Predictive Modeling: Utilizing Machine Learning to Forecast Diabetes Hospital Re-admissions

Intern Name(s): Temitope Adereni

ID: DF2025-036

Date: 12/10/2015

Email: temitopeogundare2015@gmail.com

Abstract

Hospital readmissions are a major and ongoing concern for healthcare systems worldwide and serve as a complex indicator of care quality while contributing billions in preventable costs each year. The likelihood of readmission among patients with diabetes mellitus is particularly high and this reflects the difficulties of managing multiple comorbid conditions and ensuring effective continuity of care. Despite substantial progress, many existing predictive models still face limitations such as poor generalizability, challenges in addressing class imbalance, and limited clinical interpretability. This study proposes a systematic and reproducible framework for predicting 30-day hospital readmissions using the UCI Diabetes 130-US Hospitals dataset. It involves a comparative evaluation of Logistic Regression and Random Forest classifiers, emphasizing Recall optimization through a structured assessment of class imbalance correction methods. Explainable AI (XAI) techniques, particularly SHAP values, will be applied to enhance model transparency and results will be visualized in Power BI dashboards to support data-driven decision-making by clinical and operational teams. The findings are expected to highlight the balance between model interpretability and predictive performance, and offer practical guidance for developing reliable, usable, and transparent prediction models in healthcare.

Keywords: Hospital Readmission Prediction, Diabetes Mellitus, Machine Learning, Class Imbalance Handling, Explainable Artificial Intelligence (XAI), Random Forest, Healthcare Data Analytics

Introduction

Hospital readmissions are a persistent challenge to healthcare systems in the world. Often, readmissions are viewed as a marker of healthcare quality since frequent rehospitalization can reflect inadequate discharge planning, poor continuity of care, or unmanaged comorbidities [1]. Nevertheless, the financial burden is substantial. In the United States, the Centers for Medicare & Medicaid Services (CMS) estimated that unplanned readmissions account for over $17 billion in avoidable costs annually [2]. Internationally, readmission rates have been reported across a range of conditions, with significant variability between health systems, but consistently high costs and strain on resources [3].

Beyond economics, repeated hospitalizations are associated with worsened clinical outcomes, including increased mortality, hospital-acquired complications, and lower health-related quality of life [4,5]. Studies of older populations and patients with chronic disease confirm that readmission is linked to higher six-month and one-year mortality, as well as reduced patient well-being [6,7]. These findings underscore the urgent need for accurate and interpretable predictive tools that can identify patients at high risk of readmission before discharge.

Among chronic conditions, diabetes mellitus is one of the leading drivers of hospital utilisation and readmissions [8, 9]. Its complex management involves glucose control, multiple medications and dietary adherence. This frequent monitoring creates opportunities for treatment gaps and complications that often result in returning to the hospital [9]. The UCI's Diabetes 130-US hospitals' dataset is a standard benchmark for investigating issues pertaining to readmission. The dataset covers over 100,000 patient encounters from 1999 to 2008 and includes demographic, diagnostic, and clinical variables [9]. Previous analyses of this dataset have demonstrated that patient age, length of stay, number of prior visits, and diagnosis categories are important predictors of readmission [10]. However, even with these insights, prediction accuracy remains limited and there is a continuous call for reproducible and interpretable methods that can be integrated into clinical and operational decision-making.

Existing research has provided a wide variety of approaches for hospital readmission prediction ranging from logistic regression models to advanced ensemble and deep learning techniques. However, several limitations persist. First, predictive models often exhibit limited generalizability when applied across different hospitals or patient populations. This means they struggle to be accurate or useful when applied to patients or healthcare settings other than the one they were originally trained on [11]. Second, many models underperform due to class imbalance, as readmissions occur less frequently than non-readmissions, leading to biased classifiers that favor the majority class [12]. Third, interpretability remains a concern: while clinicians value insights into why a patient is deemed at risk, many machine learning models are presented as "black boxes" without meaningful feature-level explanations [13]. Moreover, most prior studies emphasize algorithmic performance while neglecting the importance of clear preprocessing pipelines, standardized benchmarks, and clinically relevant visualization methods. There remains a gap in research that combines robust preprocessing, comparative benchmarking of interpretable models and visual exploration of risk factors.

This study aims to address these gaps through a structured and reproducible pipeline for predicting hospital readmissions using UCI Diabetes 130-US Hospitals for Years 1999-2008 dataset with a particular focus on diabetes-related admissions. The contributions are fourfold:

1. **Preprocessing pipeline**: Data cleaning, including handling of missing values, outlier detection, and standardized encoding of diagnosis codes, ensuring reproducibility.

2. **Comparative evaluation**: Use benchmark logistic regression and random forest models on the dataset to evaluate metrics such as AUC, precision, recall and calibration.

3. **Interpretability and visualization**: Provide insights into the relative contributions of patient attributes (for example, age, length of stay, and prior admissions) and visualize correlations through Python libraries and Power BI dashboards for practical interpretability.

4. **Empirical insights**: Extract actionable lessons on trade-offs between model simplicity and performance, as well as best practices for dealing with imbalanced healthcare datasets.

Scope and Limitations

This research is limited to data drawn from the UCI Diabetes 130-US Hospitals for Years 1999-2008 dataset. The study will not extend to unstructured EHR data such as clinical notes, imaging or continuous monitoring signals. The focus is confined to patients with diabetes and recognizes other conditions such as heart failure and COPD, which also represent significant contributors to readmissions. Also, the study does not aim to develop a production-ready decision support system; rather, it emphasizes methodological benchmarking, interpretability and visualization to inform future work.

Literature Review

In 2011, Kansagara *et al*. assessed twenty-six validated hospital readmission risk prediction models used either for standardizing hospital performance metrics or for identifying high-risk patients needing transitional care interventions. The core finding revealed that most models perform poorly and have limited ability to predict readmission risk accurately. Particularly, large-scale administrative models displayed low discriminative power (c-statistics typically 0.55-0.65). Although almost all models incorporate medical history and prior utilization data, the authors highlight a critical lack of variables concerning overall health, functional status, and social determinants of health. The study concluded that improved models are essential before relying on these tools to penalize hospitals or effectively triage patients [11].

The systematic review by Artetxe *et al*. also holds a similar stance. Firstly, their study reviewed 77 readmission prediction models and found that logistic regression and other classic statistical methods are still the most common approaches (68% of studies). Model performance varied widely, with AUC scores ranging from 0.54 to 0.92. However, a key difficulty in comparing these models is the lack of a standardized benchmark dataset. Newer studies suggest machine learning might offer better prediction, but difficulty comparing results remains a barrier to real progress [12].

Nevertheless, Hu *et al.,* developed and tested a machine-learning model to predict in-hospital mortality for septic patients who required readmission to the Intensive Care Unit (ICU). This study considered comorbidities like diabetes and used data from 1,117 patients. The Random Forest model performed the best, achieving an AUC of 0.81 and 85% accuracy. This offers promising prospects that machine learning can accurately predict mortality or even readmission [13].

Similarly, Hai *et al*. compared Deep Learning (DL) to traditional models for predicting unplanned 30-day hospital readmissions, using over 36,000 diabetic patients for the studies. The DL model (LSTM) significantly outperformed the next best traditional model (Random Forest), achieving an AUROC of 0.79 vs. 0.72. The DL model's accuracy confirms the superior ability of machine learning models [14].

Tang and team also introduced a novel Graph Neural Network (GNN) to predict 30-day hospital readmission and tried to overcome common model limitations like condition-specific focus and ignoring time-series data. When tested on a diverse patient population, the GNN outperformed all benchmark models, achieving an AUROC of 0.724 by adeptly capturing the complex, time-dependent relationships between various clinical variables [15].

A study by Strack *et al*., reviewed almost 70,000 hospitalizations for patients with diabetes to find out if checking their HbA1c levels helped prevent a quick readmission. These researchers found that doctors were infrequently using the test, ordering it in just 18.4% of cases. However, when the HbA1c measurement was taken, the patient's chance of being readmitted within 30 days actually dropped significantly. This beneficial association was heavily influenced by the patient's primary reason for admission. The data suggests that simply giving greater attention to

diabetes management while hospitalized, marked by ordering the test, could genuinely lead to better outcomes and lower costs [16].

The systematic review by Saranya *et al.* mapped out the latest developments in explainable artificial intelligence (XAI) across 91 recent studies of various applications. The authors highlighted XAI's core purpose to increase trust, transparency, and accountability in complex AI systems, especially in high-stakes fields like healthcare and finance. The review categorized XAI approaches, identified their common metrics for evaluation and pointed toward future research trends, emphasizing the critical shift from opaque "black box" models to more interpretable decision-making [17]. Another research analysed 22 studies and concluded that machine learning models can predict readmission from 30 days up to 3 years after achieving AUC values ranging from 0.70 to 0.99 [18].

Searches were ran across PubMed/PMC, arXiv, UCI/ML repos, Scopus/Google Scholar (2010–2025) using keywords such as "hospital readmission prediction", "UCI diabetes readmission", "random forest readmission", "LSTM readmission EHR", "readmission model calibration", "SHAP LIME readmission."

Inclusion criteria:

- Empirical models for hospital readmission (30-day or similar)
- Papers benchmarking ML methods or describing the UCI diabetes dataset
- Papers addressing evaluation/calibration/interpretability or imbalance handling

Exclusion Criteria

- Purely theoretical ML papers without clinical data
- Papers focused on other outcomes (mortality only)
- Studies older than 15 years (unless it is seminal)

Table 1: Summary of Key Machine Learning and Statistical Models for Diabetes Readmission Prediction

Theme	Author	Dataset	Method	Strength	Weakness
Classical ML baselines (Logistic regression, decision trees, Random Forest)	Kansagara *et a*l. (2011)[11]	Literature review	Systematic review of statistical models	Comprehensive overview; sets clinical expectations for model performance	Older (pre-widespread ML) and limited in evaluating modern ensemble methods.
	Strack *et al*. (2014)[16]	UCI Diabetes 130-US Hospitals (1999–2008)	Logistic regression, baseline predictors	Large, public dataset widely used as a benchmark	Historic (1999–2008), missingness and coding idiosyncrasies require careful preprocessing
Deep learning & temporal models	Hai *et al*. (2023)[14]	Diabetes readmission dataset	Deep learning (LSTM, comparisons)	Shows potential gains from sequence models (LSTM) on longitudinal EHR	Gains are sometimes modest relative to well-tuned classical models, and interpretability suffers
	Tang *et al*. (2023)[15]	Large multimodal hospital dataset	Multimodal Spatiotemporal Graph Neural Network (MM-STGNN)	Models patient similarity and temporal patterns effectively	Complex, data-hungry, and harder to reproduce with tabular public datasets
Evaluation strategies/class imbalance/calibration	Artetxe *et al*. (2018)[12]	Literature review	Survey of ML (RF, SVM, ANN, etc.)	Broad benchmarking and attention to evaluation best practices	Rapidly evolving field (post-2018 DL advances not covered)
Interpretability & explainability	Hu *et al*. (2022)[13]	Hospital EHR data	Explainable ML (SHAP, LIME)	Shows how to move beyond black-box outputs to clinician-meaningful explanations.	Local explanations may vary across instances; needs careful presentation for stakeholders
	Saranya *et al*. (2023)[17]	Various healthcare datasets	Systematic review of XAI approaches	Strong guidance on combining methods and evaluating explanation reliability	Focuses heavily on imaging; applications to tabular readmission data need adaptation
Recent reproducible/benchm	Alnomasy *et al*.	Meta-analysis (multiple	Meta-benchmarking of ML	Aggregates across model types and	Heterogeneity in included studies

arked pipelines and empirical studies	(2025)[18]	datasets)	models	prediction windows to provide empirical context	complicates direct inference

Bibliography

- Kansagara *et al.*, 2011: Systematic review of readmission risk models
  Applicability: For background and to justify rigorous evaluation metrics
- Strack *et al*., 2014: UCI diabetes dataset / HbA1c analysis
  Applicability: Primary dataset provenance; informs feature selection
- Hai *et al*., 2023: Deep learning vs classical models (LSTM)
  Applicability: To assess whether temporal/deep models are warranted
- Tang *et al*., 2023: MM-STGNN multimodal GNN
  Applicability: Reference for advanced methods and future work
- Artetxe et al., 2018: Review of ML for readmission
  Applicability: Guides benchmarking choices and evaluation protocols
- Hu *et al*., 2022: Explainable ML (SHAP/LIME) for readmission
  Applicability: Template for interpretability analyses
- Saranya *et al*., 2023: XAI systematic review
  Applicability: Provides best-practice for explanation validation
- Alnomasy *et al*., 2025: Meta-benchmarking of ML models for readmission **Applicability:** Contextualizes expected performance ranges

Differentiation Strategy of the Proposed Project

This proposed research intends to use a machine learning approach to predict readmission and emphasize on a reproducible, end-to-end pipeline for the UCI diabetes dataset. The process will involve cleaning, imputation, encoding, stratified splits, resampling experiments, and calibration reporting (AUC, precision/recall and calibration curves). Source papers often omit full preprocessing details but this will be explicit in the study.

Also, this study will focus on interpretable baselines (for example, logistic regression and random forest) with combined XAI (global feature importances and SHAP local explanations) and visualizations (Power BI + Python). This answer calls for interpretability in clinical settings. In addition, this research will use systematic comparison of resampling (SMOTE) vs cost-sensitive vs thresholding for imbalance, with transparent validation to avoid optimistic bias.

Problem Statement

Hospital readmissions are a persistent problem for healthcare systems and contribute to high costs and poor patient outcomes. Diabetes mellitus, in particular, is associated with frequent readmissions due to the complexity of managing comorbidities, medications, and follow-up care [1, 9]. Predictive modeling offers an opportunity to identify high-risk patients before discharge, but existing approaches often suffer from poor generalizability, difficulties with class imbalance, and insufficient interpretability [11, 12]. This reduces their clinical value and limits deployment in real-world hospital settings.

Given a patient encounter record $x \in X$ containing demographic, diagnostic and utilisation features, the task is to predict whether the patient will be readmitted within 30 days, represented as a binary label $y \in \{0,1\}$. The objective is to design and benchmark models $f: X \to y$ that maximize predictive performance (AUC, precision, recall, F1-score) on imbalanced data, while providing interpretable feature-level explanations.

Research Questions and Hypotheses

Research Questions (RQs):

RQ1: Can classical machine learning models such as logistic regression and random forest achieve reliable predictive accuracy for 30-day hospital readmissions in patients with diabetes?

RQ2: To what extent does feature selection, particularly variables such as length of stay, prior admission history, and diagnosis codes, improve model performance compared with demographic-only predictors?

RQ3: Does addressing class imbalance (e.g., resampling techniques or cost-sensitive learning) significantly improve recall for predicting readmitted patients without compromising overall discrimination?

RQ4: How can visualization methods enhance the interpretability and clinical utility of predictive models for readmissions?

Hypotheses (Hs):

H1: Random forest classifiers will outperform logistic regression in terms of discrimination (AUC, F1-score) on the diabetes readmission dataset.

H2: Incorporating utilisation-related features (for example, prior admissions and length of stay) will significantly improve prediction accuracy compared to models trained on demographic variables alone.

H3: Class imbalance correction methods will improve recall of readmitted cases while maintaining acceptable calibration.

Contributions

Contribution 1: Development of a reproducible preprocessing pipeline for hospital readmission prediction, including handling of missing values, outliers, and standardised encoding of diagnosis codes.
Contribution 2: Benchmarking of logistic regression and random forest classifiers on the UCI diabetes readmission dataset, with transparent reporting of performance metrics (AUC, precision, recall, F1-score, calibration).
Contribution 3: Comparative analysis of feature importance to identify clinically relevant predictors of readmission, with emphasis on demographic, diagnostic, and utilisation-related factors.
Contribution 4: Visualisation of results through Python libraries and Power BI dashboards, enabling interpretable insights for clinical and operational stakeholders.
Contribution 5: Documentation of methodological trade-offs (simplicity vs. performance, interpretability vs. complexity) and provision of guidelines for future applications of predictive modeling in healthcare readmission research.

Methodology

This study adopts an experimental research design to empirically evaluate predictive models for hospital readmissions. The approach emphasizes comparative benchmarking across multiple methodological families: (i) baseline methods, including rule-based heuristics and logistic regression; (ii) classical machine learning models, such as random forests and gradient boosting; and (iii) advanced architectures, including deep learning models (RNNs, CNNs) and transformer-based approaches where applicable. Ablation studies will be conducted to systematically assess the contribution of different feature sets, preprocessing choices, and resampling strategies to predictive performance.

Data: The primary dataset is the UCI Diabetes 130-US hospitals readmission dataset (1999–2008), sourced from the UCI Machine Learning Repository [9].

- **Size:** >100,000 patient encounters.
- **Classes:** Binary outcome (readmitted within 30 days vs. not readmitted).
- **License:** Open access for research and educational use.
- **Known biases:** Over-representation of certain age groups and ethnicities; limited to U.S. hospitals; the data may not reflect current clinical practices.

Inclusion criteria: Patients aged 18 and above
Exclusion criteria: Records with missing outcome labels, pediatric cases, or encounters flagged as data entry errors.

Ethical and legal considerations: The dataset is de-identified in compliance with HIPAA standards. No personally identifiable information (PII) is included, and all analysis complies with the UCI dataset license. If extended to other datasets, explicit consent, ethical approvals, and anonymization protocols would be required.

Preprocessing and Feature Engineering

The preprocessing pipeline includes:

- **Data cleaning:** Handling missing values through imputation (median for numerical features, mode for categorical). Outliers in length of stay and lab values flagged and truncated.
- **Encoding:** Categorical variables (e.g., diagnosis codes, admission type) transformed via one-hot encoding or grouped by ICD-9 categories.
- **Normalization:** Numerical features scaled using z-score normalization to reduce bias from magnitude differences.
- **Class imbalance handling:** Synthetic Minority Oversampling Technique (SMOTE) and cost-sensitive weighting evaluated.
- **Feature selection:** Correlation-based filtering and recursive feature elimination to reduce dimensionality.

Function Readmission_Preprocessing(Raw_Data):
1. Handle_Missing_Values(Raw_Data, Strategy='median/mode')
2. Clean_Outliers(Raw_Data, Truncate_at_Percentile=99)
3. Encode_Diagnosis_Codes(Raw_Data, Method='ICD-9 Grouping')
4. Encode_Categorical(Raw_Data, Method='OneHotEncoding')
5. Normalize_Numerical(Raw_Data, Method='Z-Score')
6. Split_Data(Raw_Data, Target, Ratio=70/15/15, Stratify=True)
7. Apply_Imbalance_Correction(Train_Set, Method='SMOTE')
8. RETURN Preprocessed_Sets

Model/System Design

Candidate Models:

- **Baseline:** Rule-based thresholding (e.g., flagging based on prior readmission count), Logistic Regression, Support Vector Machines (SVM).
- **Classical Ensemble:** Random Forests, Gradient Boosting (XGBoost).
- **Deep Learning:** Recurrent Neural Networks (RNNs) for sequential admission data, Convolutional Neural Networks (CNNs) for structured feature maps.
- **Pretrained Transformers:** Exploration of transformer encoders (e.g., BERT-style tabular adaptations) for contextual feature embeddings.
- **Final System:** Potential stacking ensemble combining logistic regression (interpretability) and random forests/XGBoost (performance).

Architecture details:

- Hidden layers tuned between 2–4 with 64–256 neurons
- Activation functions: ReLU for deep models, sigmoid/softmax for final output
- Regularization: Dropout (0.2–0.5), L2 weight decay
- Optimizers: Adam or SGD with learning rate scheduling
- Early stopping criteria: No validation improvement after 10 epochs
- Reproducibility: Random seeds fixed across NumPy, PyTorch, and TensorFlow

Validation & Experimental Protocol

This study will adopt a train/validation/test split of 70/15/15 to ensure stratification by readmission status to preserve class distribution. For robustness, five-fold stratified cross-validation will be performed during model development with repeated runs to mitigate variance due to random seed selection. When applicable, cross-dataset evaluation will be conducted by training on the UCI diabetes dataset and validating on alternative publicly available hospital readmission datasets to test external generalizability.

Hyperparameter tuning will employ a Bayesian optimization framework with well-defined search spaces for each algorithm. For logistic regression, tuning will focus on penalty type and regularization strength; for Random Forest and XGBoost, search spaces will include depth,

learning rate, and number of estimators; for neural networks, architectural depth, hidden units, dropout rates, and learning rate schedules will be tuned. A maximum of 100 optimization trials will be allocated per model to balance computational feasibility with search space coverage.

Baselines will consist of logistic regression and random forest, reflecting standard practice in healthcare prediction tasks. Ablation studies will systematically disable key components such as (i) class imbalance correction, (ii) feature engineering, and (iii) ensemble averaging. These comparisons will isolate the contribution of each methodological component to overall performance.

Evaluation Metrics

Evaluation will be driven by the class-imbalance challenge inherent in hospital readmission datasets. For classification performance, Accuracy, Precision, Recall, F1-score (micro and macro), ROC-AUC, and PR-AUC will be reported. Given the imbalance, PR-AUC and F1 will be emphasized as primary metrics. Confusion matrices will be generated to provide interpretability for hospital decision-making.

In addition, resource-centric metrics will be evaluated, including model inference latency (in milliseconds), model size (MB), and computational cost (floating-point operations, FLOPs). These criteria reflect the real-world requirement for efficient deployment in clinical environments.

Statistical testing will compare model performance using paired t-tests or Wilcoxon signed-rank tests, depending on normality assumptions, with Bonferroni correction for multiple hypotheses. Effect sizes and 95% confidence intervals will be reported to ensure clinical as well as statistical relevance.

For power considerations, a post-hoc power analysis will be performed to validate that the sample size from the UCI dataset provides sufficient sensitivity to detect performance differences at $\alpha = 0.05$ with 80% power.

Reproducibility & Code/Data Release

Reproducibility is critical in healthcare machine learning. All code will be released in a public GitHub repository under an open-source license, with detailed documentation. The repository will include:

- `README.md` describing installation and usage
- Dependency tracking via `requirements.txt` and `environment.yml`
- A `Dockerfile` for containerized execution across systems
- `run.sh` scripts reproducing core experiments end-to-end

The UCI Diabetes Readmission dataset is publicly available, and links will be provided. For components where data cannot be redistributed (e.g., derived subsets), scripts to obtain and preprocess the data will be shared. A synthetic data generator will be provided for

demonstration purposes, ensuring that code functionality can be verified without access to sensitive data.

To guarantee replicability, all random seeds (Python, NumPy, PyTorch) will be fixed, and framework/library versions will be pinned. GPU hardware specifications used for training (e.g., NVIDIA Tesla V100 or equivalent) will be reported, along with average runtime per model.

Implementation Plan & Repository Structure

To implement this project, structures such as data engineering, model experimentation, evaluation, and documentation will be implemented in three stages.

Data cleaning: This will involve importing and cleaning the UCI diabetes data set. Also, conduct exploratory analysis using Python and then implement the pipeline.

Model Development and Validation: Baseline machine learning models (Logistic Regression, Random Forest, XGBoost) will be implemented. Then, a five-fold stratified cross-validation with Bayesian hyperparameter tuning will be performed. This study will evaluate models using F1-score, ROC-AUC, and PR-AUC metrics and apply statistical significance testing.

Reporting and Visualization: This study will utilize Power BI dashboards and Python to interpret the results, summaries, and learning curves. This study will be finalized with structured documentation and reproducible scripts. Milestones will be tracked using GitHub Projects and version control commits. All experiments will be tagged with model configuration details and evaluation summaries to ensure transparency and traceability.

References

1. J. M. McIlvennan, L. Eapen, and L. Allen, “Hospital Readmissions Reduction Program,” *Circulation*, vol. 131, no. 20, pp. 1796–1803, 2015.
2. S. R. Jencks, M. V. Williams, and E. A. Coleman, “Rehospitalizations among patients in the Medicare fee-for-service program,” *N. Engl. J. Med.*, vol. 360, no. 14, pp. 1418–1428, 2009.
3. F. Foroutan et al., “Global comparison of readmission rates for patients with heart failure,” *J. Am. Coll. Cardiol.*, vol. 82, no. 5, pp. 430-444, 2023.
4. K. Dharmarajan, Y. Wang, Z. Lin, S. T. Normand, J. S. Ross, L. I. Horwitz, N. R. Desai, L. G. Suter, E. E. Drye, S. M. Bernheim, and H. M. Krumholz, “Association of changing hospital readmission rates with mortality rates after hospital discharge,” *JAMA*, vol. 318, no. 3, pp. 270–278, Jul. 2017, doi: 10.1001/jama.2017.8444.
5. J. S. Rachoin, K. Hunter, J. Varallo, and E. Cerceo, "Impact of time from discharge to readmission on outcomes: an observational study from the US National Readmission Database," *BMJ Open*, vol. 14, no. 8, pp. e085466, Aug. 2024, doi: 10.1136/bmjopen-2024-085466.
6. J. Andreasen, R. J. J. Gobbens, H. H. Eriksen, and K. Overvad, "Health-related quality of life at hospital discharge as a predictor for 6-month unplanned readmission and all-cause mortality of acutely admitted older medical patients," *Qual. Life Res.*, vol. 28, no. 11, pp. 3015–3024, Nov. 2019, doi: 10.1007/s11136-019-02259-w.
7. T. Leosdottir et al., “Self-reported health-related quality of life predicts five-year mortality and hospital readmission in patients with ischaemic heart disease,” *Eur. J. Prev. Cardiol.*, vol. 21, no. 3, pp. 389–396, 2014.
8. D. J. Rubin and A. A. Shah, "Predicting and Preventing Acute Care Re-Utilization by Patients with Diabetes," *Curr. Diab. Rep.*, vol. 21, no. 9, p. 34, 2021. doi: 10.1007/s11892-021-01402-7.
9. J. Clore, K. Cios, J. DeShazo, and B. Strack, “Diabetes 130-US Hospitals for Years 1999-2008,” *UCI Machine Learning Repository*, 2014. Accessed: Oct. 10, 2025. [Online]. Available: https://doi.org/10.24432/C5230J.
10. B. Strack, J. P. DeShazo, C. Gennings, J. L. Olmo, S. Ventura, K. J. Cios, and J. N. Clore, “Impact of HbA1c measurement on hospital readmission rates: analysis of 70,000 clinical database patient records,” *Biomed. Res. Int.*, vol. 2014, pp. 781670, Apr. 2014, doi: 10.1155/2014/781670.

11. D. Kansagara, H. Englander, A. Salanitro, D. Kagen, C. Theobald, M. Freeman, and S. Kripalani, “Risk prediction models for hospital readmission: a systematic review,” *JAMA*, vol. 306, no. 15, pp. 1688–1698, 2011.
12. A. Artetxe, A. Beristain, and M. Graña, “Predictive models for hospital readmission risk: A systematic review of methods,” *Comput. Methods Programs Biomed*., vol. 164, pp. 49–64, Oct. 2018, doi: 10.1016/j.cmpb.2018.06.006.
13. C. Hu, L. Li, Y. Li, F. Wang, B. Hu, and Z. Peng, "Explainable Machine-Learning Model for Prediction of In-Hospital Mortality in Septic Patients Requiring Intensive Care Unit Readmission," *Infect. Dis. Ther*., vol. 11, no. 4, pp. 1695–1713, Aug. 2022, doi: 10.1007/s40121-022-00671-3.
14. A. Hai et al., "Deep Learning vs Traditional Models for Predicting Hospital Readmission among Patients with Diabetes," in *AMIA Annu. Symp. Proc*., 2022, pp. 512–521.
15. S. Tang et al., “Predicting 30-day all-cause hospital readmission using a multimodal spatiotemporal GNN (MM-STGNN),” 2023.
16. B. Strack et al., ‘Impact of HbA1c Measurement on Hospital Readmission Rates: Analysis of 70,000 Clinical Database Patient Records’, BioMed Research International, vol. 2014, pp. 1–11, 2014, doi: 10.1155/2014/781670.
17. S. A. and S. R., ‘A systematic review of Explainable Artificial Intelligence models and applications: Recent developments and future trends’, Decision Analytics Journal, vol. 7, p. 100230, Jun. 2023, doi: 10.1016/j.dajour.2023.100230.
18. N. Alnomasy et al., “Predictive performance of machine learning models for hospital readmission: a meta-analysis,” 2025.