Hospital Readmission Analysis & Prediction

Analyzing Readmission Patterns to Improve Patient Outcomes

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Problem Statement

Problem Definition :

Healthcare systems worldwide face escalating costs and quality concerns related to unplanned hospital readmissions. In the United States alone, readmissions cost the healthcare system over $41 billion annually, with approximately 15-20% of patients being readmitted within 30 days of discharge.

This creates a cascading effect of increased healthcare expenditure, reduced bed availability, compromised patient satisfaction, and potential regulatory penalties for healthcare institutions.

Challenges :

Clinical Challenges:

- Difficulty identifying high-risk patients before discharge
- Inconsistent discharge planning processes across departments

Operational Challenges:

- Reactive rather than proactive approach to readmission prevention
- Lack of standardized risk assessment tools

Financial Challenges:

Financial penalties from regulatory bodies for excessive readmission rates

Increased operational costs due to unplanned admissions

Objective:

This project aims to develop a comprehensive hospital readmission analysis and prediction system that will:

- **Analyze Historical Patterns**: Examine existing readmission data to identify trends, risk factors, and contributing variables across different patient populations, diagnoses, and time periods.

- **Develop Predictive Models**: Create machine learning models capable of accurately predicting the likelihood of patient readmission within 30 days of discharge, enabling proactive intervention strategies.

- **Identify Risk Factors**: Determine the most significant clinical, demographic, and operational factors that contribute to readmission risk, providing actionable insights for clinical decision-making.

- **Enable Targeted Interventions**: Provide healthcare teams with risk stratification tools to prioritize resources and implement personalized care plans for high-risk patients.

- **Improve Care Coordination**: Facilitate better communication and planning between inpatient teams, discharge planners, and post-acute care providers.

About the Dataset:

- ***Total Records***: *101,766 patient encounters*
- ***Total Features***: 51 variables
- ***Data Type Distribution***:
  - Categorical: 38 (e.g., race, gender, medication status)
  - Numerical: 13 (e.g., time in hospital, number of medications)

Key Variables

- ***Patient Info***: race, gender, age, weight
- ***Hospitalization Details***:
  - admission_type_id, discharge_disposition_id, admission_source_id
  - time_in_hospital, number_diagnoses, num_lab_procedures
- ***Diabetes Management***:
  - Medication indicators (e.g., insulin, metformin, glipizide)
  - Lab results (max_glu_serum, A1Cresult)
- ***Target Variable***: readmitted_or not (Yes/No)

Tools Used:

pandas

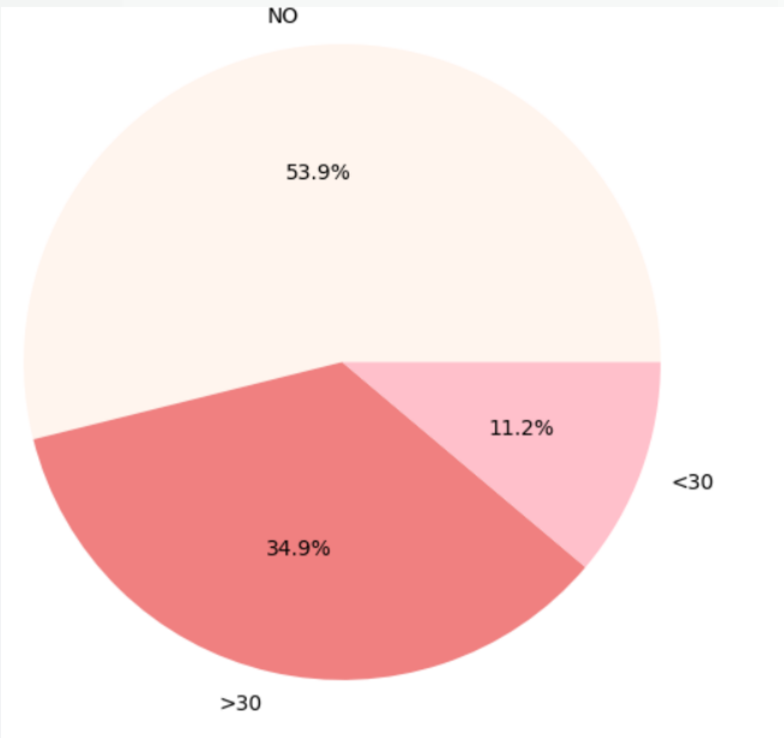
seaborn

matplotlib

Machine Learning
python

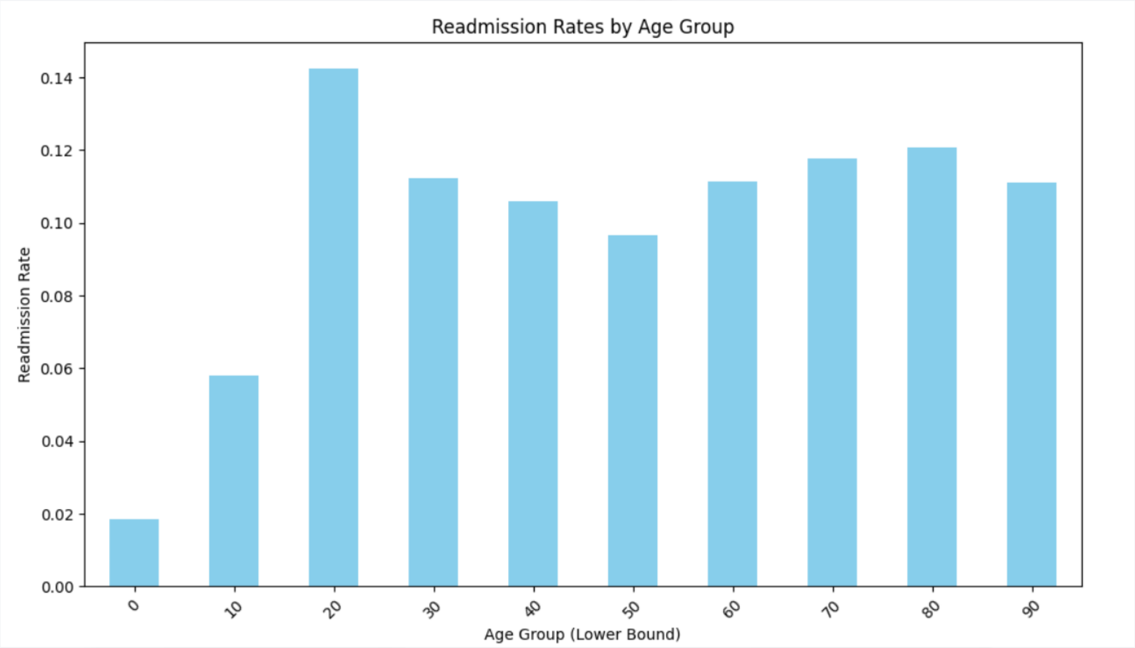
Explatory Data Analysis

Readmission Distribution by Time Frame



46.1 percent of patient get readmitted and out of readmitted patients 11.2 % get readmitted within a month and rest 34.9 % get readmitted but after a month.

Readmission Rates by Age Group



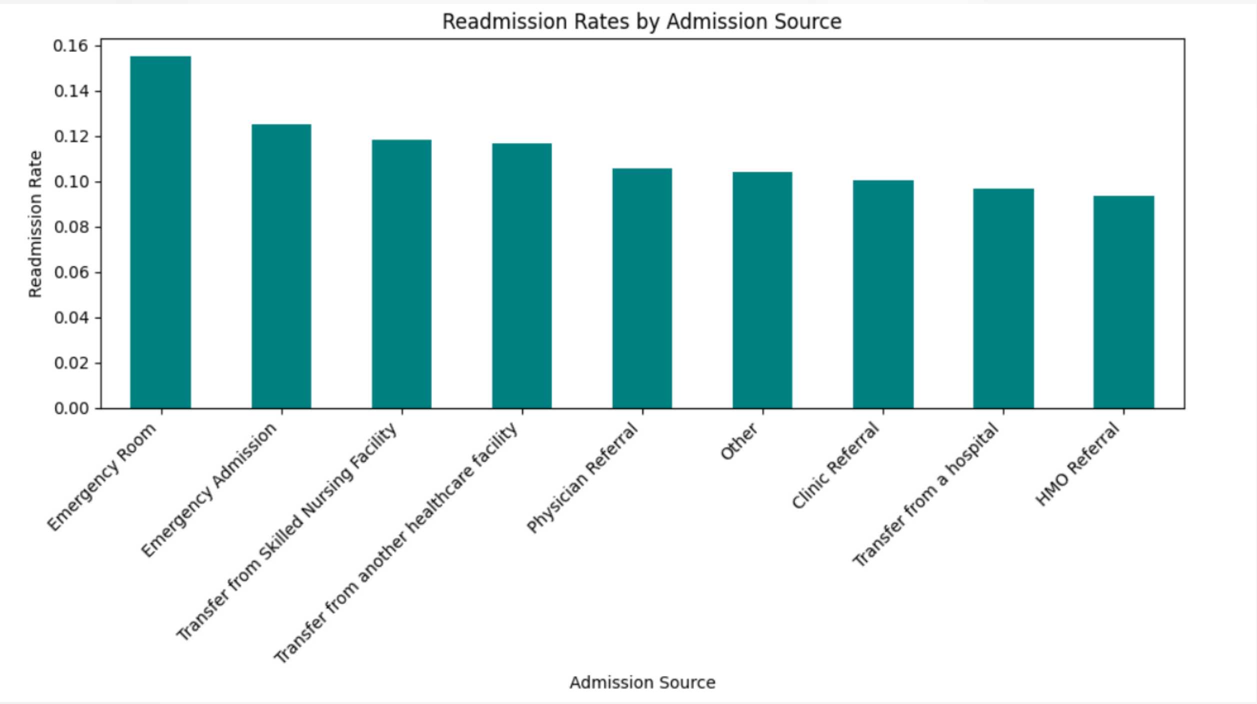
Youngest Group (0–10 years) → Lowest Readmission Rates

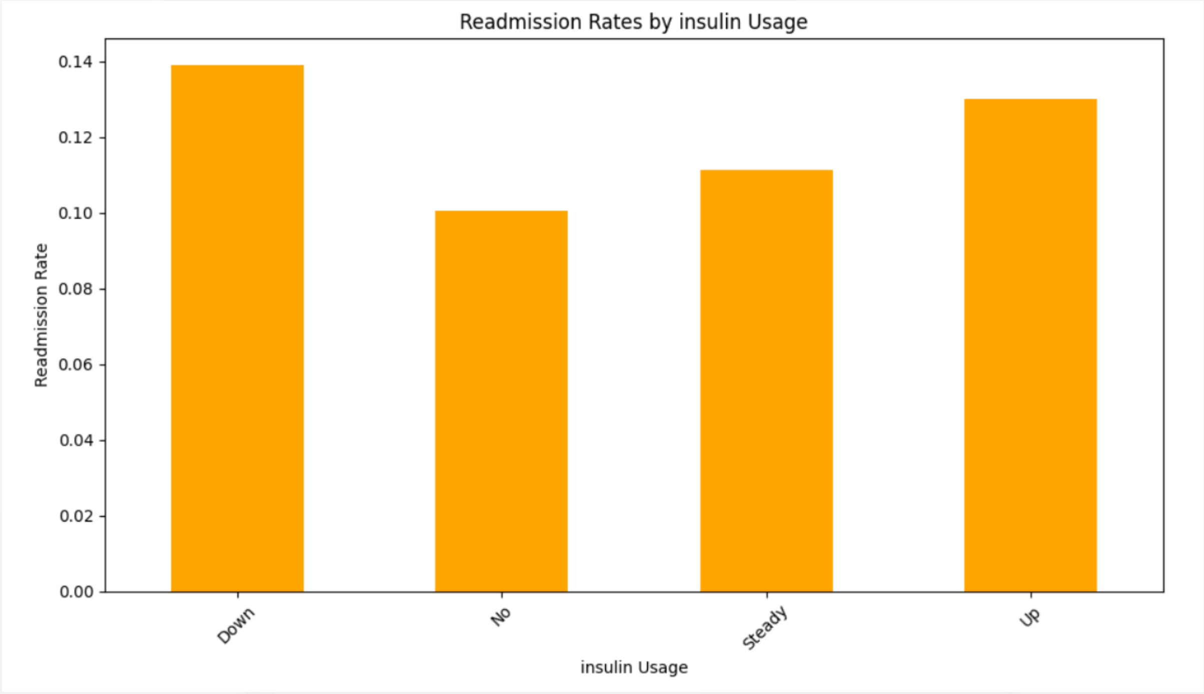
•Children and infants have the lowest readmission rate (~1.8%), likely due to fewer chronic conditions or better recovery after discharge.

Young Adults (20–29 years) → Highest Readmission Rate

Around age 20, the readmission rate spikes to the highest level (~14.3%)

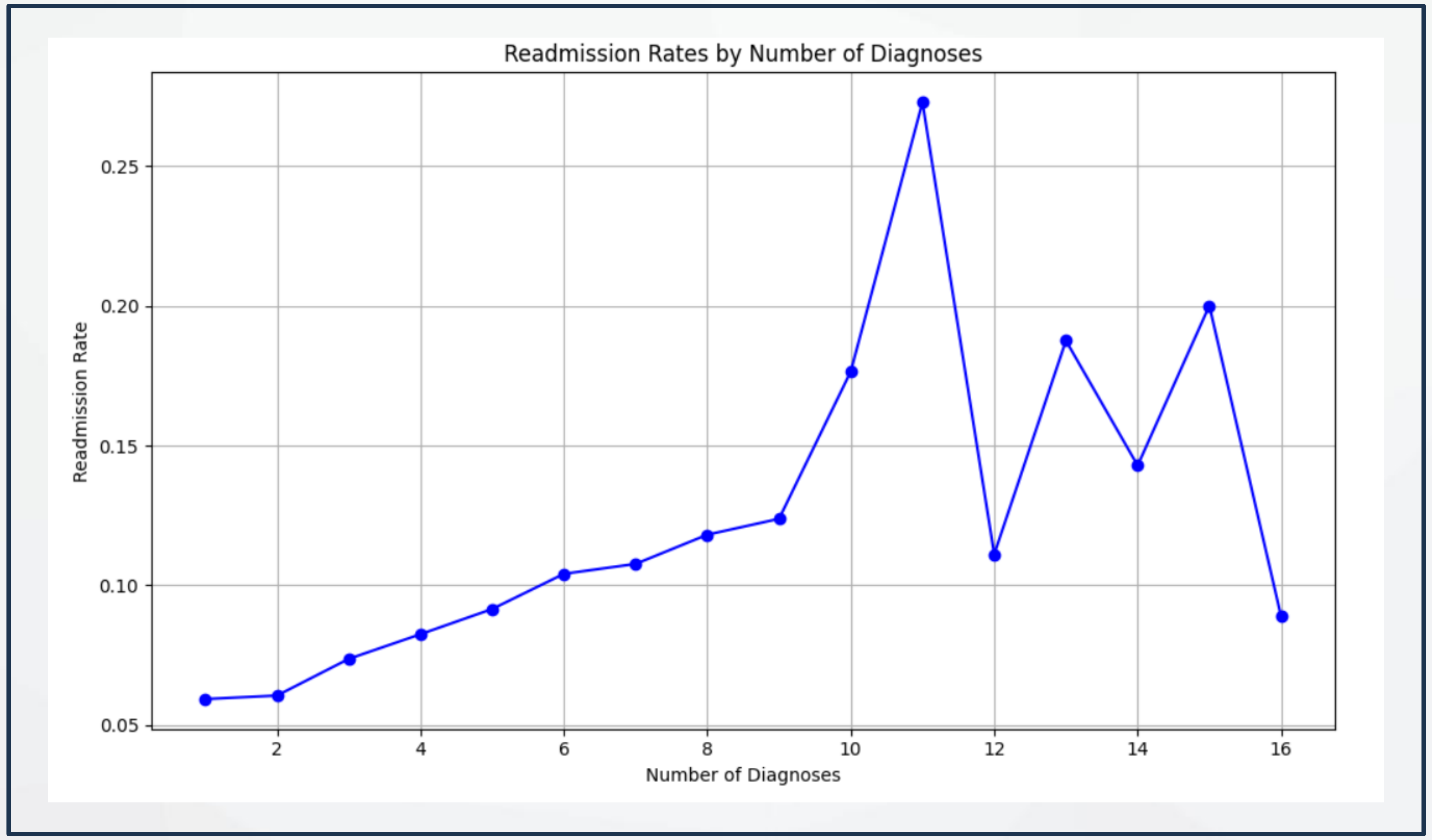
•After age 60, readmission rates again increase and stay consistently high (~11–12%).





Patients admitted through the **Emergency Room** show the highest readmission rate (~15.5%), indicating more severe or uncoordinated cases. **Emergency and facility transfers** (12–12.5%) also reflect higher risk, likely due to poor care continuity or premature discharge. In contrast, **physician, clinic, hospital, and HMO referrals** show relatively **lower readmission rates (~9–10.5%)**, suggesting better-managed transitions and care coordination. This highlights the need for targeted discharge planning and follow-up, especially for unplanned or high-acuity admissions

Patients with **increased ("Up")** or **decreased ("Down") insulin usage** have the **highest readmission rates (~13–14%)**, suggesting unstable diabetes management may lead to complications. Those with **steady insulin levels** or **no insulin use** have comparatively lower readmission rates (~10–11%), indicating more controlled conditions. This highlights the importance of closely monitoring insulin adjustments, as fluctuations are associated with higher risk of hospital return



Readmission rates increase as the number of diagnoses rises, peaking sharply around **11 diagnoses (~27%)**, indicating that patients with multiple comorbidities are at significantly higher risk of being readmitted. While the rate fluctuates slightly beyond that, the overall pattern highlights the burden of multimorbidity on patient outcomes. T

Key Takeaways:

- Where patients go after discharge significantly affects readmission rates:
  - **Patients who died**: 20.9% (This seems contradictory but might include patients who died during readmission)
  - **Skilled Nursing Facility**: 16.1% readmission rate
  - **Home with Healthcare**: 14.7% readmission rate
  - **Home** (regular discharge): 9.3% readmission rate

Patients who go home normally are least likely to return, while those needing special care are more likely to return

- Accuracy Score: 88.8%

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Conclusions

This analysis shows that while we can identify some factors that increase readmission risk (like discharge destination and length of stay), creating an accurate prediction system is challenging and requires more sophisticated approaches than what was attempted here.

Let’s Reduce Readmissions Together

Thank You

Questions and discussion welcome

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