# Quality & Readmission Data Analysis Report for Diabetic Patients

# Project Overview

This Power BI project analyzes a dataset of over 100,000 diabetic patient hospital records, focusing on patient readmission patterns, medication usage, A1C test results, and demographic factors like age, race, and gender. It helps healthcare professionals identify areas of concern, track KPIs, and improve care quality.

### **Dataset Overview**

- Rows: 101,766
- Columns: 50
- Unique identifier: encounter\_id, patient\_nbr
- **Demographic data :** race, gender, age
- ► **Hospital-related**: infoadmission\_type\_id, discharge\_disposition\_id, admission\_source\_id
- ► **Treatment metrics :** time\_in\_hospital, num\_lab\_procedures, num\_medications
- ▶ **Diagnosis codes :** diag\_1, diag\_2, diag\_3
- ▶ **Lab/test results and medication usage :** A1Cresult, insulin, metformin
- ▶ **readmitted:** Whether the patient was readmitted (NO, >30, <30)

### Business Objectives & Why It Was Requested

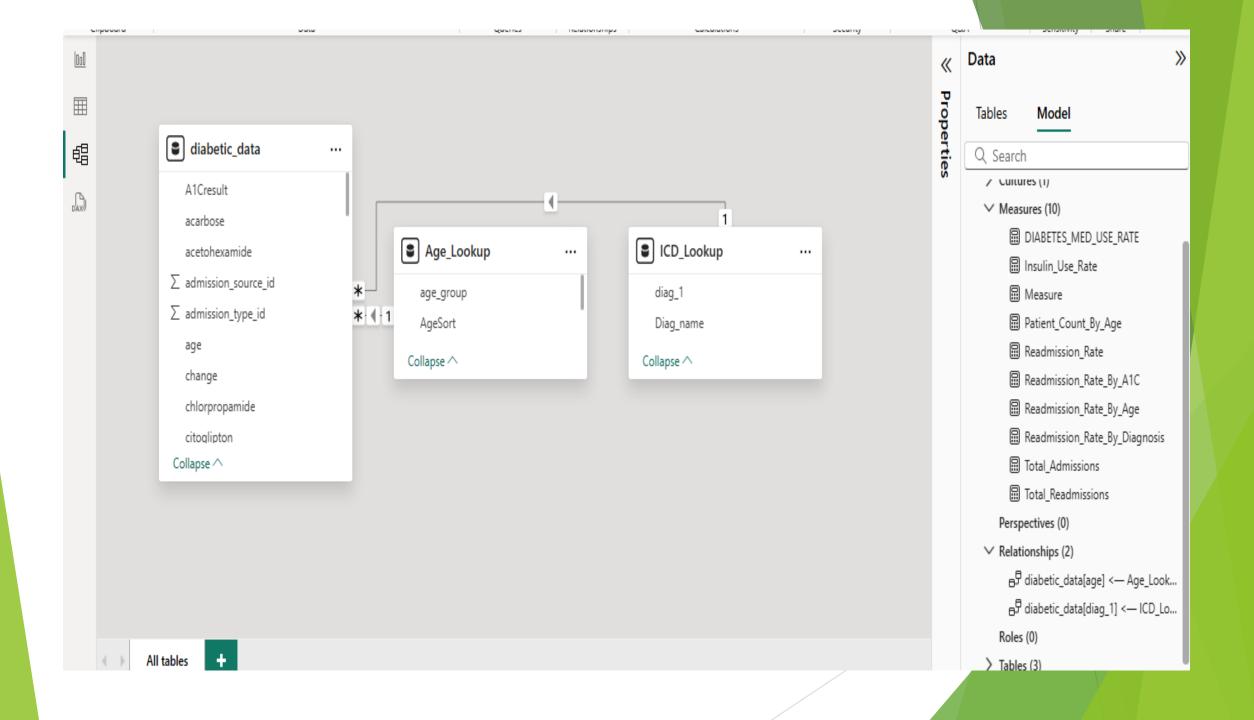
- Main Purpose:
  - To support the Quality & Safety Department in reducing hospital readmission rates for diabetic patients and improve medication management.
- ► Key Goals:
- Identify patients with a higher risk of readmission.
- Analyze medication usage trends by demographics.
- Correlate A1C test results with readmission outcomes.
- Present actionable KPIs and insights on a clear, single-screen dashboard.

# **Key Performance Indicators (KPIs)**

KPI Name	Description
Total Admissions	Total patient encounters in the dataset.
Total Readmissions (30 Days)	Number of patients readmitted within 30 days.
Readmission Rate	% of patients readmitted = Readmissions ÷ Admissions.
Insulin Use Rate	% of patients who received insulin medications.

### **Data Model Design (Backend View)**

- ► The model is built using three tables:
  - diabetic\_data: Main fact table with patient records.
  - Age\_Lookup: Lookup table to sort age groups logically using AgeSort.
  - ICD\_Lookup: Mapping table for diagnosis codes (diag\_1) to readable names.
- ► Relationships:
  - diabetic\_data[age] → Age\_Lookup[age\_group]
  - diabetic\_data[diag\_1] → ICD\_Lookup[diag\_1]



# **Data Preparation & Transformations**

- Performed using Power Query & DAX in Power BI:
  - Created calculated column readmitted\_30 (1 if readmitted within 30 days, else 0).
  - Converted diagnosis codes using ICD\_Lookup.
  - Created AgeSort for sorting x-axis.
  - Used measures for KPIs and charts.

### Measures Used:

- ► Total\_Admissions
- **▶** Total\_Readmissions
- Readmission\_Rate
- Insulin\_Use\_Rate
- DIABETES\_MED\_USE\_RATE
- Readmission\_Rate\_By\_Age
- Readmission\_Rate\_By\_Diagnosis
- Readmission\_Rate\_By\_A1C
- Patient\_Count\_By\_Age

- ▶ 1. Readmission Rate by Age Group (Column Chart)
- ▶ **Insight**: The highest 30-day readmission rate is among patients aged **70–80 years**, followed by 60-70 **years**.
- ▶ **Implication**: Elderly diabetic patients are at greater risk of being readmitted. Agetargeted post-discharge care may reduce rates.
- 2. Readmission Rate by Race (Column Chart)
- ► Insight: Caucasians patients show the highest readmission percentage, followed by African American .
- ▶ **Implication**: May highlight disparities in care or post-discharge support that require further investigation.

- 3. Readmission Rate by Diagnosis (Column Chart)
- ▶ **Insight**: **Heart Failure** diagnoses have the highest readmission rates.
- ▶ **Implication**: These conditions may need focused clinical protocols or follow-up plans.
- ▶ 4. A1C Result vs. Readmission Rate (Donut Chart)
- ► **Insight**: Patients with **no A1C result recorded** had the highest readmission rate (36%), followed by >7 and >8 groups.
- ▶ **Implication**: Monitoring and managing A1C levels is essential. Missing test data may signal care quality gaps.

- 5. Medication Use Rate by Gender (Stacked Bar Chart)
- ▶ **Insight**: Both **males and females** had high medication use rates, with females showing slightly higher usage.
- ▶ **Implication**: Medication adherence is generally strong, but gender-based differences could affect outcomes.
- 6. Average Length of Stay by Race (Pie Chart)
- ► **Insight**: **Caucasians** account for the majority of hospital stay durations (~83%). **African Americans** and **Hispanics** follow.
- ▶ **Implication**: Resource allocation should consider this distribution to optimize bed turnover and discharge planning.

- 7. Insulin Count by Age (Funnel Chart)
- ▶ **Insight**: Insulin use increases with age, peaking at **70–80 years**, and then slightly declining.
- ▶ **Implication**: Insulin therapy is more common among older patients, requiring ageadapted diabetic care strategies.
- 8. A1C Test Count by Age (Line Chart)
- ▶ **Insight**: The highest number of A1C tests occurred in the **70–80** and **60–70** age groups.
- ▶ **Implication**: Elderly patients are more closely monitored possibly due to greater clinical risk.

- 9. A1C Result vs. Age Group (Matrix Table)
- ▶ **Insight**: The patient with the age of 50-60 had the most abnormal result >8, while younger groups have fewer tests and normal values.
- ▶ **Implication**: Need to prioritize chronic care management in older populations.

- Slicers:
- Gender
- A1C Result Group

# Key Challenges & How They Were Resolved

Challenge	Resolution
1. Inconsistent Age Group Sorting	Power BI sorted age groups like [90-100) before [10-20) due to alphabetical ordering. To correct this, an AgeSort column was created in a separate Age_Lookup table, and a proper Sort By Column logic was implemented.
2. Diagnosis Code Interpretation	ICD codes like 250.13, 428, and 486 were unclear for users. A separate ICD_Lookup mapping table was created to convert these codes into understandable diagnosis names (e.g., "Heart Failure," "Pneumonia"), improving chart readability.
3. Misleading Readmission Percentage in Small Age Groups	The youngest age group (e.g., 10-30) showed high readmission rates due to small sample size. This was addressed by adding a tooltip with encounter count and considering supplementary visuals like readmission count or bubble chart with size by count for clarity.
4. Volume Overload in Diagnosis- Based Charts	Including all diagnosis codes resulted in cluttered bar charts. The solution was to limit visuals to the Top N diagnoses by volume or readmission rate using ranking logic in DAX and/or slicers.
5. A1C Result Category Inconsistency	The A1Cresult column contained mixed values like >7, >8, None, and blanks. Values were cleaned and standardized using Power Query transformations to ensure consistent grouping and accurate analysis.
6. Data Normalization & Usability	The raw dataset required data type correction, removal of nulls, and creating logical groupings (e.g., gender, race, A1C categories). These preprocessing steps ensured smooth measure creation and reliable insights across visuals.

### **Value to Business**

### **▶** Targeted Intervention Planning

Enables healthcare providers to identify high-risk patient segments (e.g., by age, diagnosis, or A1C levels), supporting focused clinical interventions to reduce preventable 30-day readmissions.

### Optimized Medication Management

Offers actionable insights into medication usage trends across demographics (e.g., gender-based differences), helping refine treatment strategies for diabetic patients.

### **▶** Enhanced Outcome Monitoring

Correlates A1C test results with readmission rates to assess the effectiveness of glycemic control, supporting continuous quality improvement in diabetic care.

### **Data-Driven Decision Support**

Delivers a clear, executive-ready dashboard that empowers stakeholders to make timely, evidence-based decisions aligned with hospital quality and safety objectives.

# **Technical Tools & Skills Applied**

- Power BI Desktop Data modeling, DAX, and visuals.
- Power Query Data transformation.
- DAX For all measures and KPIs.
- Relational Modeling One-to-many logical links.
- Best Practices Design consistency and slicer controls.