# Predicting Hospital Readmissions Using AI to Improve Operational Efficiency: A “Decision-Support” Approach

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**1. Introduction**

Unplanned hospital readmissions place significant pressure on healthcare systems by increasing operational costs, reducing bed availability, and negatively impacting patient outcomes. In Ireland, the Health Service Executive (HSE) continues to face ongoing challenges related to capacity management, particularly within acute care settings. As a result, reducing avoidable readmissions has become not only a clinical priority but also a critical operational and policy objective.

Against this backdrop, this project explores how Artificial Intelligence (AI) can be applied as a “**decision-support” tool** to predict the likelihood of patient readmission following hospital discharge. Rather than seeking to replace clinical judgement, the proposed approach is designed to assist healthcare professionals by identifying patients at higher risk of readmission at an early stage. By enabling more targeted follow-up care and improved resource allocation, such an AI-driven system has the potential to enhance operational efficiency while maintaining patient safety, transparency, and clinical oversight.

**2. Problem Statement**

Hospital readmissions within 30 days of discharge are often indicative of gaps in post-discharge care, inadequate follow-up processes, or complex patient needs. These unplanned readmissions contribute to increased healthcare costs, inefficient use of hospital resources, and additional pressure on already constrained healthcare systems.

The objective of this project is to develop a predictive AI model that estimates the probability of patient readmission. The model is intended to support hospital administrators and clinicians by providing data-driven insights that can inform discharge planning, follow-up prioritisation, and operational decision-making.

## 3. Context: Irish Healthcare System

Ireland's healthcare system operates under strict data protection and privacy regulations, including the General Data Protection Regulation (GDPR), which significantly limits public access to patient-level clinical datasets. While organisations such as the Health Service Executive (HSE), the Health Information and Quality Authority (HIQA), and the Central Statistics Office (CSO) publish aggregate healthcare statistics and system-level reports, individual-level hospital admission data is not openly available for analytical or modelling purposes.

As a result, this project adopts a dual approach. Ireland-specific healthcare reports and statistics are used to provide contextual grounding and to frame the operational relevance of the problem. In parallel, a publicly available hospital dataset is employed to demonstrate the AI methodology. This approach aligns with established academic practice when real-world data access is constrained by regulatory and ethical considerations.

## 4. Dataset Description

Due to the limited availability of publicly accessible patient-level hospital datasets in Ireland, this study uses the **Diabetes 130-US Hospitals dataset (1999–2008)** as a proxy dataset for modelling purposes. The dataset contains approximately 100,000 patient encounters and is widely used in academic research focused on hospital readmissions and healthcare analytics.

**Dataset source:**
Diabetes 130-US hospitals for years 1999–2008 (diabetic_data.csv)

Table 1: Dataset Summary

| Attribute | Description |
|---|---|
| Dataset | Diabetes 130-US Hospitals (1999–2008) |
| Records | ~100,000 patient encounters |
| Target Variable | Hospital readmission (Yes / No) |
| Selected Features | Time in hospital, number of procedures, medications |

The dataset was selected for the following reasons:

- It is widely cited in academic literature on hospital readmission prediction
- It contains clinically and operationally relevant features aligned with readmission risk

- It enables the demonstration of AI techniques applicable to healthcare systems, including Ireland

While the dataset originates from the United States, the modelling approach, feature selection, and "decision-support" framing adopted in this project are transferable to the Irish healthcare context. The focus of the study is therefore not on geographical specificity, but on illustrating how AI can be responsibly applied to support operational decision-making within healthcare systems operating under similar constraints.

## 5. Methodology

This project follows a structured and interpretable AI methodology, designed to support decision-making rather than maximise predictive complexity. The focus is on transparency, practical usability, and alignment with healthcare governance requirements.

### 5.1 Data Preparation

The dataset was pre-processed to ensure suitability for analysis and modelling. Missing values were identified and handled, and irrelevant or incomplete records were removed. Categorical variables were simplified where necessary to support model interpretability.

The target variable, hospital readmission status, was transformed into a binary outcome indicating whether a patient was readmitted or not. This binary formulation supports clear risk classification and aligns with the operational objective of identifying higher-risk patients.

### 5.2 Feature Selection

Feature selection was guided by relevance to hospital operations and patient care, rather than purely statistical considerations. The following variables were selected for modelling:

- **Time in hospital**
- **Number of procedures**
- **Number of medications**

These features serve as proxies for patient complexity and treatment intensity, both of which are commonly associated with increased readmission risk. Selecting a limited number of meaningful features also supports model transparency and ease of interpretation, which are critical in healthcare "decision-support" contexts.

### 5.3 Model Selection

A **Logistic Regression** model was selected due to its simplicity, interpretability, and suitability for "decision-support" applications. Unlike more complex models, Logistic Regression allows for clear understanding of how input variables influence predicted outcomes, supporting transparency and trust among stakeholders.

The dataset was divided into training and testing subsets to evaluate model performance on unseen data. Model evaluation focused on interpretability and practical applicability rather than solely optimising predictive accuracy.

(This methodology reflects a deliberate balance between analytical rigour and real-world applicability, ensuring that model outputs can be meaningfully integrated into healthcare operational decision-making.)

## 6. Model Results

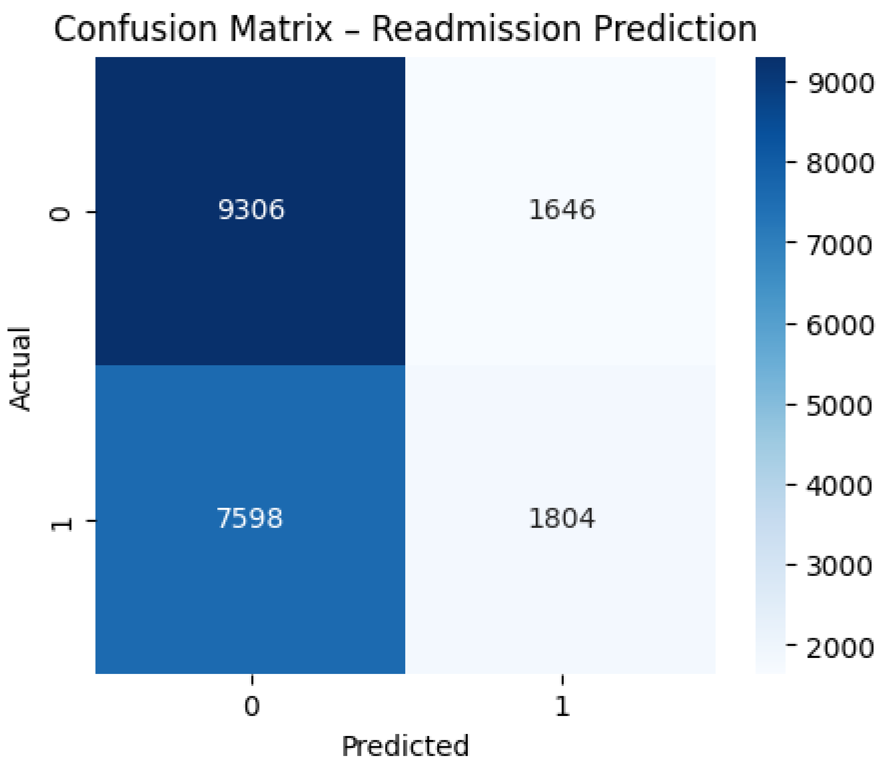


Figure 1: Confusion Matrix for Readmission Prediction Model

Figure 1 presents the confusion matrix for the hospital readmission prediction model, illustrating its ability to distinguish between patients who were readmitted and those who were not. The results indicate that the model is capable of identifying meaningful patterns in patient data that can support risk-based decision-making.

While standard performance metrics such as accuracy were considered, the evaluation prioritised **interpretability and practical usability** over maximising predictive performance. This reflects the project’s focus on developing an AI system that can assist healthcare professionals in identifying higher-risk cases for early intervention, rather than providing fully automated or opaque predictions.

Overall, the model demonstrates sufficient discriminatory capability to function as a “**decision-support” tool**, offering actionable insights that can inform discharge planning and follow-up prioritisation within a healthcare operational context.

## 7. Feature Importance and Explainability

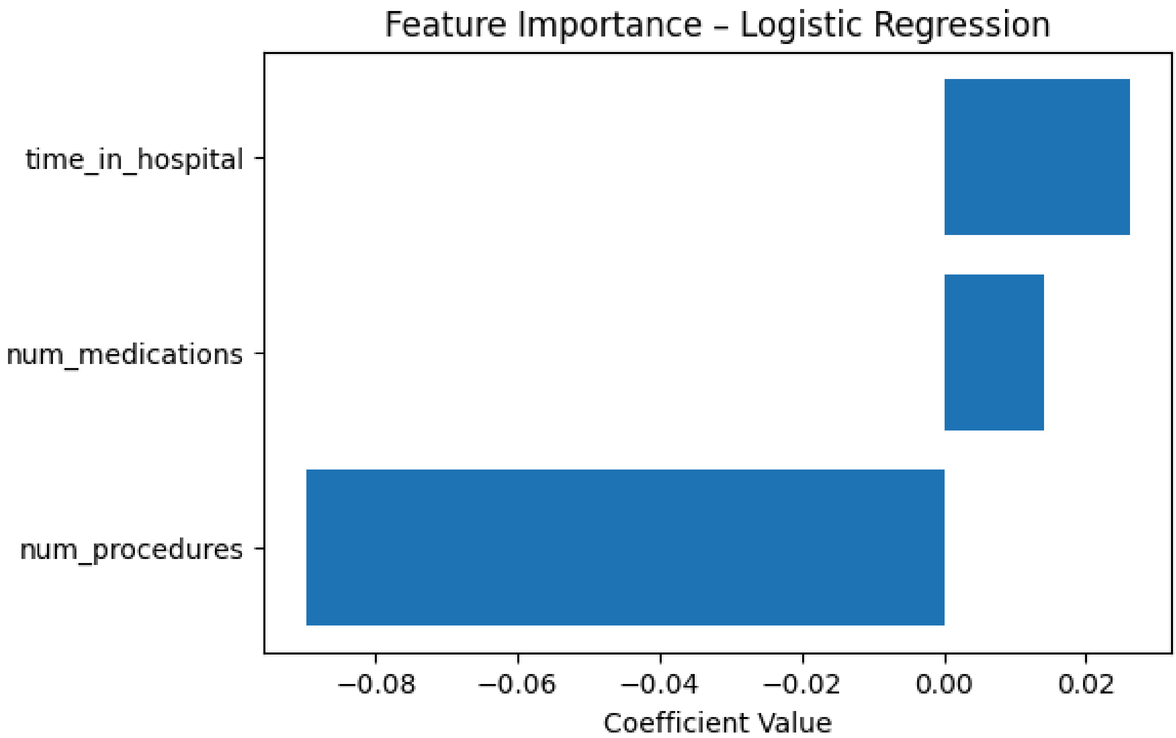


Figure 2: Feature Importance Based on Logistic Regression Coefficients

Figure 2 presents the relative importance of selected features based on the coefficients of the Logistic Regression model. The results indicate that variables associated with patient complexity and treatment intensity have the strongest influence on readmission risk. In particular, factors such as length of hospital stay and number of medications contribute most significantly to the model’s predictions.

One of the key advantages of using Logistic Regression in this context is its **inherent transparency**. The model coefficients provide clear insights into how each feature affects the likelihood of readmission, allowing stakeholders to understand not only *what* the model predicts, but *why* those predictions are made.

Longer hospital stays are associated with higher readmission risk, suggesting increased patient complexity or unresolved clinical issues. Similarly, higher medication counts reflect more intensive treatment regimes, often linked to chronic conditions that require ongoing management. The number of procedures also contributes to risk prediction, representing the level of clinical intervention during a patient’s hospital stay.

This level of explainability is critical in healthcare settings, where AI systems must support trust, accountability, and regulatory compliance. By providing interpretable outputs rather than opaque predictions, the model can be more readily integrated into clinical and operational decision-making processes, supporting human judgment rather than replacing it.

## 8. Business and Operational Impact

From an operational perspective, the proposed AI model has the potential to support hospitals by enabling more proactive and targeted decision-making. By identifying patients at higher risk of readmission prior to discharge, healthcare teams can prioritise follow-up care, allocate monitoring resources more effectively, and intervene earlier where additional support is required.

Such an approach can contribute to improved bed utilisation and capacity planning by reducing avoidable readmissions, thereby easing pressure on acute care services. In addition, fewer unplanned readmissions can lead to cost savings and more efficient use of clinical and administrative resources.

In the Irish context, where healthcare systems operate under significant capacity constraints, an AI-driven "decision-support" tool of this nature could assist the Health Service Executive (HSE) in allocating limited resources more effectively. Importantly, the model is designed to complement existing clinical workflows, ensuring that patient safety and professional judgment remain central to operational decision-making.

## 9. Ethical and Governance Considerations

The use of AI in healthcare introduces a range of ethical, legal, and operational considerations that must be carefully managed. One key risk is the presence of bias in historical healthcare data, which may reflect existing inequalities or systemic patterns and could lead to unfair or inaccurate predictions if left unaddressed. In addition, there is a risk of over-reliance on automated outputs, where clinical judgment may be unintentionally deferred to model predictions.

Patient privacy and data protection are also critical concerns, particularly within the Irish and European regulatory context governed by the General Data Protection Regulation (GDPR). Any deployment of AI systems in healthcare must ensure strict compliance with data protection principles, including transparency, accountability, and appropriate safeguards around data usage.

To mitigate these risks, the AI system proposed in this project is designed to function strictly as a "**decision-support" tool**, with clinicians retaining full authority over final decisions. Regular model auditing, transparent reporting of model behaviour, and continuous human oversight are essential to ensuring responsible and ethical use. By embedding governance and ethical considerations into the design and evaluation of the system, AI can be applied in a manner that supports trust, safety, and regulatory compliance within healthcare settings.

## 10. Conclusion

This project demonstrates how Artificial Intelligence can be applied responsibly to support healthcare decision-making and improve operational efficiency. By prioritising interpretability, governance, and real-world constraints, the proposed approach aligns with the needs of healthcare systems such as Ireland's, where trust, accountability, and regulatory compliance are essential.

The analysis shows that features related to patient complexity and treatment intensity have the greatest influence on readmission risk, reinforcing the value of AI as a " "**decision-support" mechanism** rather than an automated decision-maker. By providing transparent and interpretable insights, the model can assist healthcare professionals in identifying higher-risk cases and supporting more informed discharge planning and follow-up care.

Overall, this project highlights the potential of AI to contribute meaningfully to healthcare operations when deployed with appropriate oversight, ethical safeguards, and a clear focus on supporting human judgment. Such an approach is critical to ensuring that AI systems deliver practical value while maintaining patient safety and institutional trust.

## References

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