HENRY FORD HEALTH

INTERVENTIONAL RADIOLOGY SCHEDULING

Kyllan Wunder, Michael Ewnetu, Abigael Nyakara

Introduction / Motivation

Optimizing procedure room scheduling in Interventional Radiology (IR) is crucial for patient flow and resource efficiency. Traditional scheduling relies on manual estimates, often causing delays and higher costs.

We propose using pre-operative & post-operative data to predict patient room times, enabling accurate, data-driven scheduling.

Objective

1. Develop accurate predictive models for procedure room times
2. Incorporate patient, Room details and temporal features
3. Use preoperative (scheduling) & postoperative (post-procedure) data to enable business applications and deeper analysis.
4. Employed manual, rule-based methods, NLP & LLMs to extract features

Data Description

Data Source

The data was obtained from Henry Ford Health's Research and Development department and encompasses procedures conducted across five Henry Ford facilities. All personally identifiable information was de-identified in compliance with HIPAA regulations for medical data.

The dataset includes records of procedures performed over a two-year period, from January 23, 2023, to January 22, 2025, totaling 41,415 procedures on 22,124 unique patients

Data features

Feature Types	Examples
Time	PatientRoomTime, FirstCaseIn, First Case Delta
Physical Environment	IP Unit, Actual IR Room Name, Facility Name
Personnel	Case Provider, Procedure Nurse, Resident, Technician, Physician Assistant
Patient Characteristics	BMI, Age, Gender, ASA Classification, Admission Type
Procedure Details	Procedure Performed, CPT Code, Anesthesia Given

Data handling

Missing Data

The analysis intentionally excluded data imputation for missing values, preserving the native state of all recorded measurements. This approach was selected due to the critical nature of missingness patterns in medical procedure data, where gaps often carry meaningful information about operational workflows or documentation practices.

Data Cleaning - Encoding Variables

Feature Engineering Strategies	Features
Cyclical Encoding (sin and cosine)	Hour, Month
One Hot Encoding	Resident (Available/not), Admit Type, Case Type, ASA, Time Of Day
Frequency Encoding	Actual IR Room Name

Creating new Features from Pre-existing Data

Type	Examples
Time Features	Hour, Month, TimeOfDay, sin_time, cos_time
Personnel	Resident Present, Case Provider Experience, number of previous visits
Procedure Performed	Word count, character count

Methodology

Exploratory Data Analysis

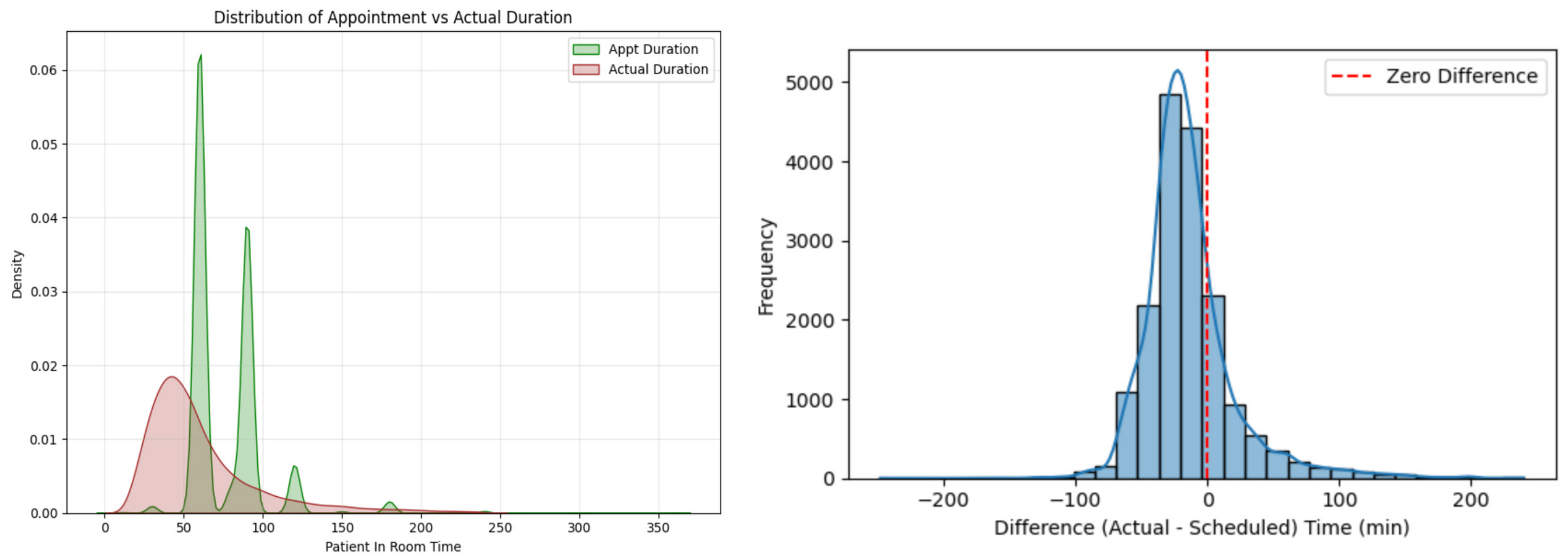
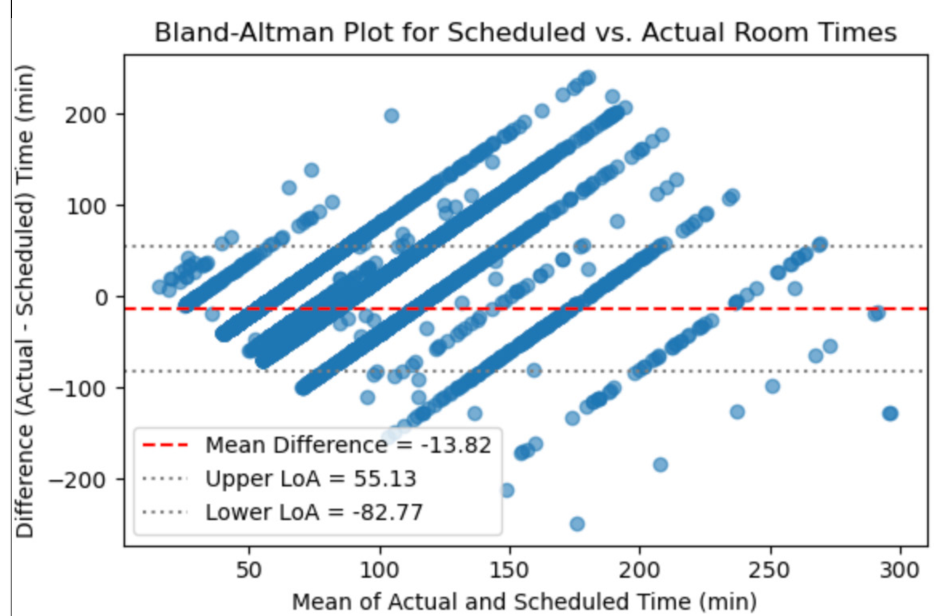


Fig1: Distribution of Scheduled Appointment Duration Vs Actual Room Time

The histogram is skewed to the left (negative values), which shows that the current system tends to overestimate procedure times (actual times are shorter than scheduled times).



- The mean difference is -13.82 minutes. This indicates that, on average, actual procedure times were about 14 minutes shorter than scheduled times.
- Upper Limit (55.13 minutes): Procedures could take up to about 55 minutes longer than scheduled.
- Lower Limit (-82.77 minutes): Procedures could also finish up to about 83 minutes shorter than scheduled.

Fig2: There's significant Variability and procedure durations are often innacurate. The variability is on both sides meaning some procedures do occasionally run significantly longer than anticipated.

Procedure Performed Column

The Procedure Performed Column contains textual data that described the Interventional Radiology procedure to be performed. The text data was highly unstructured and irregular, calling for advanced processing.

Procedure Performed Data processing	Features
Manual Extraction of Features	Body part, Procedure Name, Imaging Modality used
TF-IDF	Frequency based feature engineering from the textual data: word level and character level on ngram range of 3 to 6.
LLM Embedding	Extracting the embedding from Clinical BERT, LLM trained on medical note.
SciSpacy Medical Entity extraction	Python Library for extracting medical entities from clinical textual data

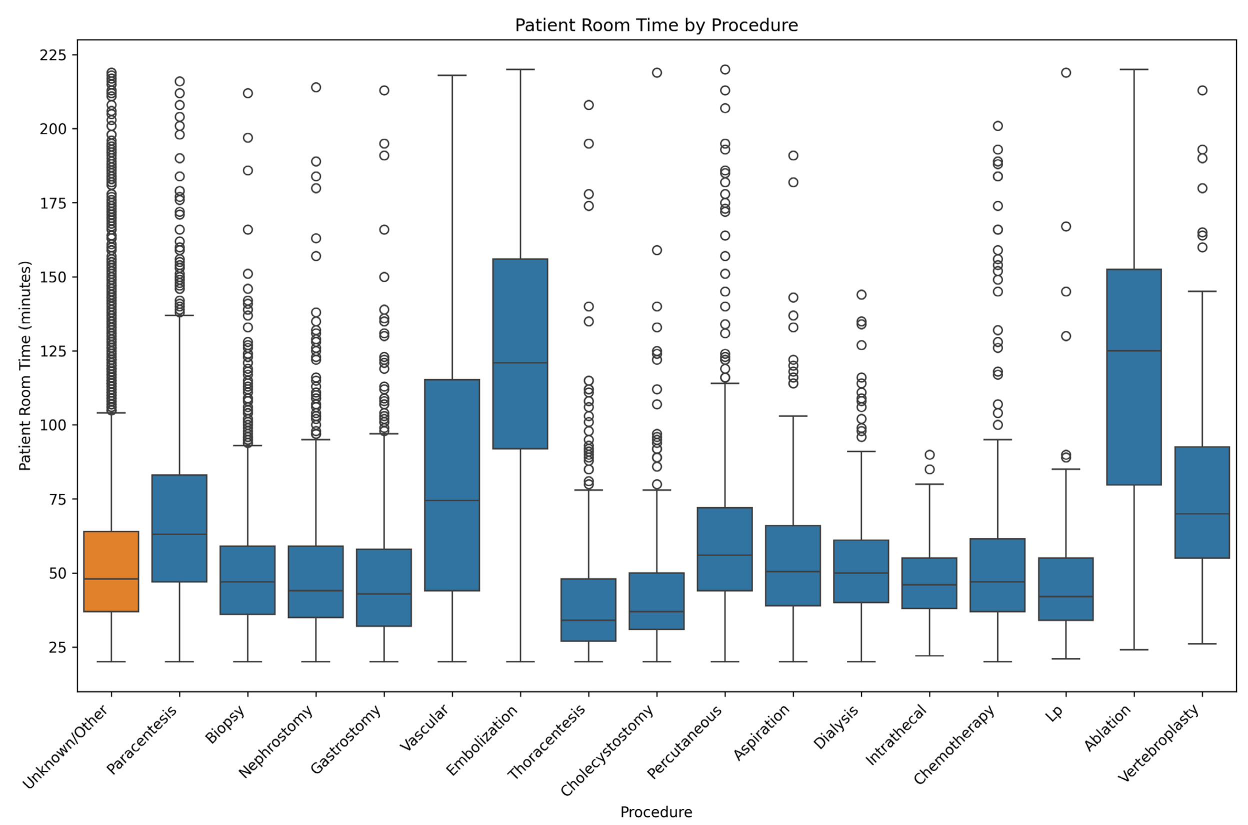


Fig 3: Procedure Durations for Different Procedure Categories

Original	image-guided paracentesis and left side port placement
Manual	image-guided paracentesis and left side port placement
Embedding	[8438.89], [79395.37], [95703.36], ... , [62635.56], [7875.69]
SciSpacy	image-guided paracentesis ~~and~~ left side port placement {TECHNIQUE}{PROCEDURE} {ANATOMY} {DEVICE}

Fig 4: Example Outputs For different text processing techniques

Modelling Results

Model	Approach	MAE (Minutes)	Relative MAE (%)	MAPE (%)	UnderEstimation Rate	Within 20%
Legacy Model	Current Scheduling	29.11	57.08%	68.70%	22.20%	26.02%
XG-Boost	Manual	**16.09**	**32.08%**	30%	40%	45.51%
XG-Boost	CinicalBERT	16.62	36%	30.83%	50.10%	44.40%
XG-Boost	Quantile Regression (QA=0.7)	20.28	39%	41.09%	31.40%	37.88%
100% Features - PostOperative Data						
CatBoost	SciSpacy	17.31	33.01%	**28.14%**	49.58%	**47.49%**
LightGBM	SciSpacy	17.24	33.80%	28.53%	48.44%	47.15%
XG-Boost	SciSpacy	17.3	33.54%	31.11%	40.85%	46.12%
Neural Additive Model	SciSpacy	19.12	37.49%	36.57%	37.02%	35.99%

Fig 5: Performance of predicted modelling vs Legacy Model

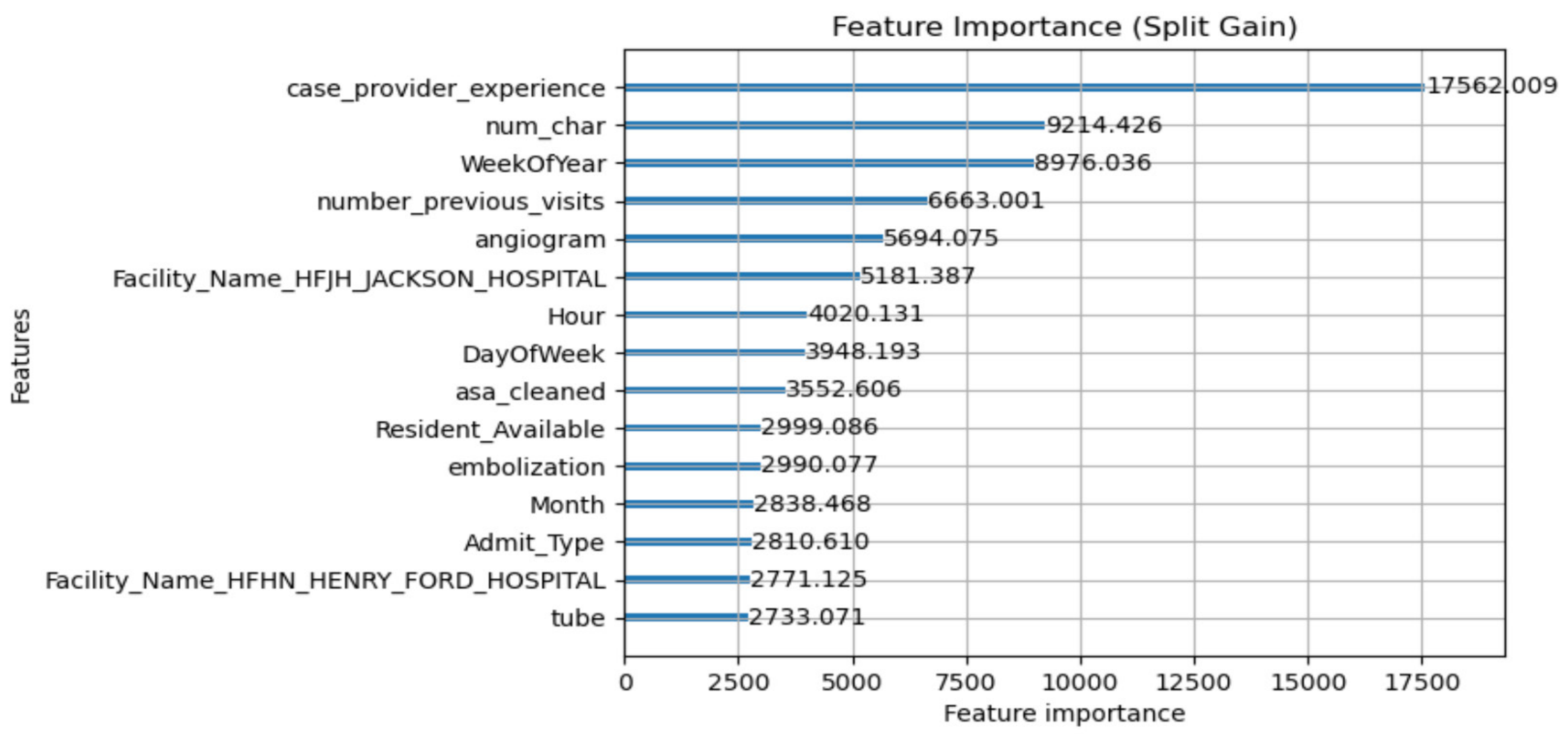


Fig 6: Post-Operative Feature Importance Plot - Light GBM

References

Kraus, M., et al. (2023). Machine Learning for the Prediction of Procedural Case Durations. Journal of Medical Internet Research, 25, e46877.

Acknowledgements

We express sincere gratitude to the Henry Ford Research and Development team especially Chad Klochko, Niky Patel and William Ferris for their invaluable support throughout this project.