Patient Treatment in Emergency Department

Course: Business Information Systems
Instructor: Prof. Paolo Ceravolo
University of Milan

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1 Introduction

The aim of this project is to implement process mining techniques to improve complex end-to-end patient treatment process in Emergency Department from arrival to discharge. The core objective is to identify current process model (AS-IS) from the given dataset, discover structural inefficiencies, and propose data-driven solutions to minimize these inefficiencies, ultimately improving the process flow towards the target process model (TO-BE model).

The report begins by outlining the Organizational Goals that drive this process improvement effort. Following this, the Knowledge Uplift Trail methodology is introduced and systematically applied in subsequent sections to guide the analysis, transitioning raw data into actionable organizational wisdom.

1.1 Methodology and Approach

This analysis is structured around the Knowledge Uplift Trail methodology, which provides a rigorous, step-by-step framework for transforming raw event data into strategic process knowledge. This involves: Data Preprocessing, Performance Analysis, Structural Inefficiency Detection Root Cause Analysis and Improvement Proposals ,Linking inefficiencies to their organizational root causes and generating data-backed TO-BE hypotheses for systemic improvement.

1.2 Tools and Technologies

This study was anchored in Python, chosen as the primary programming language for its inherent flexibility and comprehensive ecosystem vital for advanced data analysis. The initial data preprocessing was handled by the Pandas library, which furnished efficient tools for tasks such as data cleaning, transformation, and filtering. Data visualization was achieved through the collaborative use of Matplotlib and Seaborn, enabling the generation of insightful and publication-quality plots. Furthermore, the specialized field of process analysis was executed using the PM4Py library, which provided a robust suite of algorithms for process mining, allowing for in-depth discovery, conformance checking, and performance evaluation of the underlying process models.

1.3 AI Usage Disclaimer

Artificial intelligence tools, including ChatGPT and Google Gemini, were used during the preparation of this report solely to assist with language refinement, grammar correction, and improvement of clarity in written paragraphs. The conceptual content, technical analysis, methodology, results, and conclusions were developed independently by the author. The use of these tools did not influence the scientific reasoning or originality of the work.

1.4 Code and Resources

Google Colab Link

2 Organizational goals

In goal models, hard goals refer to functional, measurable objectives, while soft goals refer to qualitative objectives or Non-Functional Requirements (NFRs) that are often subjective. The following table represents the decomposition of the core objective, Improving ED Operations, into its constituent sub-goals (both Hard and Soft).

Goal Type	**Goal Name**	**Description**	**Contribution**
Soft Goal	Improve ED Operations	The overarching, high-level objective of the entire project.	Decomposed into its critical sub-goals.
Hard Goal	Analyze End-to-End Patient Treatment Process	Use the event log to understand the full patient journey.	Contributes to Improve ED Operations.
Hard Goal	Identify Structural Inefficiencies	Pinpoint bottlenecks, unnecessary steps, or resource misalignments.	Contributes to Analyze End-to-End Patient Treatment Process.
Hard Goal	Assess Conformance	Check if the actual process aligns with standard procedures or regulatory requirements.	Contributes to Analyze End-to-End Patient Treatment Process.
Hard Goal	Propose Data-Driven Improvements	Formulate specific, actionable recommendations based on the analysis.	Contributes to Analyze End-to-End Patient Treatment Process.
Soft Goal	Minimize Wait Times	A key objective for patient satisfaction and throughput.	Refined by Propose Data-Driven Improvements.
Soft Goal	Improve Patient Outcomes	The ultimate clinical benefit of an efficient process.	Refined by Propose Data-Driven Improvements.
Soft Goal	Ensure Regulatory Compliance	Meet all legal and safety standards for ED operations.	Refined by Assess Conformance.

Table 1: Organizational Goals, Descriptions, and Contributions

3 Knowledge Uplift Trail

The Knowledge Uplift Trail is a structured methodology utilized for achieving increasingly meaningful insights, transitioning from raw data through a series of refinement stages to actionable knowledge. The goal is to process the volume of available data to find meaningful information, generate strategic knowledge, and finally achieve organizational wisdom.

First, the dataset related to this case study is introduced. Next, data preprocessing steps, including data cleaning and filtering, are applied to the dataset. The following paragraphs describe the steps taken in the knowledge-uplift trail methodology for patient treatment in the ED event log.

3.1 Dataset Introduction and Overview

This section provides an overview of the data set used in this case study related to patient treatments at Emergency Department (ED). This data set has 25115 rows and 27 columns and follows essential event log structure.

Every event log must have three fundamental key columns including case ID, activity ,and time element. The case ID (Trace ID) element of this event log is represented by `stay_id` column, which is unique identifier corresponding to individual patient at ED. The activity element of event log is represented by the `activity` column and finally, the timestamp element is represented by the `time` column.

Given dataset consists of identity, and treatment information of 1820 unique patients each represented by unique `stay_id`. The activity column has following six distinct values that represent the major steps of the end-to-end ED process. This values include: `Enter the ED`, `Triage in the ED`, `Medicine reconciliation`, `Medicine dispensations`, `Vital sign check`, `Discharge from the ED` where the `Enter the ED` value indicate the starting point of process and the `Discharge from the ED` indicates the end point.

Several case-level attributes provide additional patient information. During the 'Enter the ED' activity, the dataset records the patient's arrival mode (`arrival_transport`, with five possible values), `gender` (two values), and `race` (32 values). Other case-level attributes include diagnostic codes (`diagnosis_code`), disposition (`disposition`), and acuity level assigned during triage (urgency level).

Event-level attributes contain more granular information, such as physiological measurements, administered medications, and identifiers of the clinical staff involved in specific procedures.

The full columns descriptions are provided in the Appendix.

3.2 Data Preprocessing : Data Cleaning and Data Filtering

Data cleaning, is the process of detecting and correcting (or removing) corrupt, inaccurate, or irrelevant records from a dataset to improve its quality, ensuring it's consistent, accurate, and usable for analysis.

Data filtering is the process of selecting and extracting a subset of data from a larger dataset based on specific rules or conditions, effectively removing irrelevant, erroneous, or noisy information

For this study case data cleaning and filtering was completed by following steps.

3.2.1 Convert and Validate Data Types

This step is a crucial first step that ensures columns contain values in the correct format for following calculations, especially the values of fundamental event log's columns.

Values of the `stay_id` column should be treated as categorical or string values and not arithmetic values. Values of `activity` column should be treated as categorical or string values. Finally values of `time` column should be of timestamp type to simplify time-based operations.

```
    df["activity"] = df["activity"].astype("string")
    df['time'] = pd.to_datetime(df['time'])
    df['stay_id'] = df["stay_id"].astype("string")
```

Listing 1: Converting key columns value types

In addition, other columns with textual descriptions including, were converted to the string data type, and the values of `diagnosis_sequence` were converted to float64 data type during the data cleaning process. After that, `lower()` and `strip()` functions were applied for columns containing string values as an initial step to ensure that similar values were represented consistently. Although this conversion is not strictly necessary for the current analysis, it was performed to improve clarity and consistency in the dataset. Using the string type makes the intended use of these columns explicit and allows for easier extension of the data processing steps in the future, particularly if additional text-based operations are required.

3.2.2 Key Process Variables Preprocessing

As mentioned before, the event log's fundamental structure relies on the presence of the `case_id`, `timestamp`, and `activity` for every event. Firstly, a validation step was executed to remove any rows where these fields were missing or null. The results indicated that the dataset is highly complete, as zero rows met the deletion criteria. This confirms that all recorded events are properly anchored to a case and have a valid execution time and description.

```
    df[df['stay_id'].isna()]
    df[df['time'].isna()]
    df[df['activity'].isna()]
```

Listing 2: Search for key process variable missing values

Secondly, the entire event log was sorted based on `stay_id` and then `time`, ensuring that activities related to each patient are sorted from earliest event to latest.

```
    df = df.sort_values(by=['stay_id', 'time'],
                        ascending=[True, True])
```

In addition, the values in the 'activity' column were checked to be meaningful and granular enough.

3.2.3 Filling patients information

To standardize key patient attributes, a canonical subset containing stay_id, gender, race, and arrival_transport from rows with the "Enter the ED" activity was created, keeping only unique entries. This subset was merged back into the main dataframe, and the canonical values were used to overwrite the corresponding columns, ensuring consistency. Temporary merge columns were then removed. This step is necessary in preprocessing the event log to eliminate inconsistencies and potential errors in patient information, which can arise from multiple entries across different activities, thereby ensuring accurate and reliable downstream analyses.

3.2.4 Non-Informative Value Replacement

This is a critical initial phase in data cleaning. This step was performed across several categorical columns. This process involved inspecting the unique values in the columns arrival_transport, race, and disposition, and replacing various non-standard string representations of missing or non-informative data with the unified numerical placeholder, np.nan (Not a Number).

```
    # non-informative values in arrival column
    df.loc[df["arrival_transport"] == "unknown"
          , "arrival_transport"] = np.nan
    df.loc[df["arrival_transport"] == "other"
          , "arrival_transport"] = np.nan
    df['arrival_transport'].unique()

    # non-informative values in race column
    df.loc[df["race"] == "unable to obtain", "race"] = np.nan
    df.loc[df["race"] == "patient declined to answer", "race"] = np.nan
    df.loc[df["race"] == "other", "race"] = np.nan
    df.loc[df["race"] == "unknown", "race"] = np.nan

    # non-informative values in race disposition column
    df.loc[df["disposition"] == "other", "disposition"] = np.nan
```

Listing 3: Example of Replacing non-informative values with nan using pandas

3.2.5 Vital Signs Normalization

This section details the data preprocessing and normalization steps applied to all nine vital sign and assessment parameters based on the criteria established in the scenario's Appendix. The process ensures data consistency and quality by executing three primary functions: unit reconciliation , the removal of non-physiological or incorrectly entered values (validation) , and the unification of semantically similar but heterogeneously recorded string values . This standardized approach was systematically applied across all columns, regardless of their initial cleanliness, to guarantee a uniform and robust dataset.

Temperature Attribute (temperature)

The minimum value recorded in the temperature column, which represents patients' body temperature and possible fever, is 34.4, while the maximum recorded value is 104.8. This range indicates that body temperatures were recorded using different measurement units. As part of the data preprocessing procedure, all temperature values were converted to a single unit. Since the majority of the records are in Fahrenheit, the seven values recorded in Celsius were converted to Fahrenheit.

```
df.loc[df['temperature'] <= 60, 'temperature'] = (
df.loc[df['temperature'] <= 60, 'temperature'] * 9/5 + 32)
```

Heart Rate Attribute (`heartrate`)

The Heart Rate attribute is clinically defined with a normal range of $60-100$ bpm(beats per minute). Readings >100 bpmare classified as abnormal . For data validation, acceptable HR values are strictly confined to the physiological range of $30-220$ bpm. Any raw data entry found outside this $30-220$ bpminterval is presumed to be entered incorrectly (a data entry error) and will be replaced with the null placeholder `np.nan`.

Respiratory Attribute (`resprate`)

The Respiratory Rate attribute has a clinically defined normal range of $12-20$ breaths/min. Readings >20 breaths/min are classified as abnormal (tachypnea). For data validation, acceptable respiratory rate values are strictly confined to the physiological range of $5-40$ breaths/min. Any raw data entry found outside this $5-40$ breaths/mininterval is presumed to be entered incorrectly (a data entry error) and will be replaced with the null placeholder `np.nan`.

Oxygen saturation Attribute (`o2sat`)

The Oxygen Saturation attribute has a clinically defined normal range of $95-100\%$. Readings$<90\%$ are classified as abnormal, specifically hypoxemia . For data validation, acceptableo2satvalues are strictly confined to the physiological range of $65-100\%$. Any raw data entry found outside this $65-100\%$interval is presumed to be entered incorrectly (a data entry error) and will be replaced with the null placeholder `np.nan`.

Systolic BP Attribute (`sbp`)

The Systolic Blood Pressure attribute has a clinically defined normal range of $90-120$ mmHg, with values >120 mmHgbeing considered abnormal. For data validation, acceptable SBP values are strictly confined to the physiological range of $50-250$ mmHg. Any raw data entry found outside this$50-250$ mmHginterval is presumed to be entered incorrectly (a data entry error) and will be replaced with the null placeholder `np.nan`.

Diastolic BP (`dbp`)

The Diastolic Blood Pressure attribute has a clinically defined normal range of $60-80$ mmHg, with values >80 mmHg being considered abnormal. For data validation, acceptable DBP values are strictly confined to the physiological range of $30-120$ mmHg. Any raw data entry found outside this $30-120$ mmHg interval is presumed to be entered incorrectly (a data entry error) and will be replaced with the null placeholder `np.nan`.

Pain Attribute (`pain`)

The raw pain data, which contained inconsistent string values, was standardized to a $0-10$ numeric scales. Clinically, any value>0 is defined as abnormal. A custom lookup dictionary was utilized to convert the mixed string entries (including non-informative or descriptive terms) into the target $0-10$ range. The output includes the standard numeric values, alongside two special string markers, `'>0'` and `'>10'`, to flag cases of recorded pain without a specific score, and pain exceeding the maximum limit, respectively.

Rhythm Attribute (`rhythm`)

Sinus rhythm is defined as the normal state, with all other rhythms classified as abnormal. The initial raw data contained various string representations for recorded sinus rhythm (eg, 'sr', 'nsr'). In this step, a detection and mapping process was implemented to convert all these diverse values into the uniform string literal: `'sinus rhythm'`. Additionally, non-informative or missing string entries were replaced with the `np.nan` placeholder for subsequent handling.

Acuity Attribute (`heartrate`)

This attribute captures the patient's severity level, typically assessed using a triage scale like the Emergency Severity Index (ESI). The data is categorized based on severity: Low Acuity (Normal) is defined by ESI levels 4 or 5. High Acuity (Abnormal) corresponds to ESI levels $1-3$, indicating a greater need for immediate resources and intervention.For the purpose of normalization, the attribute is expected to contain integer values corresponding to the ESI levels. Any raw data entries that are non-numeric, non-standard ESI values (ie, not 1, 2, 3, 4, or 5), or otherwise non-informative are presumed to be errors and will be replaced with the null placeholder `np.nan`.

3.2.6 Final Data Persistence

After completing all the cleaning steps—making sure the units are correct, removing bad values, and standardizing the text—the final, clean dataset was saved. This makes sure we have one reliable set of data to use for all the future analysis, including process mapping and calculating business results. This saved data is now the official source for the rest of this report.

3.3 Performance Analysis

3.3.1 Define Key Performance Indicators

An organization's performance can be evaluated across the dimensions of time, quality, and revenue. For the Emergency Department, based on the information available in the event log and the defined primary goal of optimizing the end-to-end patient treatment process, the following measures can be defined and applied.

1. Time to Treatment : Time from arrival/triage until the commencement of definitive treatment (e.g., initial assessment, IV cannulation, nurse-initiated medication). For each patient, this duration can be calculated as the difference between the timestamp of the activity labeled `enter the ed` and the timestamp of the subsequent activity.

2. Length of Stay (LOS): The total time a patient spends in the ED (from arrival to discharge, transfer, or admission). For each patient, this duration can be calculated by finding the difference between the timestamp of patients `enter the ed` activity and `discharge from the ed` activity.

3. Left Without Being Seen (LWBS) Rate: Percentage of patients who leave the ED before receiving a medical evaluation from a provider. This percentage can be calculated by searching for individual who had no medical activity recorded.

4. Left Against Medical Advice (AMA) Rate: This measures the proportion of ED visits that end with patients leaving despite a clinician's recommendation to stay.

5. Mortality Rate: Tracking the percentage of patient deaths in the ED or shortly after admission from the ED.

6. Triage Acuity Mix: The distribution of patients across Triage Categories (1 to 5)

7. Other Indicators: The following list presents additional key performance indicators for the Emergency Department that were not included in this study due to limited available information or time constraints.

- Unplanned Revisit Rate: Percentage of patients who return to the ED within a short window (e.g., 72 hours) for the same or a related complaint. This measure can be calculated if an unique patient identifier was provided.
- Door-to-Provider Time (DTP): Time from patient arrival (registration/triage) until they are first seen by a physician or advanced practice provider. There is no activity recorded for getting visited by physician.
- Patient Satisfaction Scores: This measure can get collected through surveys.
- Admit Decision-to-Departure Time: Time from when the decision to admit the patient is made until the patient physically leaves the ED for an inpatient bed. There is no record of making decision activity in the current event log.
- Complaints and Commendations: Tracking feedback regarding care, staff interaction, and the physical environment.
- Ambulance Offload Time: Time from ambulance arrival until the patient is transferred off the stretcher and the ambulance crew is ready to leave.
- ED Occupancy Rate: The number of patients currently in the ED divided by the available bed capacity. There is no information on total number of available beds in ED.
- Staff-to-Patient Ratios: The ratio of nurses and physicians to the current patient load. There is no information on total number of staffs.
- Diagnostic Turnaround Time: Time from ordering a key diagnostic test (e.g., lab, radiology) until the result is available. There is no recorded activity as taking these tests or their results.
- Time-Sensitive Protocol Compliance: Adherence to critical pathways for conditions like Sepsis, Stroke, and STEMI.

3.3.2 Processing Time (PW) Calculation

The processing time is equal to duration of each activity. Since the event log provided contains only the start timestamp for each recorded activity (singular timestamp), the duration of an individual activity is calculated by taking the time difference between its recorded start time and the start time of the immediately succeeding activity within the same process instance (case).

```
    df["activity_duration"] =
            (df.groupby("stay_id")["time"] .shift(-1) - df["time"])
```

3.3.3 Current-State (AS-IS) Performance Evaluation

1. Occupancy Analysis

The figure below presents the Emergency Department (ED) Occupancy Heatmap , which visually models the concentration of patients across time. The horizontal axis (x-axis) represents the Hour of the Day (ranging from 0 to 23), while the vertical axis (y-axis) indicates the Day of the Week (where 0 corresponds to Monday and 6 corresponds to Sunday). This visualization is fundamental for identifying peak demand periods and patterns. .

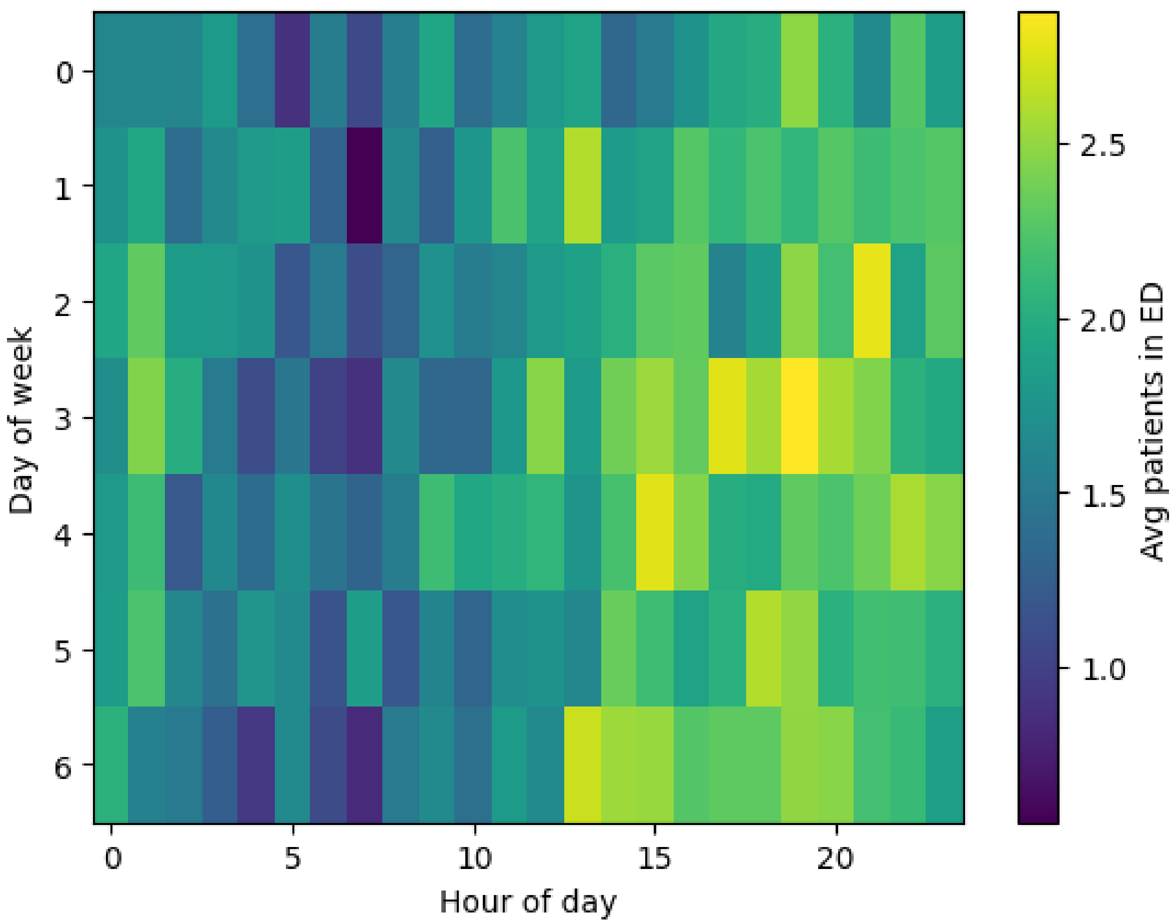

Figure 1: Emergency Department Occupancy Heatmap

The data clearly shows a pattern of crowding during specific times. The highest concentration of patients is consistently observed in the afternoon and early evening hours (approximately 15:00 to 22:00) on weekdays and Saturdays (Days 2, 3, 4, and 5). Conversely, the ED experiences its lowest volume during the overnight hours (0:00 to 6:00) and appears to have a relatively lower volume on one of the weekend days (Day 6, likely Sunday). The darkest cell, indicating a sudden spike or minimum volume, is observed on Day 1 around 7:00, which might represent a quick turnover or the lowest point before the morning rush.

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2. Length of Stay (LOS)

The Length of Stay (LOS) for the 1,820 patient encounters is highly variable and skewed. The average LOS is 408 minutes (6.8 hours) , but half of all patients are discharged within 301 minutes (5.0 hours) . This difference shows that a few very long stays pull the average up, with the longest stay lasting over 5,065 minutes (84 hours) . The data confirms a significant backlog, as the top 25% of patients remain in the system for more than 7.6 hours.

Statistic	**LOS (Minutes)**
Count	1820
Minimum	4.0
Maximum	5065.0
Mean	408.4
Median (50th %)	301.0
25th Percentile	194.2
75th Percentile	458.3

Table 2: Descriptive Statistics for Patient Length of Stay (LOS) in Minutes (As-Is Model)

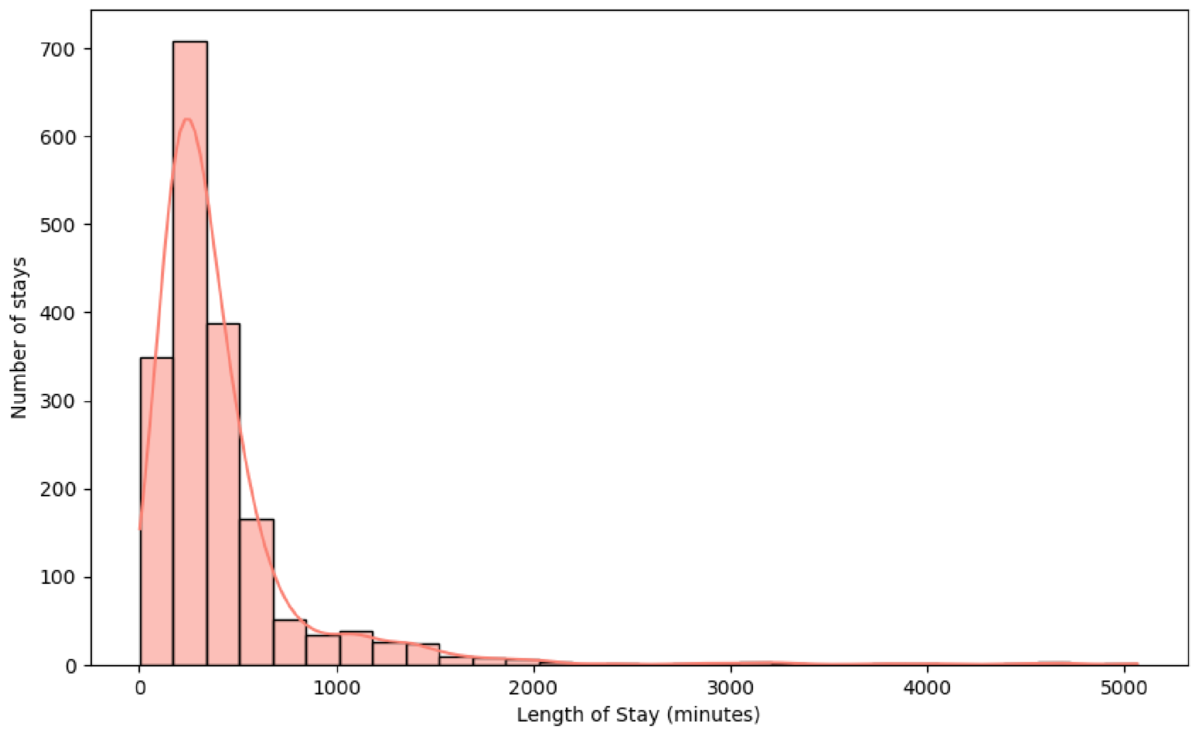

Figure 2: Distribution of Length of Stay (LOS) measure in Minutes (As-Is Model)

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3. Time to Treatment

The Time-to-Treatment (t2t), shows a performance profile that is highly efficient for the majority of the 1,771 patient encounters, yet struggles with a persistent subset of long waits.

The median t2t is only 3.0 minutes, indicating that half of all patients receive their initial treatment activity extremely quickly. However, the mean t2t is 37.2 minutes—a stark difference caused by the data's severe positive skew. The high standard deviation (69.4 minutes) further highlights this variability.

While 75% of patients receive treatment within 40.5 minutes, the longest recorded t2t is an extreme outlier lasting 583.0 minutes (nearly 9.7 hours). This suggests that while triage and initial assessments are fast for most, the system faces significant delays or bottlenecks in initiating treatment for a small, critical group of patients.

Statistic	**t2t (Minutes)**
Count	1,771
Minimum	0.0
Maximum	583.0
Mean	37.2
Median (50th %)	3.0
25th Percentile	1.0
75th Percentile	40.5

Table 3: Descriptive Statistics for Time-to-Treatment (t2t) measure in Minutes (As-Is Model)

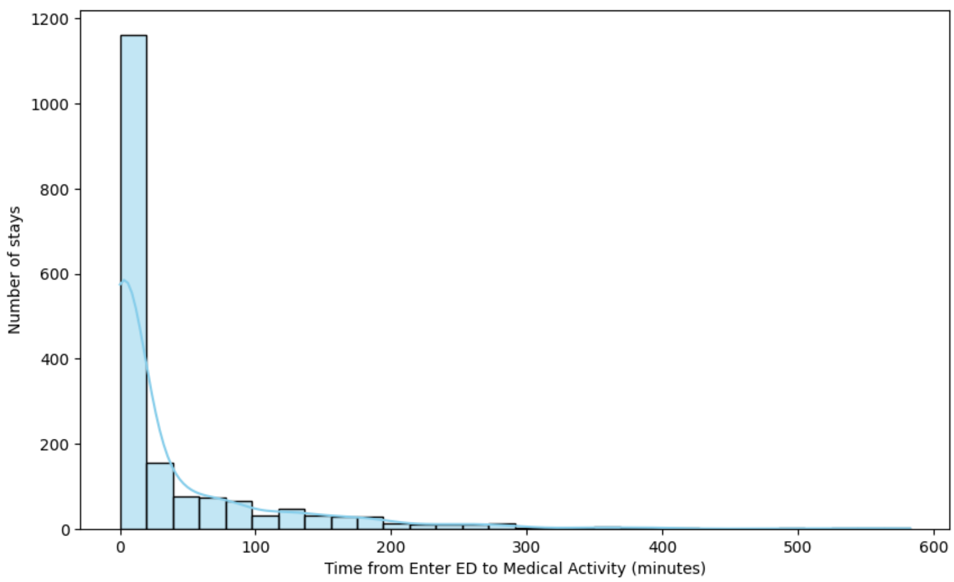

Figure 3: Distribution of Time-to-Treatment (t2t) measure in Minutes (As-Is Model)

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4. Triage Acuity Mix

The provided chart and table detail the distribution of patient acuity levels across the Emergency Department (ED) stays, classified using a standardized triage scale (Level 1 being the highest acuity/most urgent, and Level 5 the lowest/least urgent). The results show that the ED manages a moderately complex patient population, with the overwhelming majority of cases falling into the intermediate categories: Level 3 (Urgent) and Level 2 (Emergent). Level 3 (Urgent) is the largest single group, accounting for nearly 50% of all patient visits (approximately 49.72%). Level 2 (Emergent) follows closely as the second largest group, making up over 34.5% of visits. Combined, these two intermediate acuity levels represent over 84% of the ED's workload, indicating that the department is primarily managing urgent and emergent conditions rather than simple, non-urgent issues. The highest-acuity patients, Level 1 (Resuscitation), represent a small but critical 7.31%, while the lowest-acuity patients, Level 4 (Less Urgent) and Level 5 (Non-Urgent), account for only approximately 8.05% and approximately 0.40%, respectively. This distribution profile is crucial for resource allocation, as it suggests staffing and bed capacity must be optimized for the high volume of Level 2 and Level 3 patients.

Acuity Level	Acuity Mix (%)
1	7.312925
2	34.523810
3	49.716553
4	8.049887
5	0.396825

Table 4: riage Acuity Mix (%) in AS-IS model

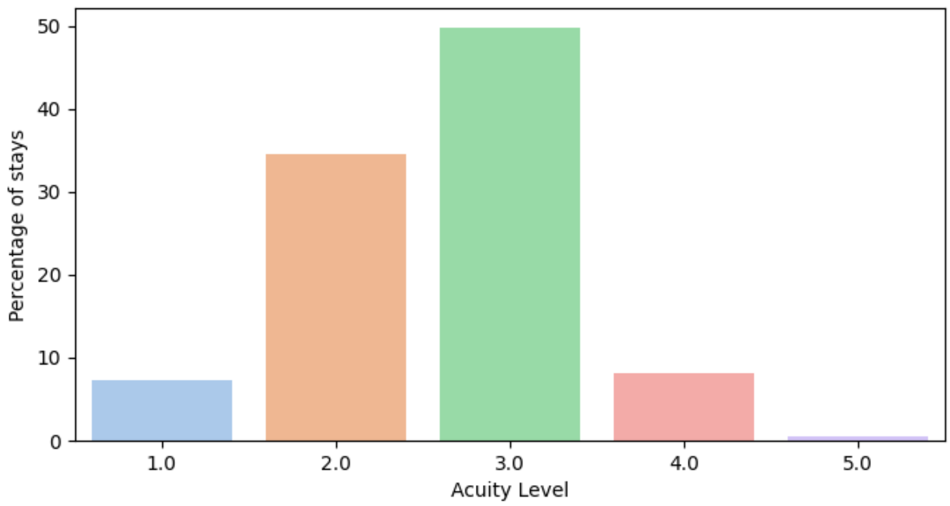

Figure 4: Triage Acuity Mix (%) in AS-IS model

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KPI	Rate (%)
Left Without Being Seen (LWBS) Rate	1.32
Left Against Medical Advice (AMA) Rate	0.33
Mortality Rate	0.16

Table 5: Key Emergency Department Rates in AS-IS model

5. Left Without Being Seen (LWBS) Rate

A high LWBS rate directly indicates poor patient flow and excessive wait times in the ED triage and waiting areas. A rate of 1.32% suggests a moderate, but manageable, issue with patient frustration and safety, as these patients might have genuine medical needs that go unaddressed.

6. Left Against Medical Advice (AMA) Rate

A rate of 0.33% is relatively low. This typically suggests issues with patient engagement, communication, or perceived quality of care (eg, long waits after initial assessment, or disagreement with the recommended treatment/admission).

7. Mortality Rate

A rate of 0.16% represents the overall safety performance of the ED in handling critical cases. This is a primary measure of the clinical effectiveness and quality of immediate care provided, particularly the success of resuscitation and rapid stabilization efforts.

8. Activity Duration Analysis

Analyzing the duration of different activities can provide helpful insights into the current state of the model. The following tables report the minimum, maximum, count, mean, median, and standard deviation of each activity across the entire event log. Although these statistics are not fully reliable—since activity durations are inferred from the timestamp of the subsequent activity—they still offer a useful high-level overview of the process.

Activity	Count	Mean	Median
Discharge from the ED	1832	0 days 00:00:00	0 days 00:00:00
Enter the ED	1820	0 days 00:00:00.8	0 days 00:00:01
Medicine Dispensations	5802	0 days 00:28:08.9	0 days 00:02:00
Medicine Reconciliation	6112	0 days 00:11:47.6	0 days 00:00:00
Triage in the ED	1820	0 days 01:00:22.2	0 days 00:24:29
Vital Sign Check	5909	0 days 01:07:20.7	0 days 00:39:00

Table 6: Count and Central Tendency by Activity

Activity	Min	Max
Discharge from the ED	0 days 00:00:00	0 days 00:00:00
Enter the ED	0 days 00:00:00	0 days 00:00:01
Medicine Dispensations	0 days 00:00:00	0 days 09:31:00
Medicine Reconciliation	0 days 00:00:00	0 days 07:45:00
Triage in the ED	0 days 00:00:59	0 days 09:42:59
Vital Sign Check	0 days 00:00:01	0 days 15:03:00

Table 7: Minimum and Maximum Duration by Activity

Activity	Standard Deviation
Discharge from the ED	0 days 00:00:00
Enter the ED	0 days 00:00:00.400110
Medicine Dispensations	0 days 00:54:31.186940
Medicine Reconciliation	0 days 00:37:18.323615
Triage in the ED	0 days 01:22:56.601688
Vital Sign Check	0 days 01:22:12.094236

Table 8: Standard Deviation of Duration by Activity

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Nurse Work Load

After removing duplicate records with identical time, activity, and stay_id—to prevent double counting patients who underwent multiple medication reconciliation events—the frequency of nurse ID appearances was analyzed.

- Nurse 1 : 1939 cases (approximately 91%)
- Nurse 2 : 162 cases (approximately 8%)
- Nurse 3 : 19 cases (<1%)

Unless nurse 1 is intentionally assigned 90% of all reconciliations (which is rare and risky), this is not balanced workload distribution.

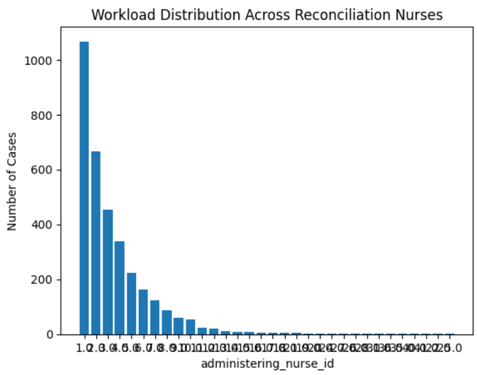

Figure 5: Administrative Nurse Workload Distribution

3.3.4 Root-Cause Analysis

Observed Inefficiency / Bottleneck	**AS-IS Evidence**	**Root Cause**
Incomplete/Inconsistent Information Flow	Frequent and repetitive `Medication Reconciliation` loops (seen in top paths with counts up to 113).	**Poor Interoperability:** Lack of seamless, integrated communication between the ED system and external data sources (e.g., pharmacy, clinic records). This forces manual re-verification of critical information.
High Variability and Delay in Treatment Initiation	Mean Time-to-Treatment (t2t) is 37.2 min, significantly higher than the median (3.0 min), with extreme outliers (Max: 583 min).	**Delayed Resource Allocation Post-Triage:** A structural failure to immediately move some patients out of triage due to bed scarcity or overwhelmed staff. This creates a holding pattern, severely skewing the t2t and LOS metrics for critical cases.
Crowding and Prolonged LOS	Average Length of Stay (LOS) is 408 minutes, with the top 25% exceeding 7.6 hours. Peak patient concentration occurs consistently between 15:00 and 22:00.	**Mismatched Resource-to-Demand Ratio:** Staffing levels are likely fixed or based on a smooth average, failing to meet the high surge demand identified during the afternoon/evening peak hours (refer to Occupancy Heatmap).
Structural Process Variance / Inconsistent Handoffs	High Standard Deviation in the duration of `Triage in the ED` (0 days 01:22:56.6).	**Unstandardized Handoff Protocol:** The transition from triage to the next stage of care is a bottleneck governed by individual staff capacity and manual coordination rather than a reliable, standardized, and streamlined protocol.
Over-Monitoring and Nurse Workload	`Vital Sign Check` is the single most frequent activity (Count 5909) and is heavily repeated in top process paths.	**Lack of Acuity-Based Monitoring Protocol:** Vital sign checks are likely performed at a fixed interval or at staff discretion, leading to **over-monitoring** of low-acuity (ESI Level 4/5) patients and unnecessary consumption of valuable nursing time.
Delayed Operational Execution	Repetitive `Medication Dispensation` loops.	**Lag Between Decision and Administration:** The delay in the execution of treatment orders (dispensation) is caused by bottlenecks in the pharmacy fulfillment process or high nursing workload preventing immediate drug administration.

3.4 Process Models

The activities performed in the Emergency Department (ED) are highly personalized for each patient case. The goal process sequence in Emergency Department is :

Enter the Ed → Triage in the Ed → Assessment/Consultation → Treatment→ discharge from the Ed.

Despite potential variation in the micro-process (the specific sequence and count of events), the macro-process follows a universal structure for most of the patients (1456):

enter the ed → triage in the ed → ... → discharge from the ed .

Key medical activities that occur in between—such as vital sign checks, medication reconciliation, and medication dispensation—can vary in their order and frequency depending on the patient's evolving situation.

- Medication reconciliation primarily ensures informational consistency.
- Medication dispensation represents the operational execution of treatment.

The observed repetition (loops) of these activities reflects the iterative nature of clinical decision-making and information refinement within the ED process. For instance, reconciliation may occur early, again after triage, and potentially before discharge. Dispensation may be repeated as symptoms evolve, vital signs change, or test results become available.

Medication Reconciliation Loops: Incomplete information upon arrival, Poor system interoperability, Handoffs between different roles (e.g., nurse → physician → pharmacist)

Medication Dispensation Loops: Iterative adjustments to the treatment plan , Symptom monitoring requirements , Delays between a clinical decision and medication administration.

The following diagram is a Petri Net model generated through process mining, illustrating the typical flow of a patient through an Emergency Department (ED). The process begins with the activity "enter the ed" (Transition), leading to a split. The patient's journey then follows one of two paths, which can occur concurrently:

1. Triage Path: The patient undergoes "triage in the ed," followed by a complex subprocess involving "medicine reconciliation" (a review of current and necessary medications). A loop is visible here, suggesting that the reconciliation might be repeated or checked before proceeding.

2. Vital Signs Path: The patient has a "vital sign check." Both paths eventually merge, indicating that the initial assessment phases must be completed. Following this, the patient may undergo "medicine dispensations" before proceeding to the final stage. The entire process concludes after the "discharge from the ed" activity, which leads to the final, double-ringed place, signifying the completion of the patient's visit. The structure clearly models both sequential and parallel operations, as well as decision points within the patient flow.

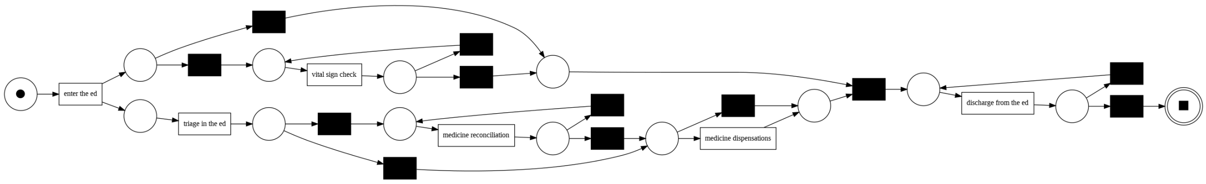

Figure 6: Petri Net model

This table summarizes the ten most frequently observed process paths (sequences of activities) in the Emergency Department (ED) event log, along with their corresponding frequency counts.

Sequence	**Count**
enter the ed → triage in the ed → vital sign check→ discharge from the ed	195
enter the ed→ triage in the ed→ vital sign check→ medicine dispensations→ vital sign check→ discharge from the ed	121
enter the ed→ triage in the ed→ vital sign check→ medicine reconciliation→ vital sign check→ discharge from the ed	113
enter the ed→ triage in the ed→ medicine reconciliation→ vital sign check→ discharge from the ed	80
enter the ed→ triage in the ed→ medicine dispensations→ vital sign check→ discharge from the ed	79
enter the ed→ triage in the ed→ medicine reconciliation→ medicine dispensations→ vital sign check→ discharge from the ed	62
enter the ed→ triage in the ed→ vital sign check→ medicine reconciliation→ medicine dispensations→ vital sign check→ discharge from the ed	51
enter the ed→ triage in the ed→ discharge from the ed	49
enter the ed→ triage in the ed→ vital sign check→ medicine reconciliation→ vital sign check→ medicine dispensations→ vital sign check→ discharge from the ed	47
enter the ed→ vital sign check→ triage in the ed→ vital sign check→ discharge from the ed	46

Table 9: Top ten repeating sequence of activities in ED event log

3.4.1 Conformance Checking

First step was to find any process that began or ended with false activity. There results showed that all the recorded cases began and ended with correct activities.

```
    #False Begining
    event_log = sorting.sort_timestamp(event_log, timestamp_key='time')
    bad_cases = []
    for trace in event_log:
        first_activity = trace[0]["concept:name"]   # event-level
        if first_activity != "enter the ed":
            bad_cases.append(trace.attributes["concept:name"])  # case-level

    #False Ending
    for trace in event_log:
    first_activity = trace[-1]["concept:name"]   # event-level
    if first_activity != "discharge from the ed":
        bad_cases.append(trace.attributes["concept:name"])  # case-level
```

Listing 4: Code Example Of Finding Incorrect Processes with pm4py

Conformance checking was performed to evaluate how closely patient care traces adhered to the defined normative process: Enter → Triage → Vital → Treatment → Discharge, where the treatment step included either Medicine Reconciliation or Medicine Dispensations. The alignment analysis yielded an overall fitness score of 0.56, indicating that, on average, only 56% of the activities in the patient traces followed the ideal process order. Analysis of deviations highlighted the most common discrepancies: missing or unexpected steps (represented as) occurred 16,867 times, Medicine Reconciliation appeared out of sequence 473 times, Vital Sign Checks were repeated or misplaced 340 times, and Triage in the ED was skipped or reordered 39 times. These results indicate substantial variation from the ideal workflow, particularly in early and mid-process activities, suggesting opportunities to improve adherence to the standard care path and reduce redundant or missing steps in patient management.

3.5 Variant Analysis

Process analysis yields deeper insights when variant analysis is applied. This method involves grouping similar cases into distinct variants to monitor the specific paths and activity sequences each follows. Within the provided event log, cases can be categorized based on various attributes, such as:

- Clinical Dispositions: Grouping by medical outcome or department.
- Operational Metrics: Segmenting by the shortest or longest Length of Stay (LOS),or any other measure.
- Clinical Condition: A specialized grouping method proposed in this scenario involves calculating a binary value for each case based on the presence or absence of abnormal vital signs.

By isolating these variants, we can identify bottlenecks and deviations that are unique to specific patient profiles rather than analyzing the log as a single, homogenous process.

1. Clinical Condition

Phase 1: Variant Binary Encoding The initial step in the analysis involved calculating a Variant Binary Number for every row in the dataset. This encoding allows for a standardized comparison of clinical states across cases where data density varies.

To ensure consistency in the calculation, the following logic was applied:

- Handling Null Values: As vital sign columns may contain empty cells due to irregular monitoring intervals, all empty cells are treated as 0, representing a "normal" or baseline condition.
- Temporal Changes: Since vital sign values fluctuate throughout a patient's stay, the binary status is updated per row to reflect the most current state recorded in the log.
- Bit Assignment: Each bit within the binary number corresponds to a specific physiological indicator, as defined in the table below:

Bit Position	Bit Value	Clinical Condition
1	1	Temperature > 100
	0	Temperature ≤ 100
2	1	Heart rate > 100
	0	Heart rate ≤ 100
3	1	Respiratory rate ≥ 20
	0	Respiratory rate < 20
4	1	Oxygen saturation < 90
	0	Oxygen saturation ≥ 90
5	1	Systolic blood pressure > 120
	0	Systolic blood pressure ≤ 120
6	1	Diastolic blood pressure > 80
	0	Diastolic blood pressure ≤ 80
7	1	Pain score $\neq 0$
	0	Pain score $= 0$
8	1	Cardiac rhythm $\neq$ sinus rhythm
	0	Cardiac rhythm $=$ sinus rhythm
9	1	Acuity level ≥ 3
	0	Acuity level < 3

Table 10: Definition of bits in the pattern-based feature generation

```
variant_bits = pd.DataFrame({
"b1_temp": (df["temperature"] > 100).fillna(False).astype(int),
"b2_hr": (df["heartrate"] > 100).fillna(False).astype(int),
"b3_resp": (df["resprate"] >= 20).fillna(False).astype(int),
"b4_o2": (df["o2sat"] < 90).fillna(False).astype(int),
"b5_sbp": (df["sbp"] > 120).fillna(False).astype(int),
"b6_dbp": (df["dbp"] > 80).fillna(False).astype(int),
"b7_pain": (df["pain"].fillna("0") != "0").astype(int),
"b8_rhythm": (df["rhythm"].fillna("sinus rythm") != "sinus rythm").astype(int),
"b9_acuity": (df["acuity"] >= 3).fillna(False).astype(int),})
df["variant_binary"] = variant_bits.astype(str).agg("".join, axis=1)
powers = 2 ** np.arange(len(variant_bits.columns) - 1, -1, -1)
df["variant_int"] = (variant_bits * powers).sum(axis=1)
```

The resulting `variant_int` may change multiple times for a patient. In this study, the first non-zero `variant_int` is considered as the health condition of patient on arrival. There are 90 variants of patients health condition on arrival. Following table represents top five variants of arriving at Emergency department health condition.

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For each stay, performance KPIs, including Length of Stay (LOS) in hours and time-to-treatment (t2t) was extracted.The IDs were grouped by their first non-zero variant and calculated the mean KPI values, the number of cases per variant, and the deviation of each variant's mean from the overall average.

The results reveal substantial variation across variants. For example, patients with variant 110000001 had a mean LOS of 33.28 hours, which is 26.39 hours above the overall average, indicating that this variant is associated with particularly long hospital stays. Other high-impact variants include `000111000` (mean LOS 16.82 hours) and `011011000`

Variant_binary	mean_LOS	mean_t2t	count	LOS_dev	t2t_dev
000010101	6.229505	-1.666840e+17	166	-0.660888	2.910541e+16
000011101	5.512525	-3.764610e+17	147	-1.377868	-1.806716e+17
000010000	9.223497	-2.034551e+17	136	2.333105	-7.665708e+15
000010100	6.849312	1.193000e+12	120	-0.041080	1.957906e+17
000011100	8.051005	-7.686079e+16	120	1.160612	1.189286e+17

Table 11: Top Five Repeated Combination Of Abnormal Health Conditions On Arrival

(mean LOS 15.59 hours). Variants with larger patient counts, such as `000010000` (136 cases), had a mean LOS of 9.22 hours, slightly above the overall mean. These findings highlight that specific patterns of abnormal clinical indicators correlate with longer LOS, supporting targeted interventions for high-acuity patients and prioritization of workflow standardization to reduce delays in care.

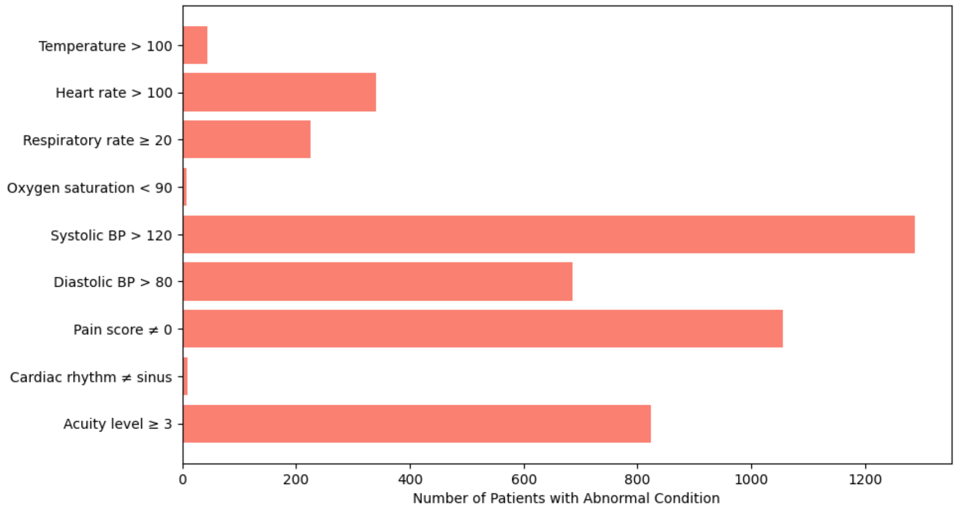

Figure 7: Number Of Patients With Specific Abnormal Condition On Arrival

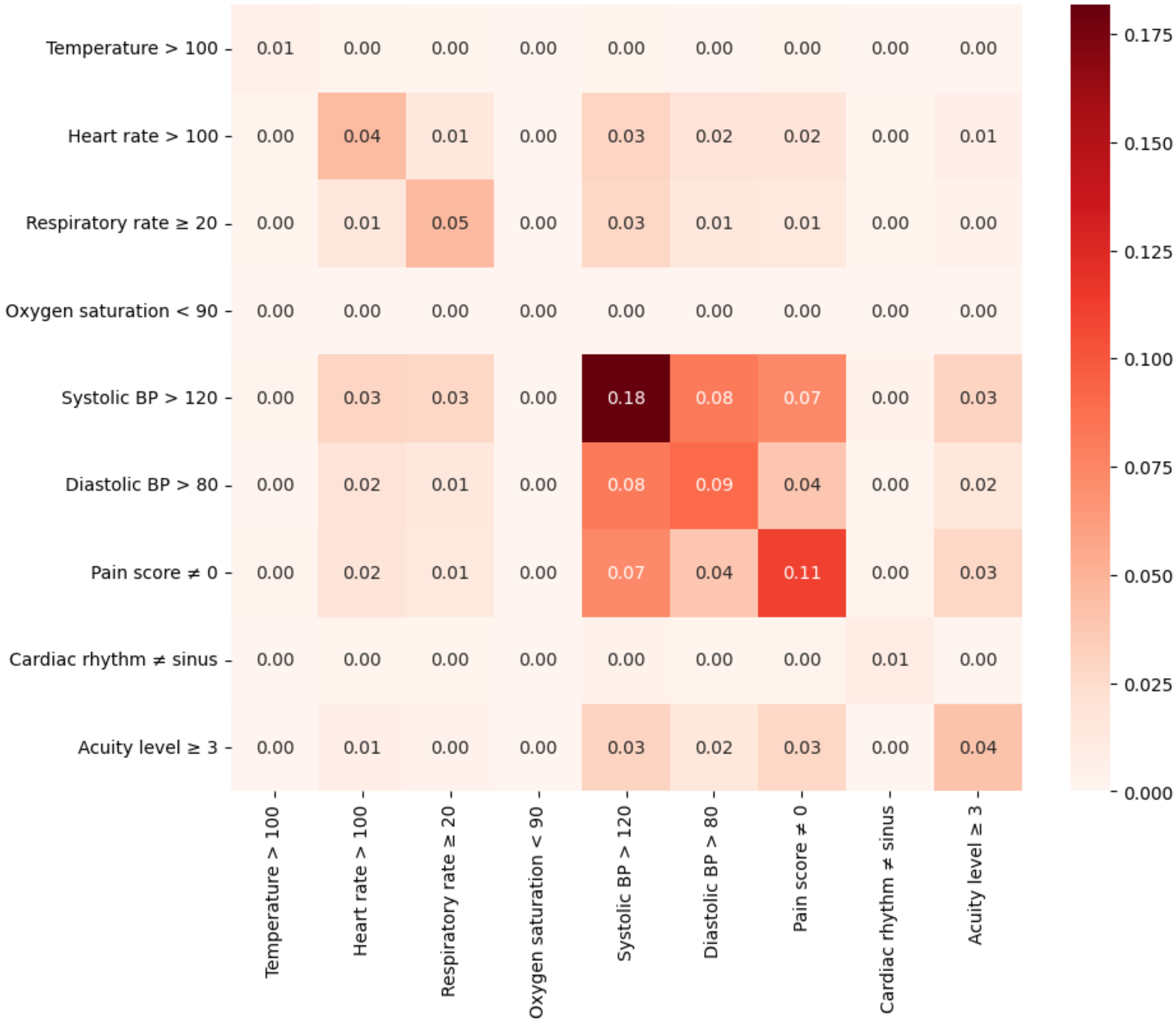

Figure 8: Co-occurrence of Abnormal Health Conditions On Arrival

3.6 Potential Improvements

TO-BE improvement hypotheses

Inefficiency Identified	AS-IS Evidence	TO-BE Improvement Hypothesis
Outlier Delays in Time-to-Treatment (T2T)	Median t2t is 3.0 minutes, but the mean is 37.2 minutes, with an extreme maximum of 583.0 minutes.	**Hypothesis 1: Standardize Initial Treatment Protocol.** Implement a high-acuity, nurse-initiated 'Order Set' that automatically triggers initial treatment activities (e.g., IV access, labs, key medications) immediately following triage for ESI Level 1 and 2 patients, significantly reducing outlier delays.
Repetitive Medication Reconciliation Loops	Loops signal incomplete information, poor interoperability, or handoffs between roles.	**Hypothesis 2: Implement Pre-Arrival Reconciliation & System Interoperability.** Integrate a patient portal or external records to complete or pre-populate the medication list *before* the patient reaches the ED physician, reducing reconciliation loops and the associated time cost.
High Occupancy & Crowding	Highest patient concentration observed in the afternoon/early evening hours (15:00 to 22:00) on weekdays and Saturdays.	**Hypothesis 3: Dynamic Staffing Model.** Adjust staffing levels for nurses and physicians to match the peak demand hours (15:00-22:00) identified by the Occupancy Heatmap, improving throughput and reducing waiting times during crowding periods.
Inefficient Handoffs (Triage to Treatment)	The standard deviation for `Triage in the ED` duration is high (0 days 01:22:56.6). The majority of patients (84%) are Level 2 and Level 3.	**Hypothesis 4: Co-located Triage and Initial Assessment.** Use a fast-track system or dedicated area for the high volume of Level 2 and Level 3 patients to immediately transition from Triage to an initial assessment/treatment area, bypassing the main waiting room and reducing the variability of the time spent between activities.
Frequent Vital Sign Checks	`Vital Sign Check` is the most frequent activity (Count 5909) and appears repeatedly in the top process paths.	**Hypothesis 5: Link Monitoring to Acuity.** Optimize the monitoring frequency (Vital Sign Checks) by explicitly linking the rate of repetition to the patient's ESI Acuity Level, ensuring high-acuity patients are monitored more frequently while reducing unnecessary checks for low-acuity cases to free up nursing staff.

Step	Input (Data Source)	Transformation / Analysis	Output (Resulting Artifact)	Knowledge Type
1.Data Collection	Raw event log dataset (25,115 rows, 27 columns).	Data type conversion, missing value removal, column sorting by `stay_id` and `time`.	Structured Event Log (Anchored to Case ID, Activity, and Timestamp).	World Knowledge
2.Data Preprocessing	Structured Event Log.	Vital Signs Normalization: Unit reconciliation, physiological range validation, and non-informative value replacement.	Clean and Standardized Event Log (The definitive source for analysis).	Conceptual Knowledge
3.Performance Evaluation	Cleaned Event Log.	Calculate Key Performance Indicators (KPIs): Length of Stay (LOS), Time-to-Treatment (t2t), LWBS Rate, and Mortality Rate.	Performance Metrics.	Strategic Knowledge
4.Structural Inefficiency Detection	Performance Metrics and Event Log.	Activity Duration Calculation. Process Modeling	Identifying repetitive activities and Inefficiency Report.	Epistemic Knowledge
5.Improvement Proposal	Inefficiency Report & Organizational Goals.	Formulate specific, actionable TO-BE Improvement Hypotheses.	TO-BE Improvement Hypotheses.	Conceptual Knowledge → Human Artifact
6.Knowledge Uplift	TO-BE Hypotheses.	Propose system or procedural changes to minimize waste and variability, aligning the process with organizational goals.	Target Process Model (TO-BE Model) to achieve organizational goals (Minimize Wait Times, Improve ED Operations).	Organizational Wisdom

Table 12: Final Knowledge Uplift Trail Steps

4 Future Work

This section outlines potential extensions of the present study that could not be completed due to limitations in time and data availability.

First, future work will focus on defining and computing additional Key Performance Indicators (KPIs) categorized under Other Indicators in the Performance Analysis section. Incorporating these KPIs would enable a more comprehensive evaluation of system performance and operational effectiveness (e.g. calculating lead time).

Second, Natural Language Processing (NLP) techniques can be applied to the descriptive text columns through appropriate preprocessing steps. This would allow the identification of cases with similar underlying issues, as well as the detection of urgent or high-priority cases, ultimately supporting faster and more informed decision-making.

To uncover deeper operational insights, additional forms of variant analysis can be implemented by grouping similar cases into cohorts.

- Temporal Variants: Grouping cases based on the *extremes* of Length of Stay (LOS) and Time-to-Treatment. By isolating the longest and shortest paths, we can identify the specific bottlenecks or efficiencies that characterize each group.
- Dispositional Variants: Segmenting cases with similar clinical dispositions or discharge statuses. This is particularly valuable for analyzing non-standard exits, such as patients who Left Without Being Seen (LWBS) or were discharged Against Medical Advice (AMA).

Given the availability of more granular data, the study could be extended to a Value Model using the e3value framework. This methodology moves beyond activity sequences to analyze the Emergency Department (ED) as a network of value exchanges. The analysis would focus on two primary dimensions: Cost Dimension and Service Quality Dimension.

Building on the current pattern-based feature generation, future research should focus on developing real-time predictive models to forecast patient outcomes at the point of triage. By integrating machine learning with the existing physiological variant analysis, the ED could implement an early-warning system that flags patients likely to experience extended Length of Stay (LOS) or clinical deterioration based on their initial "9-bit health pattern." Furthermore, leveraging the unstructured text in the chiefcomplaint column through Natural Language Processing (NLP) could provide deeper insights into patient needs, allowing for the automated categorization of cases that traditional diagnosis codes might miss during the initial assessment.

Another critical avenue for future work involves a deep dive into resource-centric process mining and social network analysis. While this report identified structural loops in medication reconciliation, future studies should utilize the administering_nurse_id and reconciliation_nurse_id to map the social network of the ED. This would allow for the identification of "bottleneck roles" or specific handoff patterns that contribute to delays. Analyzing the interaction between different staffing levels and patient volume peaks could lead to a dynamic staffing model that adjusts resources in real-time based on the incoming "acuity mix," effectively mitigating the afternoon crowding identified in the root-cause analysis.

Finally, future iterations of this study should prioritize a comprehensive health equity analysis by cross-referencing clinical KPIs with the race and gender attributes. Investigating whether specific demographic groups experience statistically significant differences in Time-to-Treatment (t2t) or access to medication reconciliation would align the ED's operational improvements with broader organizational goals of clinical justice and equitable care. Coupled with Discrete Event Simulation (DES), these findings could be used to test the "TO-BE" model in a virtual environment, quantifying the impact of proposed changes—such as nurse-initiated order sets—on different patient populations before full-scale clinical implementation.

Column Name	Category	Data Type	Description
gender	Demographics	Categorical	The patient's recorded gender (e.g., M, F, Other).
race	Demographics	Categorical	The patient's recorded race or ethnicity.
arrival_transport	Admission	Categorical	The method by which the patient arrived (e.g., Ambulance, Private, Transfer).
disposition	Outcome	Categorical	The final outcome or disposition of the patient from this visit.
diagnosis_sequence	Clinical Code	Integer	The order of the diagnosis in the primary diagnosis list.
diagnosis_code	Clinical Code	String/Categorical	The standardized clinical diagnosis code (e.g., ICD-9 or ICD-10).
diagnosis_description	Clinical Text	Text	The human-readable description of the diagnosis.
temperature	Vitals	Float/Numeric	Body temperature measurement.
heartrate	Vitals	Integer/Numeric	Heart rate measurement (beats per minute).
resprate	Vitals	Integer/Numeric	Respiratory rate measurement (breaths per minute).
o2sat	Vitals	Integer/Numeric	Oxygen saturation percentage (SpO_2).
sbp	Vitals	Integer/Numeric	Systolic blood pressure (mmHg).
dbp	Vitals	Integer/Numeric	Diastolic blood pressure (mmHg).
pain	Vitals	Integer/Numeric	Pain score on a 0–10 scale.
acuity	Triage	Integer/Categorical	A measure of illness severity or urgency (e.g., ESI score 1–5).
chiefcomplaint	Triage	Text	The patient's reported reason for seeking care (unstructured text).
rhythm	Vitals	Categorical	The heart rhythm observed (e.g., Sinus, A-fib, Tachycardia).
drug_name	Medication	Text	The brand or full name of the administered drug.
generic_drug_code	Medication	String/Categorical	A standardized code for the generic drug.
national_drug_code	Medication	String/Categorical	The official 10- or 11-digit NDC identifying the drug.
reconciliation_nurse_id	Provider	String/Categorical	De-identified ID of the nurse who performed medication reconciliation.
drug_class_code	Medication	String/Categorical	A code for the drug's therapeutic class.
drug_class_classification	Medication	Text	The name of the drug's therapeutic class.
administering_nurse_id	Provider	String/Categorical	De-identified ID of the nurse who administered the drug.

Table 13: Appendix A: Full Data Dictionary