the beginning of the project including the methodology that was used and results- including Table 1*
4. *Discussion of present results*
5. *Work plan of the work from the interim report until the end of the project- Table 2 and planned changes (if any) in the gant-chart proposed at the proposal form (with explanation) and updated risk management table*
6. *References*

מכון טכנולוגי חולון
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B. Project Name:

Anomaly Detection in Operating Room Performance Metrics and Development of a Bed Occupancy Prediction Model.

How many meetings have been held with the supervisor(s) so far: __4________

Abstract

Efficient utilization of operating rooms (ORs) is essential for optimizing hospital resources and financial performance. At Assuta Ramat HaHayal, OR schedules are structured into predefined time blocks, considering factors such as medical staff availability, surgeon preferences, and specific OR requirements. However, data analysis shows that surgeries often end approximately 30 minutes earlier than scheduled, creating gaps of an hour or more between procedures. These unutilized periods contribute to financial losses, as ORs remain operationally costly even when not in use.

Additionally, bottlenecks in recovery and inpatient bed availability delay OR turnover, further reducing efficiency. This project aims to analyze OR usage data, identify inefficiencies, and develop data-driven solutions to minimize unutilized time. The focus is on predicting bed occupancy trends, optimizing scheduling, and implementing a real-time monitoring dashboard to support hospital decision-making. By leveraging exploratory data analysis (EDA) and predictive analytics, the project seeks to improve resource allocation and OR efficiency.

Introduction

Operating rooms (ORs) are among the most valuable and resource-intensive assets in a hospital. Efficient OR scheduling is critical for maximizing resource utilization, minimizing downtime, reducing patient wait times, and improving hospital financial performance. However, scheduling inefficiencies, variability in surgery durations, and inpatient bed availability constraints create operational challenges that impact the hospital's ability to optimize surgical capacity and revenue generation.

At Assuta Ramat HaHayal, operating rooms are scheduled into predefined time blocks allocated to surgeons based on multiple logistical and operational constraints, rather than a fixed mathematical formula. The scheduling process considers several factors, including the availability of medical staff such as surgeons, anesthesiologists, and OR nurses, as well as the individual preferences of surgeons and their past scheduling patterns. Additionally, the complexity and type of surgeries assigned to each surgeon play a crucial role in determining the allocation of time blocks. Certain specialists, such as cardiac surgeons, can only perform procedures in specific operating rooms equipped with the necessary facilities for their surgical needs. These constraints shape the structure of OR scheduling, ensuring that resources are allocated as efficiently as possible while accommodating the specific requirements of both the hospital and its medical professionals.

Unlike public hospitals where scheduling is often dictated by administrative availability, Assuta Ramat HaHayal operates as a private hospital, meaning that patients have the ability to choose their surgeon and schedule surgeries directly with them. This flexibility, While beneficial for patient autonomy and satisfaction, creates additional constraints in scheduling, as it requires aligning patient requests with surgeon availability, OR resources, and post-surgical bed occupancy.

Although this scheduling system is designed to balance surgeon availability with patient demand, inefficiencies have emerged that significantly impact OR utilization. One of the primary issues is that surgeries frequently finish earlier than scheduled. Data analysis has shown that, on average, surgeons complete their procedures approximately 30 minutes earlier than their allocated time. Since time blocks cannot be dynamically adjusted in real-time, these early completions create gaps of an hour or more between one block and the next, as the next surgery cannot always begin immediately. This results in a significant loss of operational efficiency.

Another major challenge is the financial impact of unused OR time. Every unused hour in an operating room represents a substantial financial loss for the hospital. ORs are among the most expensive hospital resources, incurring high operational costs due to medical personnel salaries, specialized equipment, and ongoing maintenance.
In a private hospital setting, where revenue primarily depends on patient fees and insurance reimbursements, maximizing OR usage is related to hospital profitability. Inefficient scheduling, therefore, leads to unnecessary financial strain and a reduction in the hospital’s capacity to perform more procedures.

Additionally, bed availability bottlenecks further affect OR turnover. A critical issue in OR efficiency is the limited availability of recovery and inpatient beds. If a post-operative patient cannot be transferred to a recovery bed on time, the OR remains occupied longer than necessary, delaying subsequent surgeries and reducing overall efficiency. Some departments experience longer-than-average post-operative stays, leading to bed shortages that disrupt OR scheduling and create further inefficiencies in hospital operations.

<u>This project aims to:</u>

1. Analyze historical OR usage data to quantify the impact of scheduling inefficiencies, unused OR time, and bed availability constraints.
2. Identify the primary causes of early surgery completion and determine how to optimize scheduling to reduce unused OR time.
3. Develop a predictive approach to anticipate bed occupancy trends, enabling better patient flow and resource allocation.
4. Propose scheduling optimizations that align with actual surgery duration trends, minimizing financial losses associated with underutilized ORs.
5. Design a real-time monitoring dashboard to assist hospital administrators in making data-driven scheduling decisions and reducing inefficiencies.

By leveraging exploratory data analysis (EDA), statistical modeling, and future predictive analytics, this project seeks to enhance OR utilization, improve patient flow, and reduce hospital operational costs.

Table 1 - Interim summary • part of section 3		
Refer to each of the sections listed below and state the status in detail		
Task	**Task Status**	**Details** **Please provide explanation for deviation (if any)**
A. Detailed tasks performed at the Specification stage		
Project Proposal Form Submission	Completed	The project proposal was submitted in both PDF and Word formats according to the required guidelines.
Data Collection	Completed	The dataset, including OR schedules, surgery durations, and info about the patient availability, was received from the hospital. The collected data provides sufficient information for

		exploratory analysis and model development.
Data Cleaning & Preparation (Basic EDA)	In Progress	The dataset has been structured for analysis. Missing values were handled, and outliers were identified. Some unexpected missing values required additional cleaning, causing slight delays.
Analyzing Trends and Patterns (Advanced EDA)	In Progress	The target variable, OR Utilization Rate, was successfully calculated. Initial statistical analysis and visualizations were created to examine OR scheduling efficiency, surgery durations, and inpatient length of stay. Additional analysis is ongoing to explore the impact of early surgery completion.

Identification of Scheduling Gaps	In Progress	Initial findings indicate that some surgeons finish surgeries 30 minutes earlier than scheduled, leading to unutilized OR time between blocks. AI-driven pattern recognition is now being integrated to analyze surgeon and anesthesiologist behavior. This tool aims to optimize scheduling and minimize unused OR time between procedures, reducing hospital costs.
Submitting an Interim Report	Completed	The report is being drafted, summarizing findings from data collection, cleaning, and EDA progress.
B. Work progress according to specification: Detail the work\tasks done according to the specification. If there are deviations from the		

specification please specify the changes and the reason for the changes		
Data Collection	Completed	Data was collected from hospital records, including OR schedules, surgery durations, and info about each patient. No deviations from the specification at this stage.
Data Cleaning & Preparation	In Progress	The dataset was preprocessed: missing values were handled, and outliers were identified. However, some unexpected missing values required additional cleaning, causing slight delays.
Initial Data Analysis	In Progress	Statistical analysis and visualizations were created to examine OR scheduling efficiency, surgery durations, and inpatient length of stay. Additional analysis is ongoing

		to explore the impact of early surgery completion.
Identification of Scheduling Gaps	In Progress	Initial findings showed that some surgeons finish surgeries earlier than scheduled, leading to unutilized OR time. Based on this, the hospital's Nursing Department requested the development of an AI-driven dashboard to predict precise block times for each surgeon, considering the anesthesiologist assigned to the procedure. This represents a deviation from the original plan, as AI-driven predictive scheduling was not initially included in the project specification.
Submitting an Interim Report	In Progress	The report is being drafted, summarizing findings from

		data collection, cleaning, and initial analysis.

Discussion of present results

The dataset contains numerous duplicate rows representing the same surgery for the same patient, with the primary difference being the type of anesthesia used. Additionally, there are many missing values that should be completed using duplicate rows or other available data sources. A strong correlation (0.86) between planned and actual operating room numbers confirms that the scheduling system is highly reliable, while a similar correlation (0.86) between the main surgeon code and activity type suggests that specific surgeons consistently perform certain procedures, likely due to specialization or hospital policies. A moderate correlation (0.57) between planned operating room number and main surgeon code indicates that certain surgeons are consistently assigned to specific rooms, possibly reflecting workflow efficiency or logistical preferences. A notable correlation (0.50) between anesthesia code and activity code reinforces the structured assignment of anesthesia types to procedures, and a similar association (0.50) between anesthesiologist code and anesthesia code suggests specialization patterns. The correlation between surgical team codes and activity type code (0.62) highlights the structured approach in assigning surgical teams based on procedure type.

Analyzing numerical variables using Spearman correlation revealed a moderate correlation (0.49) between height and weight, yet no strong correlation between patient characteristics and surgical planning variables, suggesting that physical attributes minimally influence decision-making. Weak correlations were observed between weight (0.29) and patient age (0.26) with planned surgery duration, implying that these factors are not significant predictors. The daily operating room utilization rate had weak correlations with other variables, suggesting that efficiency is influenced by external

factors rather than direct patient or surgery attributes. Planned and actual surgery duration were highly correlated (1.00), confirming accurate scheduling, but weight, age, and utilization rates showed only minor associations with planned durations.

Key insights from the 2018 dataset reinforced several trends. A strong relationship was observed among surgery time-related variables, such as S_p_limited, S_p_hours_limited, SU_p_limited, SH_r_hours, and total_usage, confirming that longer surgeries naturally lead to increased overall room usage. High correlations were also identified between surgery start and end times, such as closure time, end of surgery, and exit OR datetime, reflecting structured scheduling practices. A strong correlation between daily utilization rate and total usage suggests that as total room usage increases, utilization rate rises proportionally. However, patient characteristics, including weight, height, and age, exhibited low correlation with surgery duration, suggesting minimal influence on procedural duration. If anesthesia code correlates strongly with time-related variables, some anesthesia types might prolong surgeries, warranting further investigation.

Regarding patient data, height and weight contained extreme values, suggesting possible unit inconsistencies or data entry errors, while patient age ranged from 0 to 118 years, potentially including newborns or misrecorded values. The most common procedures were associated with surgeon code 16917, activity code 13, and general anesthesia. Planned surgery duration had an average of minutes, with a maximum of 10 hours, highlighting extreme outliers. Surgery timing variables, such as planned start and end time for doctor block, displayed values between 0.01 and 0.98, suggesting fractional time encoding. The daily utilization rate averaged 61.83% but exceeded 100% in some cases, raising concerns about potential data inconsistencies or overutilization.

Post-surgery data revealed missing values in approximately 13% of recovery room entry and exit times, with the most common post-surgery discharge time being 11:00, possibly reflecting standardized hospital practices. Further statistical analysis identified a moderate correlation (0.487) between height and weight, a moderate positive correlation (0.477) between weight and patient age, and a strong correlation (0.7) between planned surgery duration and S_p_limited/S_p_hours_limited, confirming that longer planned surgeries require increased surgical time utilization. A perfect correlation (1.0) between S_p_limited and S_p_hours_limited suggests redundancy, meaning one of these variables could be removed without affecting analysis quality. A strong correlation (0.598) between SH_r_hours and total_usage indicates that more shift hours lead to increased operating room use, while a very weak correlation (0.022) between total_usage and daily_utilization_rate suggests that utilization rate is influenced by other factors, such as scheduling constraints or operational inefficiencies.
These findings highlight key patterns in surgical scheduling and operating room utilization, indicating that some variables are highly interrelated, while others exhibit anomalies requiring further validation. To enhance data quality and improve analysis accuracy, inconsistencies in height, weight, and time variables should be addressed, encoding formats should be confirmed, and the causes of high missing data percentages in certain columns should be investigated. Additionally, understanding the operational

constraints leading to utilization rates exceeding 100% could provide insights into whether these represent actual overutilization or data artifacts.

Table 2 – Future work plan **part of section 5**	
In this chapter the students will detail the Future work-plan (until the end of the project) n details (a resolution of weeks)	
Week number	**Project progress plan (to be filled out by the student)**
1	Finalizing Data Cleaning & Handling Duplicates – Address duplicated rows and inconsistencies found in the dataset. Ensure missing values are handled properly. Perform final Exploratory Data Analysis (EDA) to validate the cleaned data.
2	Advanced Data Analysis & Feature Engineering – Perform deeper statistical analysis of surgery duration, OR efficiency, and bed occupancy trends. Engineer new features to improve predictive models.
3	Developing Surgery Duration Prediction Model – Implement machine learning models to predict surgery durations. Evaluate model performance using MAE and R^2. Perform hyperparameter tuning to improve accuracy.

4	Developing Bed Occupancy Prediction Model – Train a forecasting model using time-series or regression-based approaches. Test different algorithms to improve accuracy in predicting inpatient bed usage. Integrate external factors like patient recovery time.
5	Developing Real-Time Dashboard & Final Testing – Implement a Power BI dashboard displaying OR utilization, predicted surgery durations, and bed availability. Test the full system for validation. Document final results and prepare for project submission.
6	Final Testing & Debugging of Prediction Models – Conduct performance evaluations on both models (surgery duration & bed occupancy). Optimize models by testing different ML techniques. Address any overfitting/underfitting issues.
7	Integration of Predictive Models into Dashboard – Embed AI-driven predictions into the Power BI dashboard. Ensure visualization clarity and real-time updates work smoothly.
8	Final Refinements & Optimization – Make final adjustments based on feedback.
9	Project Book & Report Writing – Start drafting the final project book, summarizing methodology, findings, challenges, and results.
10	Final Presentation Preparation – Prepare slides, visual materials, and a project video for the final oral exam.

11	Project Submission – Submit all deliverables: project book, report, final code, dashboard files, and supporting materials.
12	Oral Exam & Final Evaluation – Present findings and demonstrate the working solution to academic supervisors and external reviewers.

6. References

1. Dexter, F., & Traub, R. D. (2007). Operating room efficiency and hospital capacity: Factors affecting operating room turnover and utilization. *Journal of the American College of Surgeons, 204*(5), 845–852. https://doi.org/10.1016/j.jamcollsurg.2007.01.030

2. Marmor, Y. N., Rohleder, T. R., Huschka, T., Cook, D., & Thompson, J. (2011). A simulation tool to support recovery bed planning for surgical patients. *Proceedings of the 2011 Winter Simulation Conference*, 1338–1344. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=16ba94de21edc49d85136d465c6fb15719a80bb8

3. Dulskas, A., Samalavicius, N. E., & Urbanavicius, R. (2023). Operating Room Performance Optimization Metrics: A Systematic Review. *Journal of Medical Systems, 47*(2), Article 19. https://doi.org/10.1007/s10916-023-01912-9

4. Tumin, D., & Tobias, J. D. (2022). Operating Room Relay Strategy for Turnover Time Improvement: A Quality Improvement Initiative. *BMJ Open Quality, 11*(3), e001957. https://doi.org/10.1136/bmjoq-2022-001957

Department of Digital Medical Technologies

Research & Development - Final Projects

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Date:__25/02/2025___