

# **PROJECT REPORT / DOCUMENT OUTLINE**

## **TOPIC: Diabetes Patient Readmission Analysis**

**Sector:** Healthcare Analytics

### **Team Members Details:**

| <b>Name</b>             | <b>Enrolment Number</b> | <b>Role</b>        |
|-------------------------|-------------------------|--------------------|
| Mitul Bhatia            | 2401010279              | Project Lead       |
| Ramani Dhruv Dineshbhai | 2401010153              | Analysis Lead      |
| Divya Singh             | 2401020020              | Data Lead          |
| Anushka Tyagi           | 2401010090              | PPT & Quality Lead |
| Daniel Tayal            | 2401010140              | Strategy Lead      |
| Aaryan Gera             | 2401010009              | Dashboard Lead     |

# 1. Executive Summary

Hospital readmissions within 30 days are a major performance and cost indicator in healthcare systems. Frequent readmissions increase hospital burden, raise costs, and indicate possible gaps in discharge planning or disease management.

This project analyses the **Diabetes 130-US Hospitals dataset (1999–2008)** to identify key drivers of 30-day readmission. The goal was to understand which clinical and demographic factors are associated with higher readmission risk and to translate those findings into actionable hospital-level recommendations.

Using Google Sheets for cleaning, transformation, pivot analysis, and dashboard development, we:

- Reduced raw data (~101,766 rows) to **14,116 unique patients**
- Built binary risk flags
- Created ICD-9 condition groupings
- Estimated financial impact of readmissions
- Designed an interactive dashboard

## Key Insights

- Overall 30-day readmission rate: **13.2%**
- Emergency admissions show highest readmission rate (14.1%)
- 83.1% of patients had no A1C test recorded
- 94.9% had no max glucose test
- Emergency admissions account for **\$12.3M of \$20.49M total estimated cost**

## Key Recommendations

- Standardize A1C testing at discharge
- Strengthen emergency discharge protocols
- Flag long hospital stays (>4.5 days) before discharge
- Prioritize elderly and high-risk patients for follow-up

This analysis provides a structured risk-identification framework that can support hospital administrators in reducing avoidable readmissions.

## **2. Sector & Business Context**

### **Sector Overview**

The healthcare sector continuously monitors 30-day readmission rates as a quality and financial performance indicator. In the United States, high readmission rates may lead to financial penalties under reimbursement models.

### **Current Challenges**

- Poor chronic disease monitoring
- Incomplete discharge planning
- Inconsistent follow-up systems
- High emergency admission burden

### **Why This Problem Was Chosen**

Diabetes is a chronic condition requiring continuous management. The dataset provides a strong opportunity to evaluate readmission drivers in a structured manner.

---

## **3. Problem Statement & Objectives**

### **Problem Statement**

To identify key demographic, clinical, and administrative factors that influence 30-day hospital readmission among diabetic patients.

### **Project Scope**

- Analyze first hospital encounter per patient
- Focus on 30-day readmission
- Perform data cleaning and transformation in Google Sheets
- Build interactive dashboard
- Estimate financial impact

## **Success Criteria**

- Accurate readmission rate calculation
  - Clear KPI framework
  - Identifiable high-risk segments
  - Business-level recommendations supported by data
- 

## **4. Data Description**

### **Dataset Source**

Diabetes 130-US Hospitals Dataset

UCI Machine Learning Repository

Original Period: 1999–2008

<https://archive.ics.uci.edu/ml/datasets/Diabetes+130-US+hospitals+for+years+1999-2008>

### **Raw Dataset Size**

- ~101,766 rows
- 50+ columns

### **Final Analytical Dataset**

- 14,116 rows
- Single encounter per patient
- Cleaned and structured and randomized

### **Data Structure**

The dataset includes:

- Patient identifiers
- Demographics
- Admission details
- Clinical test results
- Medication information
- Readmission outcome

## Key Limitation

- Data is historical (1999–2008)
  - No BMI data (weight dropped due to 97% missing)
  - No socioeconomic variables
- 

## 5. Data Cleaning & Preparation

All cleaning was performed in **Google Sheets**, as required.

### Single Encounter Rule

Multiple visits existed per patient.

We sorted by patient\_nbr and encounter\_id and retained only the first encounter.

### Missing Value Handling

- race: 2,273 "?" replaced with mode (Caucasian)
- gender: 3 invalid rows deleted
- medical\_specialty: "?" replaced with "Missing"
- weight: dropped (>97% missing)
- payer\_code: dropped (>40% missing)

### Column Reduction

- 24 medication columns removed
- And other no involved columns

### Feature Engineering

Created derived columns:

- median\_age
- Primary\_Condition (ICD-9 grouping)
- A1C\_None
- A1C\_High
- max\_glu\_high
- Readmission Rate (binary)
- High\_Risk\_Flag

- Admission\_Group
- Medication\_Status
- Total Cost

All formulas documented in Data Dictionary.

---

## 6. KPI & Metric Framework

### KPI 1 – 30-Day Readmission Rate

Formula:

Readmission Rate = (Readmitted <30 days) / Total Patients

Result: 13.2%

### KPI 2 – Untested A1C Rate

Formula:

A1C\_None = 1 if test not performed

Result: 83.13%

### KPI 3 – High Risk Flag

Patients with:

- Readmission = 1  
AND
- A1C\_High = 1

Result: 7.2%

### KPI 4 – Estimated Financial Impact

Assumption:

Average cost per readmission = \$11,000

Total cost =  $1,863 \times 11,000$

= **\$20,493,000**

---

# 7. Exploratory Data Analysis (EDA)

## Admission Type Analysis

Emergency admissions:

- 56% of total
- 14.1% readmission rate
- Highest cost contribution

## Age vs Readmission

Highest readmission seen in age group 80–90 (14.7%).

Hospital stay increases with age.

## Length of Stay

- Non-readmitted: 4.27 days
- Readmitted: 4.78 days

Longer stay signals higher risk.

## A1C Testing Gap

83.1% of patients were not tested.

Indicates process gap in chronic disease monitoring.

## Medication Change Impact

- Stable medication: 12.2% readmission
- Changed medication: 14.3% readmission

Medication instability correlates with readmission.

---

# 8. Advanced Analysis

## ICD-9 Grouping

522 primary diagnosis codes grouped into:

- Diabetes
- Circulatory
- Respiratory
- Other

Circulatory conditions show the highest readmission share.

## High Risk Segmentation

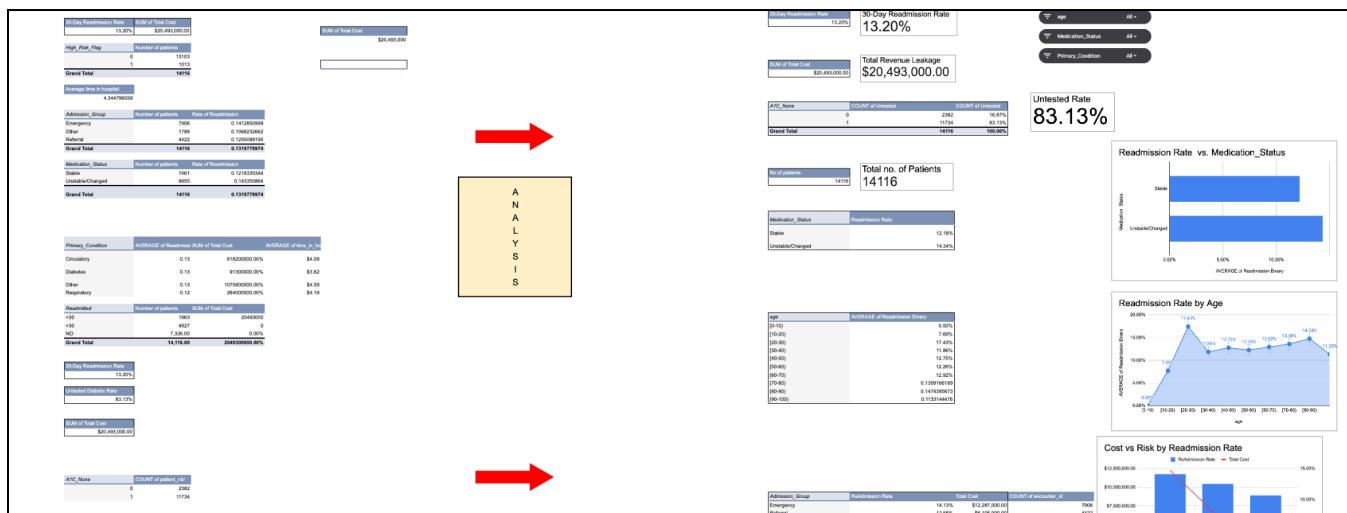
High\_Risk\_Flag identified 1,013 patients  
(7.2% of dataset)

These patients represent the highest ROI intervention group.

## Cost Breakdown by Admission Group

Emergency admissions account for:

\$12.28M of total \$20.49M



# 9. Dashboard Design

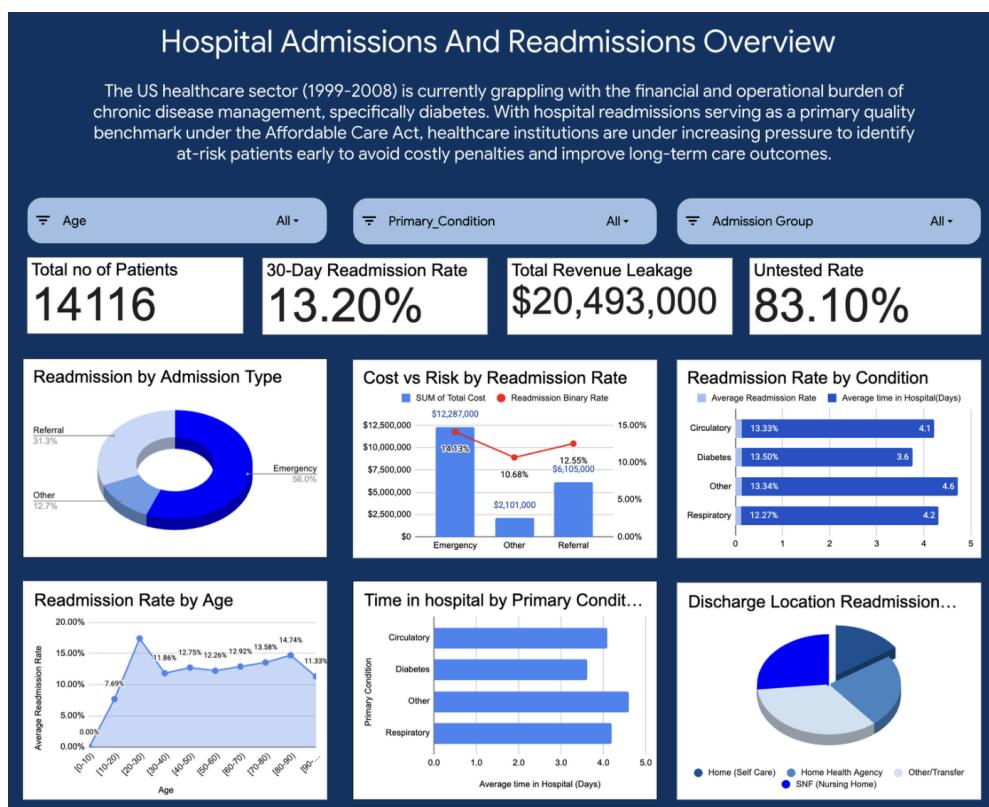
Developed in Google Sheets using:

- Pivot tables
- Binary flags
- Conditional formatting
- Interactive filters

## Dashboard Objective

Provide hospital administrators with:

- Readmission overview
- Cost impact
- Risk segmentation
- Filterable demographic insights



## Filters Available

- Age group (0-100)
  - Primary condition ( Circulatory , Diabetes , Respiratory , other )
  - Medication status ( Emergency , Referral , other )
- 

## 10. Insights Summary

1. 13.2% overall readmission rate
2. Emergency pathway drives highest cost
3. 83% A1C testing gap
4. 94.9% glucose test gap
5. Older age increases risk
6. Longer stays increase risk
7. Medication instability increases risk
8. Circulatory conditions contribute significantly
9. 7.2% patients are high-priority intervention group
10. \$20.49M estimated cost impact

## 11. Recommendations

### 1. Standardize A1C Testing

Addresses 83% testing gap.

### 2. Emergency Discharge Checklist

Focus on the highest cost pathway.

### 3. Auto-Flag Long Stay Patients

Stay > 4.5 days triggers review.

### 4. High-Risk Follow-Up Program

Target High\_Risk\_Flag patients first.

Each recommendation has high feasibility and moderate implementation cost.

---

## **12. Impact Estimation**

If readmission reduces by 5%:

Savings  $\approx \$1\text{--}2\text{M}$  annually (scaled hospital estimate)

Benefits:

- Reduced penalties
  - Better bed availability
  - Improved patient outcomes
- 

## **13. Limitations**

- Historical dataset (1999–2008)
  - Cost assumption fixed at \$11,000
  - No causal inference (correlation only)
  - No socioeconomic data
- 

## **14. Future Scope**

- Predictive ML model
  - Logistic regression risk scoring
  - External validation on modern data
  - Integration with EMR systems
- 

## **15. Conclusion**

This project successfully:

- Cleaned and structured complex healthcare data

- Identified readmission risk drivers
- Quantified financial impact
- Developed actionable dashboard insights

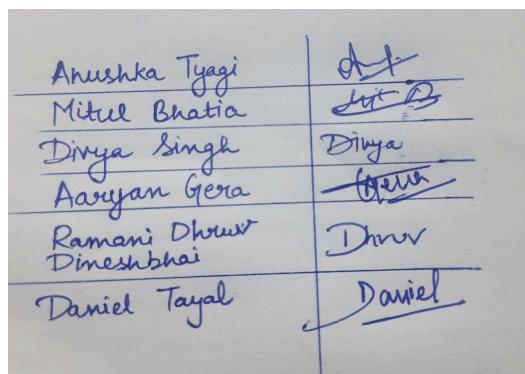
The framework can support hospital administrators in prioritizing high-risk patients and reducing avoidable readmissions.

---

## 16. Contribution Matrix

| Team Member   | Dataset & Sourcing | Cleaning | KPI & Analysis | Dashboard | Report Writing | PPT | Overall Role       |
|---------------|--------------------|----------|----------------|-----------|----------------|-----|--------------------|
| Mitul Bhatia  | ✓                  | ✓        | ✓              | ✓         | ✓              | ✓   | Project Lead       |
| Divya Singh   | ✓                  | ✓        | ✓              |           | ✓              |     | Data Lead          |
| Dhruv Ramani  | ✓                  | ✓        | ✓              | ✓         |                |     | Analysis Lead      |
| Aaryan Gera   | ✓                  |          | ✓              | ✓         |                |     | Dashboard Lead     |
| Anushka Tyagi |                    | ✓        | ✓              |           | ✓              | ✓   | PPT & Quality Lead |
| Daniel Tayar  |                    | ✓        | ✓              | ✓         |                |     | Strategy Lead      |

Declaration: We confirm that the above contribution details are accurate and verifiable.



Team Signature:

---