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## What is LOS?



## Key Implications of Inaccurate LOS

### 1 Clinical

Impaired clinical capabilities  
Resources inefficiency

### 2 Financial

Stagnancy of patient throughput  
Slower revenue & wasted opportunities

### 3 Operational

Inefficient patient intake  
Delayed Procedures  
Lesser available wards

### 4 Experiential

Compromise patient experiences  
Increase in the risk of infections

### 5 Health

Insufficient LOS  
Unnecessarily long LOS



## African Healthcare System

- One of the worst healthcare systems in the world
- Lowest government funding in the world for health
- Far behind in technology

1

2

## Resulted in

- Inadequate Human Resource
- Poor Resource Allocation
- Poor Healthcare Infrastructure

## Raw Information

- Raw and disorganized Information
- No in-built system to guide doctors

3

4

## Root Cause

- Wide range of data that doctors are unable to process
- Uninformed and Inaccurate Prescription of LOS



# Problem Statement

## Root Cause

### 1 Wide range of information for doctors to process

- Doctors neglect the efficient management of hospital resources when assessing a patient's needs

## Problem Identification

Inaccurate prescription of patient  
**Length of Stay (LOS)**

**Over prescription**

**Under prescription**



## Better Resource Allocation

Reduce wastage of resources

Better manpower allocation

## Enhanced Inpatient Experience

Better Quality of Service

Greater Patient Flow & Reduce Waiting Time

Minimised Risk of Spread



## How Might We?

### Target 1

**Develop a system to assist doctors in prescribing LOS consistently & accurately?**

### Target 2

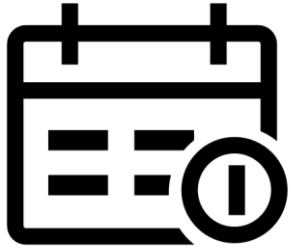
**Determine the most significant actionable areas for Hospital Management to directly reduce unnecessary LOS?**





# Approach 1: Consistent & Accurate LOS Prediction

Prescribe LOS consistently & accurately



Who is the target audience?

**Doctors** who prescribe inpatient stay to patients

What is the solution ?

- 1 Accurate Machine Learning-Generated Predictions of LOS to guide doctors' decisions
- 2 Interactive Hospital Management Dashboard for comprehensive overview of data

What is the impact ?

- 1 Minimize under / over-prescription of LOS
- 2 Efficient macro-managing of inpatient stay



# Approach 1: Consistent & Accurate LOS Prediction

## Predictive Modelling Approach

Data Preparation

Machine Learning

Evaluation

Hospital  
Inpatient Data

Multi-Adaptive  
Regression Splines

Classification and  
Regression Tree (CART)

Random Forest

Selected Best Model



# Approach 1: Consistent & Accurate LOS Prediction

## Comparison of Predictive Models

Model	Normalised RMSE
MARS Degree 1 (Original Dataset)	7.484%
MARS Degree 2 (Original Dataset)	6.877%
MARS Degree 1 (Log Dataset)	12.918%
MARS Degree 2 (Log Dataset)	11.657%

Model	Normalised RMSE
CART Optimal Max Depth 7 (Original Dataset)	6.776%
CART Optimal Max Depth 9 (Log Dataset)	12.243%

Model	Normalised RMSE
Random Forest Optimized Model (Original Dataset)	6.757%
Random Forest Optimized Model (Log Dataset)	11.377%

Model	Normalised RMSE
MARS, Degree 2 with Original Dataset	6.877%
CART, Max Depth of 7 with Original Dataset	6.776%
Random Forest with Original Dataset	6.757%



# Approach 1: Consistent & Accurate LOS Prediction

## Evaluation of Model

### Prediction Accuracy

#### 1 RMSE

Model	Normalised RMSE
MARS, Degree 2 with Original Dataset	6.877%
CART, Max Depth of 7 with Original Dataset	6.776%
Random Forest with Original Dataset	6.757%

- All models perform better than accuracy benchmark of 9.524%

#### 2 Overprediction / Underprediction

Model	Overprediction (%)	Underprediction %
MARS, Degree 2 with Original Dataset	55.536%	44.464%
CART, Max Depth of 7 with Original Dataset	59.112%	40.887%
Random Forest with Original Dataset	64.375%	35.615%

- Underprediction holds a greater implication than overprediction

### Explainability



- Ease of understanding of the model

### Ease of Implementation

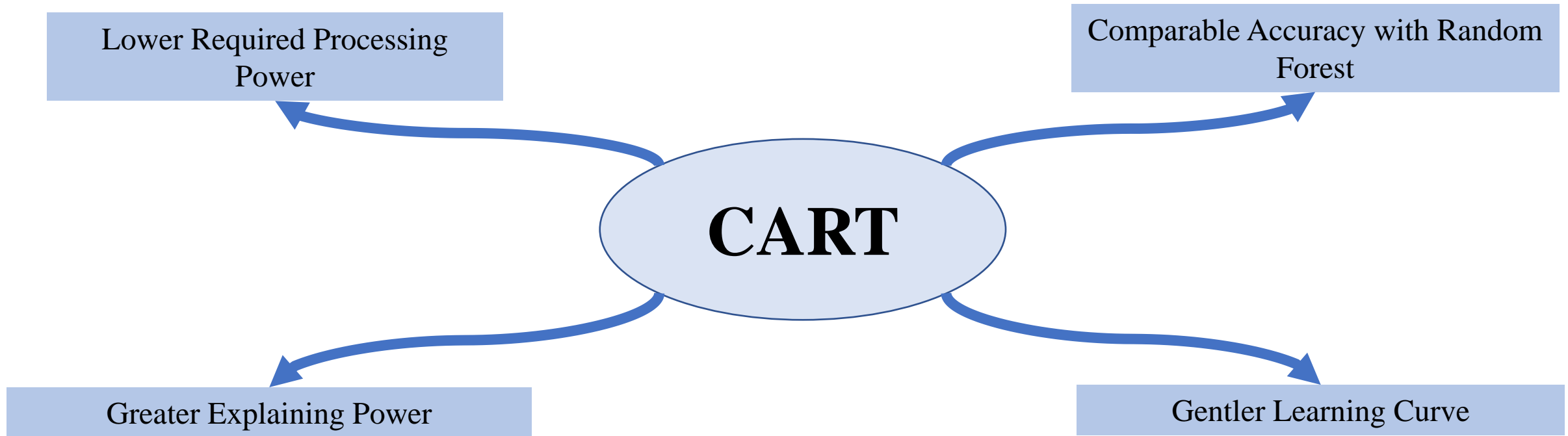
Model	Prediction Time
MARS, Degree 2	0.03992 s
CART, Max Depth of 7	0.04991 s
Random Forest	35.686 s

- Have a minimal impact in a clinical situation



# Approach 1: Consistent & Accurate LOS Prediction

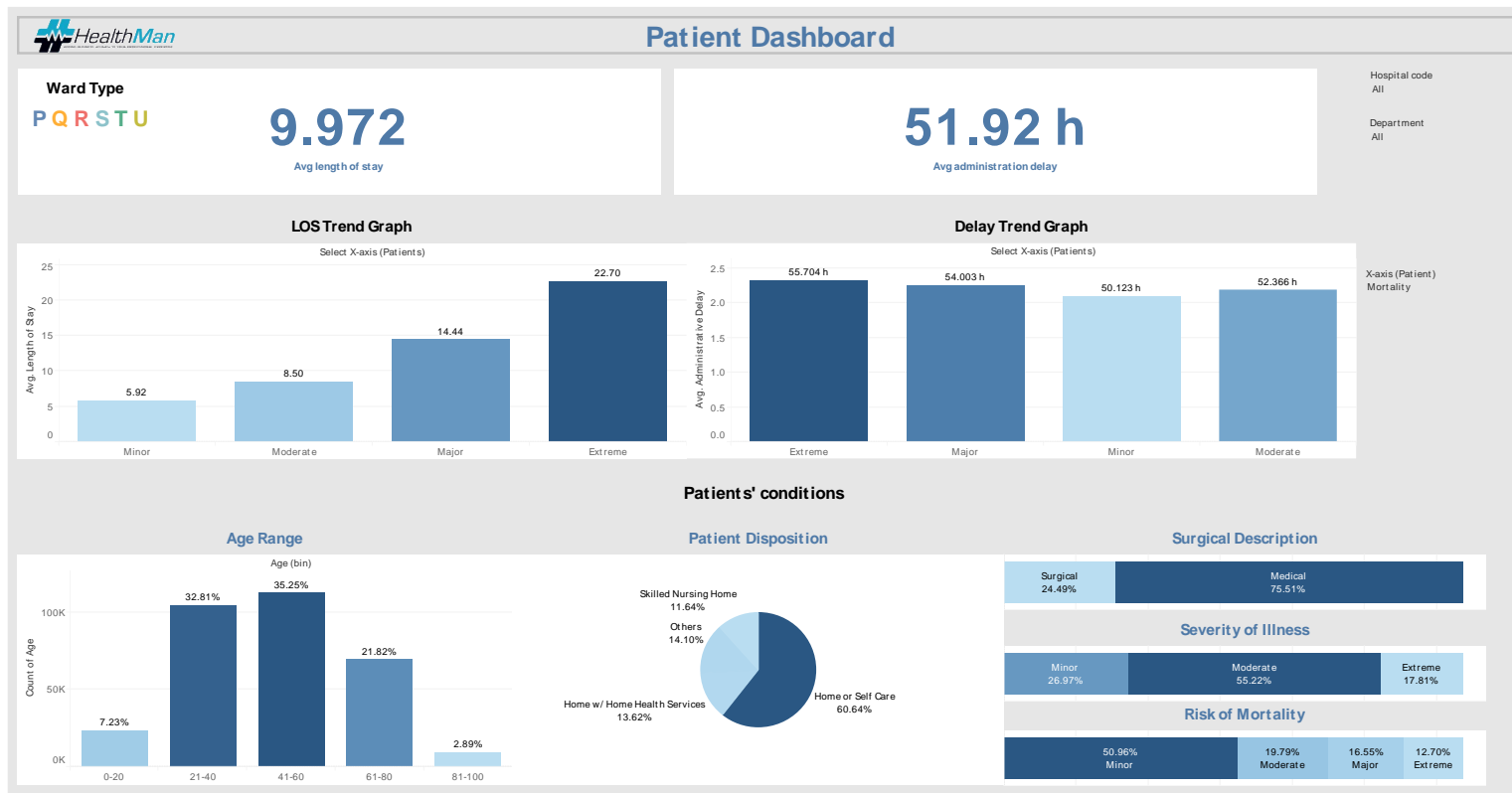
## Model of Choice



# Approach 1: Consistent & Accurate LOS Prediction

## Interactive Dashboards for Doctors

### Dashboard



### Use Cases

Support doctor's decision making beyond numerical predictions by CART

Non-Technical Overview of Patient Status

- Length of Inpatient Stay
- Surgical Procedures
- Severity of Illness
- Discharge or Transfer Plans

Reference when making Ward Rounds



# Approach 2: Targeting unnecessary LOS

Identify priority areas to reduce unnecessary LOS



Who is the target audience?



Hospital  
management

What is the solution ?

What is the impact ?

- 1 To prepare an accurate CART model with significant actionable variables
- 2 Use of Dashboard to enhance explainability
  - Identify potential bottle necks



- 1 Helps identify specific target areas to rectify
- 2 Ensures efficient resource allocation & faster decision making



# Identify priority areas to reduce unnecessary LOS

## Variable Importance

Directs hospitals to channel resources towards significant actionable areas to reduce unnecessary LOS

### Medical + Administrative Variables

	Feature Importance
Administrative_Delay	0.668621
Severity_of_Illness	0.119980
APR_Medical_Surgical_Description_Surgical	0.104354
APR_Risk_of_Mortality	0.041229
APR_Medical_Surgical_Description_Medical	0.016504
Patient_Disposition_Home or Self Care	0.010561
Patient_Disposition_Skilled Nursing Home	0.008066
Payment_Typology_1_Medicare	0.007202
Patient_Disposition_Home w/ Home Health Services	0.006695
Payment_Typology_1_Medicaid	0.006291

Most significant variable in predicting the LOS

Top 3 problems: Paper-based, Analogue data & Information collection methods

Serve as a pivotal cause of Administrative Delay





# Identify priority areas to reduce unnecessary LOS

## Variable Importance

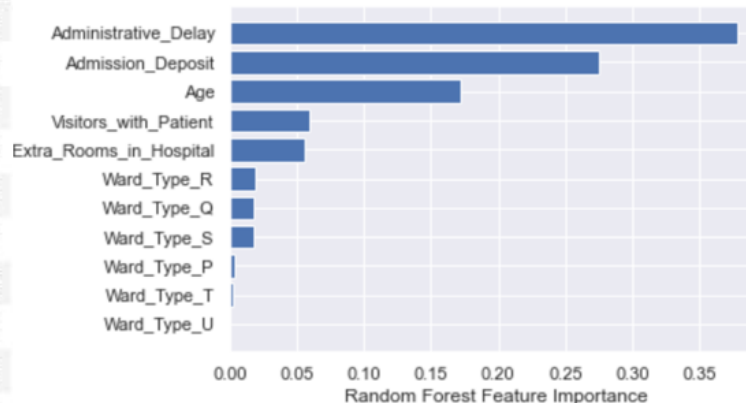
### Actionable Variables

### RMSE

Model with all predictors	6.776%
Model with the subset of predictors	7.408%

### Feature Importance

Administrative_Delay	0.974970
Admission_Deposit	0.012506
Age	0.007073
Visitors_with_Patient	0.003200
Ward_Type_Q	0.001252
Ward_Type_S	0.000511
Ward_Type_T	0.000282
Ward_Type_R	0.000131
Available_Extra_Rooms_in_Hospital	0.000076
Ward_Type_P	0.000000
Ward_Type_U	0.000000



## Feature Importance across CART and Random Forest are consistent

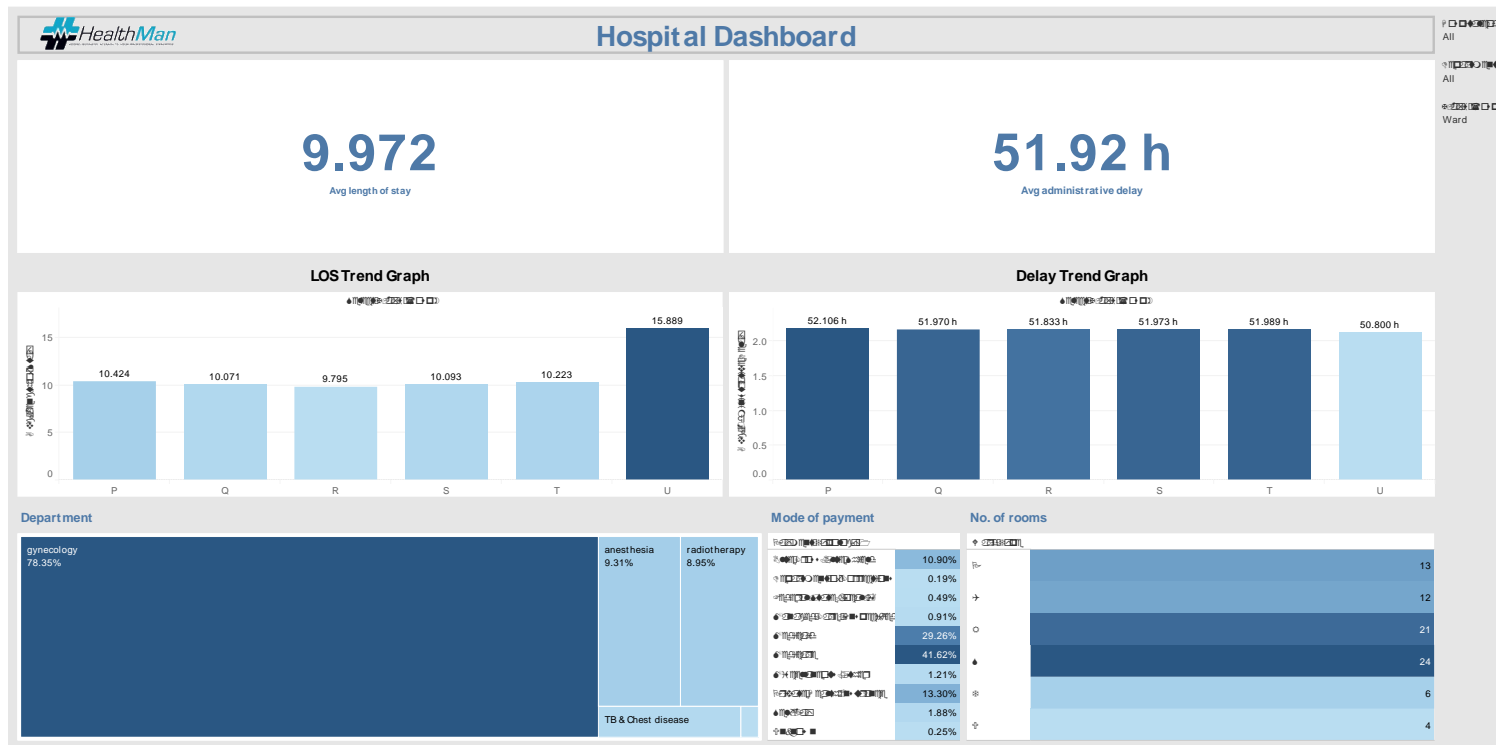
- **Administrative Delay** is still the most significant variable
- Other variables also play a role in influencing LOS



# Identify priority areas to reduce unnecessary LOS

## Interactive Dashboard for Hospital Management

### Dashboard



### Use Cases

#### Non-Technical Overview of Facilities

- Mode of Payment
- Availability of Extra Rooms
- Department

Relevant Information for potential bottlenecks and target areas (Administrative delay)

#### Objective:

User-Friendly Interface for Consolidated Facilities Information





**+ a b | e a u**

## Live Demonstration



**Hospital Dashboard**



**Patient Dashboard**



...interesting findings from dashboard that hospital could act on.

## Possible recommendation from Dashboard Findings

### Spread of Patients within Wards

#### Observation

Patients are not split according to the severity



Disorganized management process

Better segmentation of their patients to prevent prolonged length of stay

### Inefficiencies in Transfer Processes

#### Observation

High delays in discharging of patients



Increase unnecessary stay in hospital

Implementation of a shared discharge plan to enhance communication among caregivers



# Areas for Improvement

Limitations	Elaboration
Limited data on higher LOS	<ul style="list-style-type: none"> <li>• Data imbalance</li> <li>• Collect more data with patients of higher stay</li> <li>• Creating separate models for different severity types</li> </ul>
Limited Qualitative Predictors	<ul style="list-style-type: none"> <li>• Some predictors were left out in our machine learning approach</li> <li>• A time series forecast for patient inflow would value add to a hospital management's decision making</li> </ul>
Limited Information	<ul style="list-style-type: none"> <li>• Limited information for some factors</li> <li>• Unable to analyze factors in greater detail</li> </ul>
Manpower	<ul style="list-style-type: none"> <li>• Our solution facilitates the planning and allocation of resources by hospital management</li> <li>• Limited by the amount of resources hospitals can work with</li> </ul>



# Conclusion

In all..

## Problem Statement



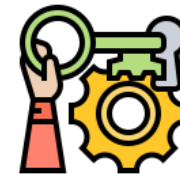
**Inaccurate Prescription of LOS is detrimental to patients and hospitals**

## Analytics Solution



- 1 **ML Model (CART) for consistent and accurate LOS prediction**
- 2 **Interactive Dashboard for monitoring of significant actionable areas**

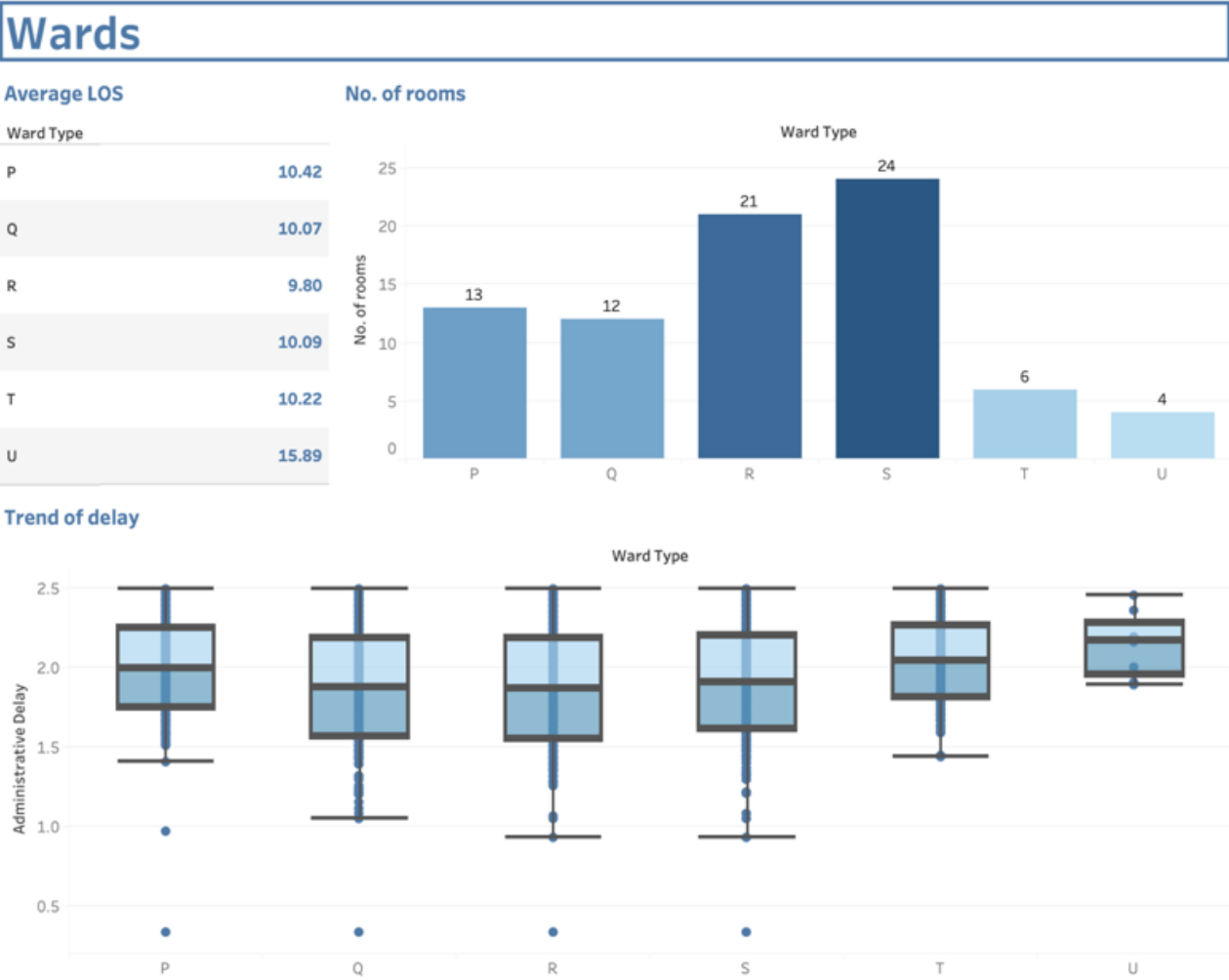
## Recommendations



- 1 **Improve segmentation of patients to prevent prolonged length of stay**
- 2 **Shared Discharge Plan**



**Thank you**



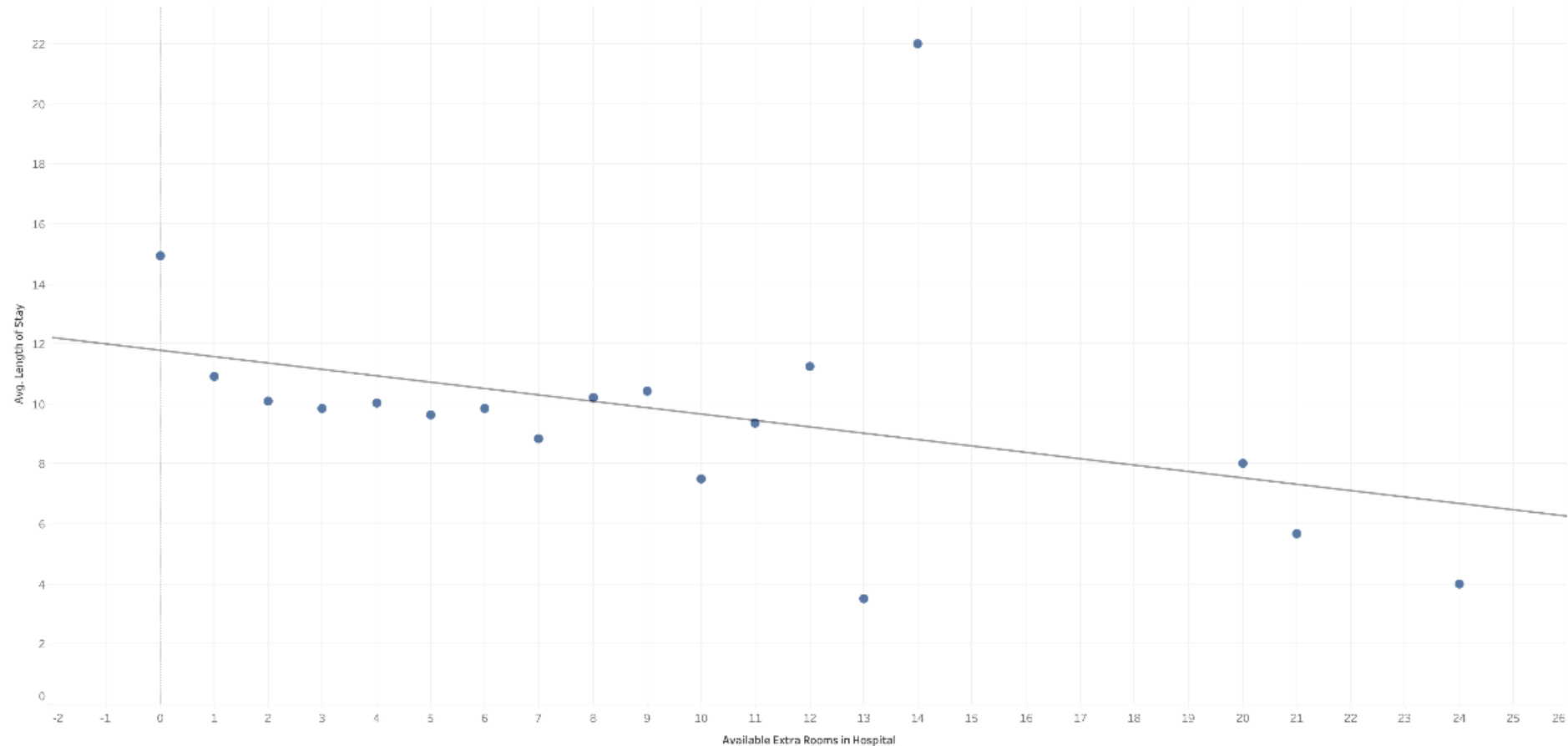
*The lower the number of available rooms per ward,  
the higher the average administrative delay.*





# Appendix

LOS against No. of rooms available

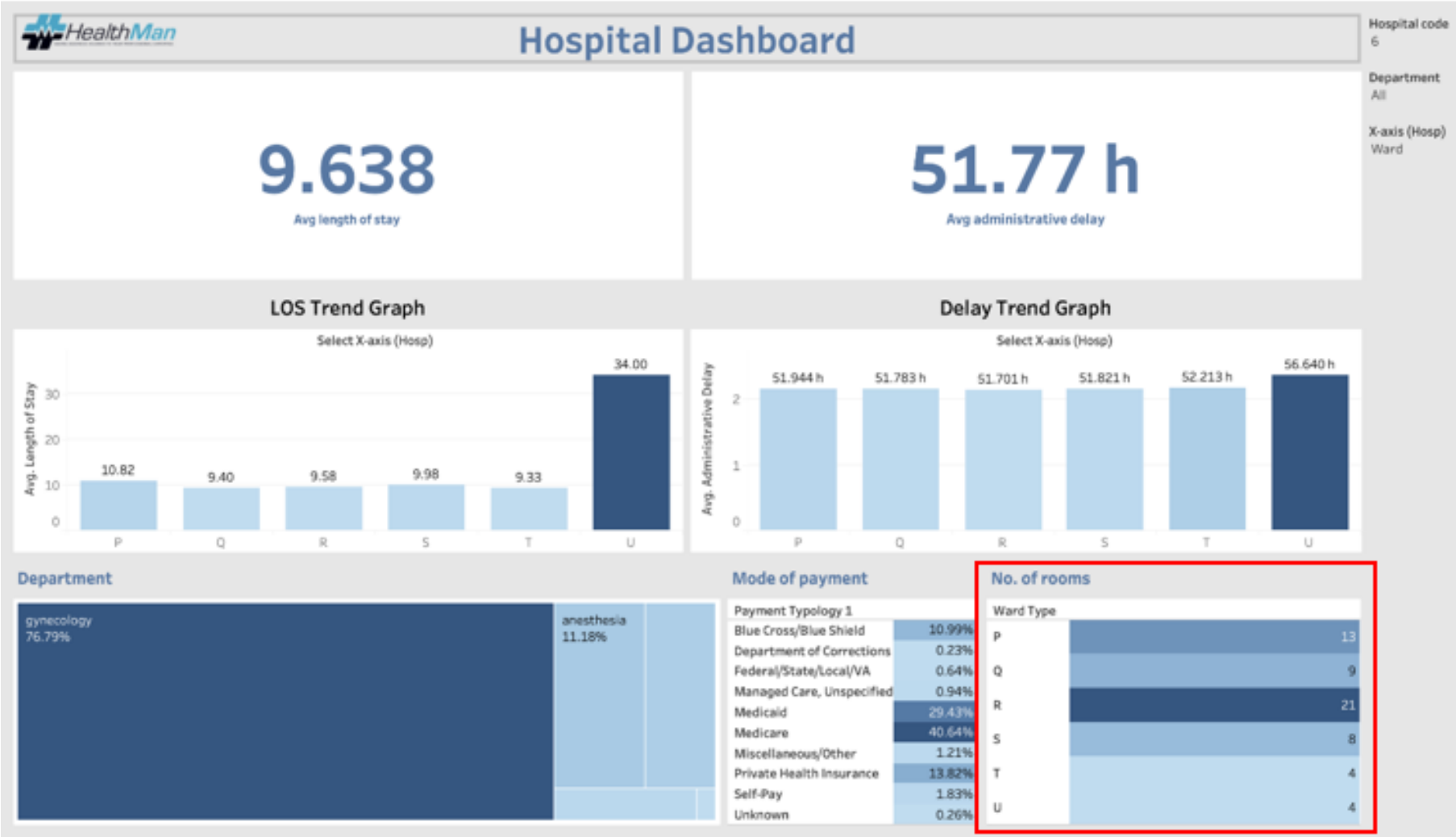


The plot of average of Length of Stay for Available Extra Rooms in Hospital.

***The greater the number of available rooms per ward,  
the lower the average length of stay***



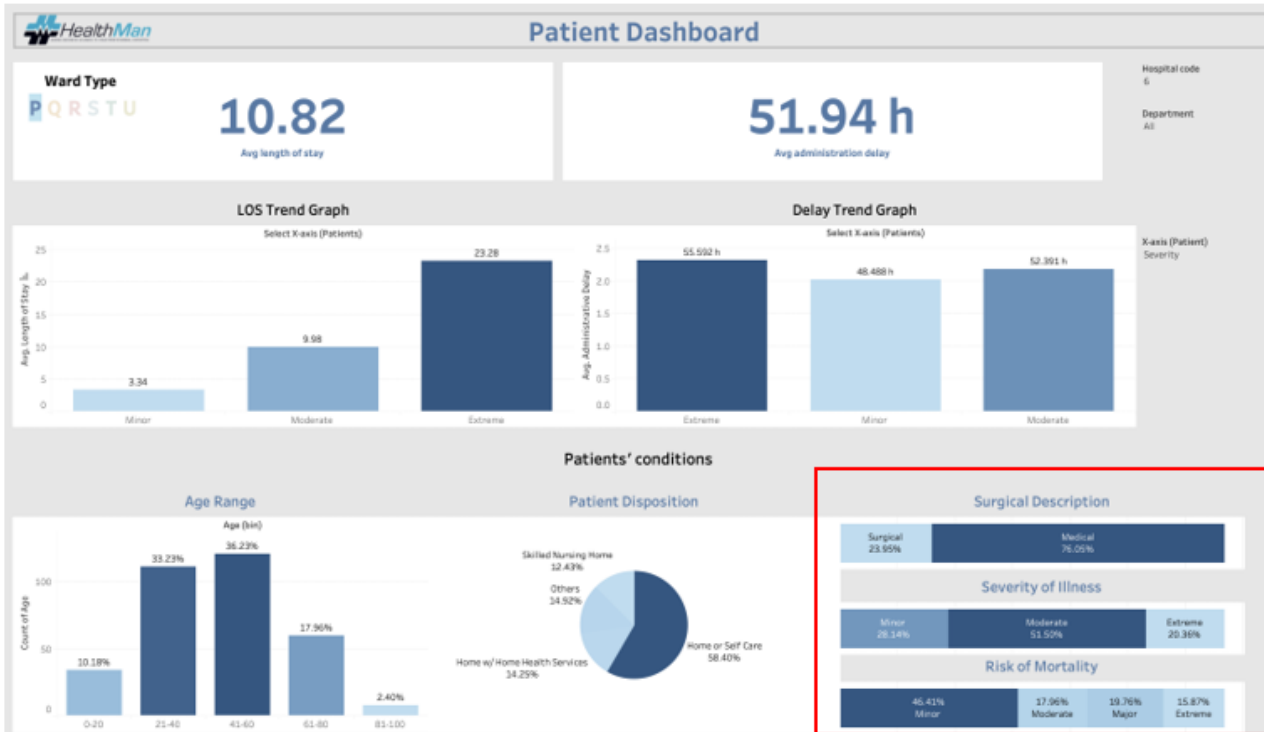
# Appendix



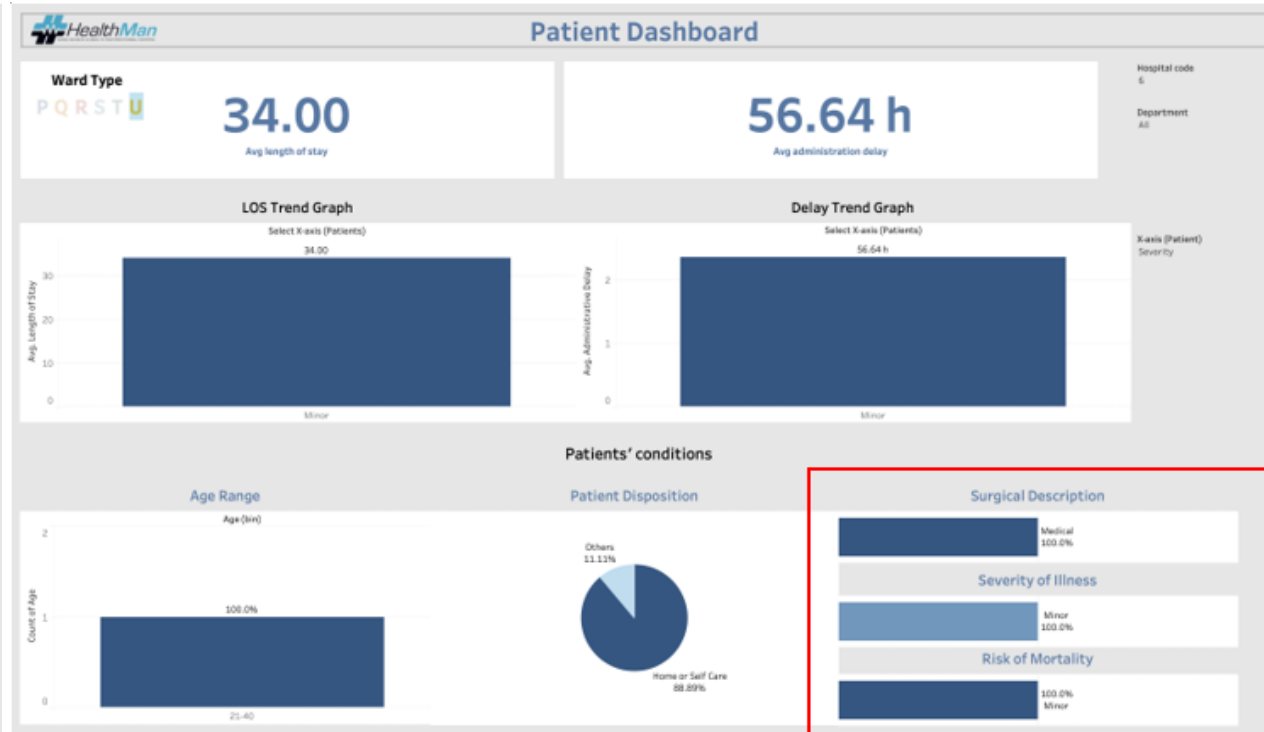
Section 9.2.1 in written report  
(Help doctors understand vacancy to prevent overcrowding in wards )



# Appendix



Before

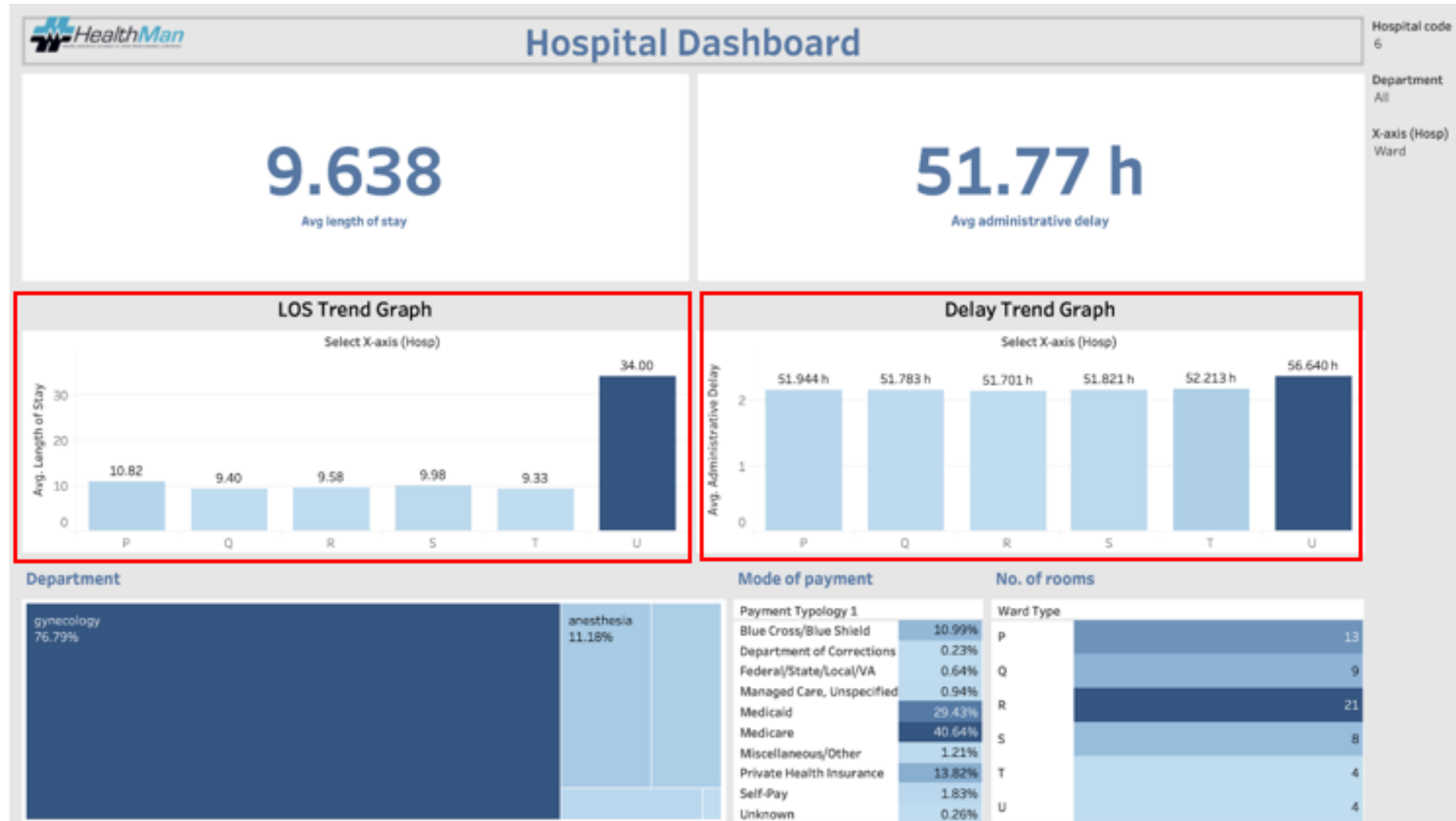


After

Section 9.2.1 in written report (Help doctors understand severity spread of patients in different wards)



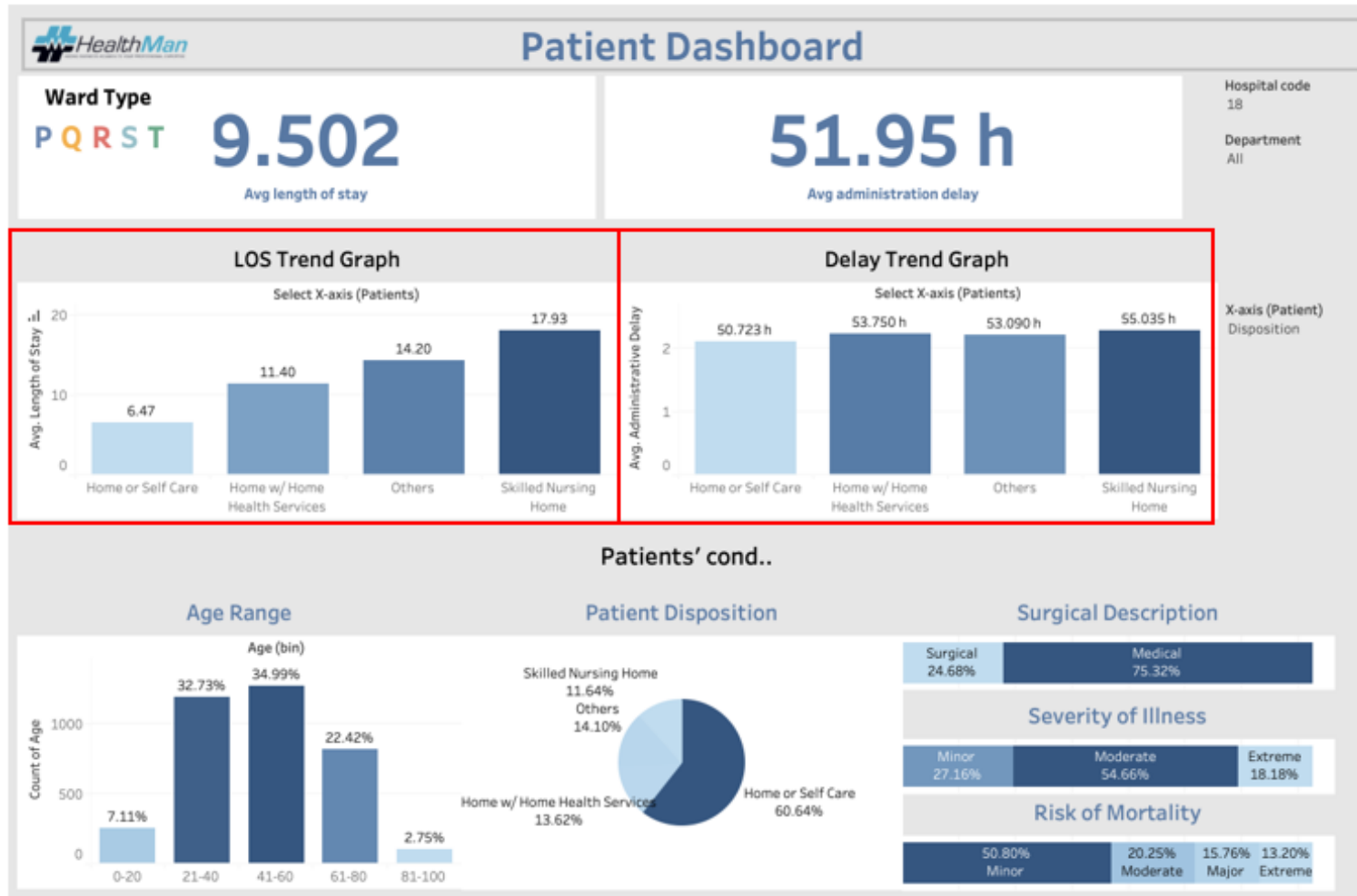
# Appendix



**Section 9.2.2 and 9.2.3 in written report**  
**(Help hospital management identify high LOS/Delay, eg ward U highest LOS/Delay**  
**Further prevents bottlenecks)**



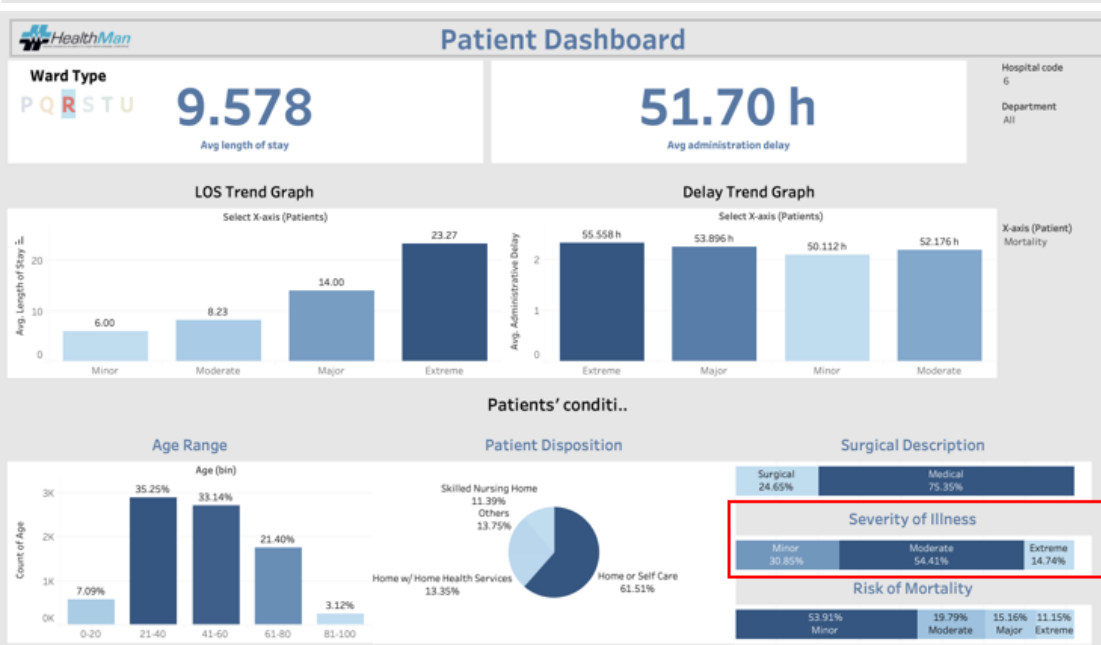
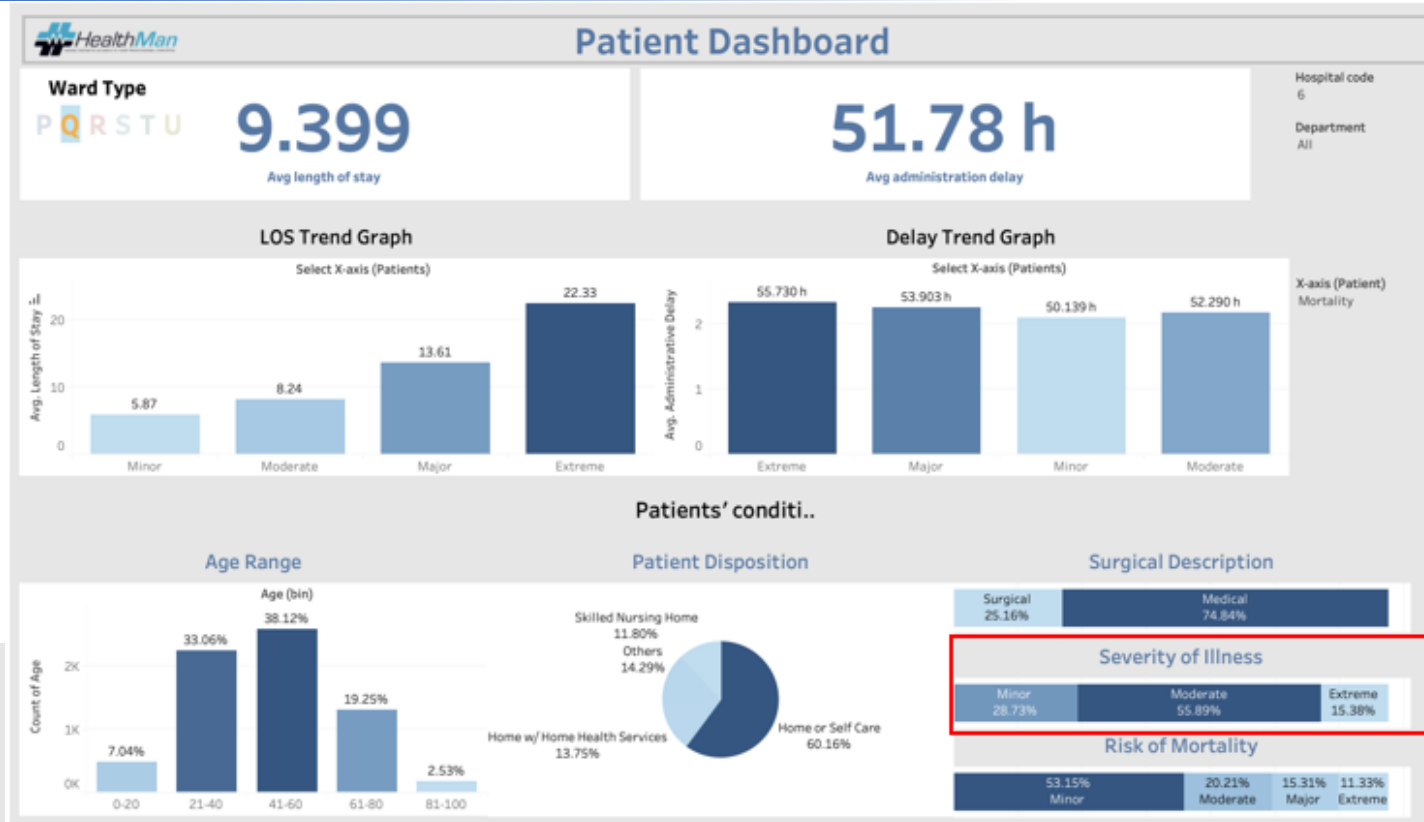
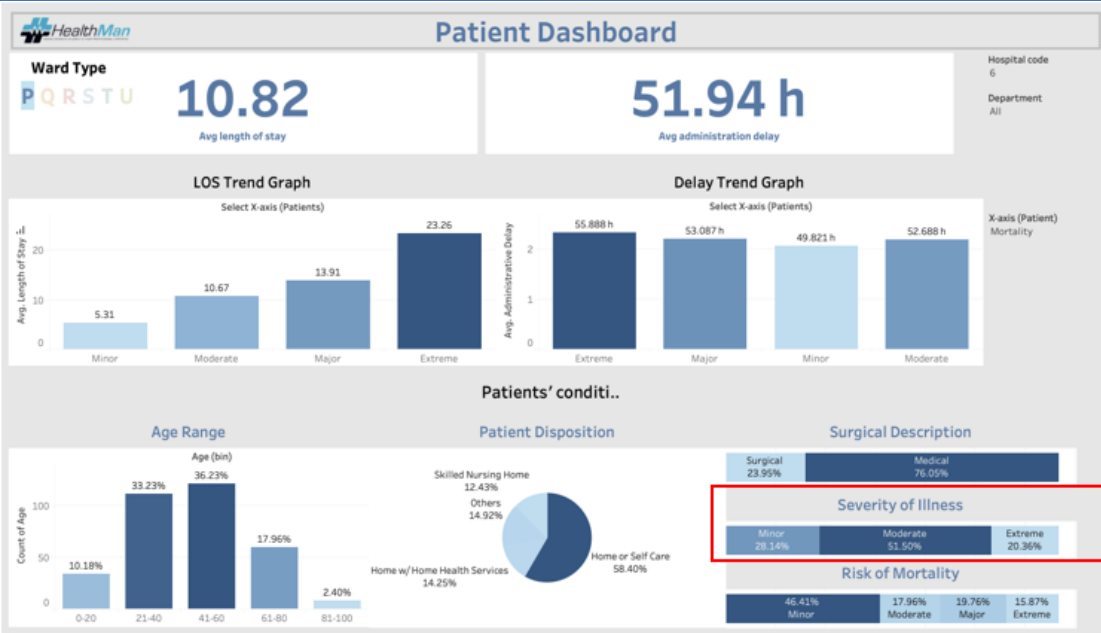
# Appendix



**Section 9.2.2 in written report**  
**(Help hospital management target patient related processes with high LOS/Delay,**  
**EG: Discharge to skilled nursing home has highest LOS/Admin Delay)**



# Appendix



Section 10.1 in written report  
(Similar severity spread within different ward types  
which could prolong LOS)

