Understanding the AI Development Workflow: Predicting Patient Readmission Risk

Prepared by: Irene Ouko
Course: AI for Software Engineering (PLP Academy)
Email: ireneouko45@gmail.com
GitHub Repository: https://github.com/Irene-ops-ai/readmission_ai_repo.git
Date: November 2025

Abstract

This report explores the AI Development Workflow through a real-world healthcare case study. The project focuses on predicting patient readmission risk using a machine learning approach, from problem definition to deployment and ethical considerations. The workflow demonstrates the integration of data science and software engineering principles to deliver an impactful and ethical AI solution.

Part 1: Short Answer Questions (30 points)

1. Problem Definition (6 points)

Problem:
Predicting patient readmission risk within 30 days of hospital discharge.

Objectives:

- Identify patients at high risk of readmission early.
- Optimize hospital resource allocation and reduce costs.
- Improve overall patient care and outcomes.

Stakeholders:

- Hospital administrators and medical staff.
- Patients and caregivers.

KPI:
Area Under the Curve (AUC) – measures model performance and discrimination ability.

2. Data Collection & Preprocessing (8 points)

Data Sources:

- Electronic Health Records (EHR) containing patient history and visit data.
- Demographic and socioeconomic datasets from hospital surveys.

Potential Bias:
Data imbalance across age groups or socioeconomic backgrounds could bias predictions, leading to unfair treatment of underrepresented groups.

Preprocessing Steps:

1. Handle missing data using median imputation.
2. Normalize continuous features like age and blood pressure.
3. Encode categorical variables such as gender and diagnosis type.

3. Model Development (8 points)

Model Choice:
Gradient Boosting Classifier – chosen for its effectiveness with tabular healthcare data and ability to model non-linear relationships.

Data Split:
70% training, 15% validation, and 15% testing for proper tuning and unbiased performance evaluation.

Hyperparameters to Tune:

- **n_estimators:** Controls the number of boosting stages to balance learning speed and accuracy.
- **learning_rate:** Adjusts how much each tree contributes to the final prediction to avoid overfitting.

4. Evaluation & Deployment (8 points)

Evaluation Metrics:

- **Precision:** Measures the accuracy of positive predictions (patients flagged as at risk).
- **Recall:** Measures how effectively true readmissions are identified.

Concept Drift:
Occurs when patient demographics or treatment practices change over time. To manage this, monitor prediction performance regularly and retrain models with recent data.

Deployment Challenge:
Scalability — integrating the model with large EHR systems can cause performance lags due to the high data volume.

Part 2: Case Study Application (40 points)

Problem Scope (5 points)

The hospital's objective is to predict the likelihood of patient readmission within 30 days to improve healthcare quality and reduce costs.

Objectives:

- Enable preventive care by identifying high-risk patients.
- Reduce hospital penalties due to frequent readmissions.

Stakeholders:

- Doctors, nurses, and hospital management.
- Patients and insurance providers.

Data Strategy (10 points)

Proposed Data Sources:

- Electronic Health Records (EHRs): Admission, diagnosis, and discharge details.
- Demographic data: Age, gender, income level, and geographic location.

Ethical Concerns:

1. **Patient Privacy:** Sensitive health data must be encrypted and anonymized.
2. **Data Bias:** Overrepresentation of specific groups may cause discriminatory outcomes.

Preprocessing Pipeline (Text-Style):

Data Collection

↓

Data Cleaning

↓

Normalization

↓

Feature Engineering

↓

Train/Test Split

Feature Engineering:

- Calculate length of hospital stay.
- Encode diagnosis codes.
- Aggregate prior readmission counts.

Model Development (10 points)

Model Selected: Gradient Boosting Classifier
Justification: Robust for small-to-medium structured datasets, interpretable, and high-performing.

Hypothetical Confusion Matrix:

	Predicted Yes	**Predicted No**
Actual Yes	424	86
Actual No	136	353

Precision: 0.7571
Recall: 0.8314
F1-Score: 0.7925
AUC: 0.8375

These metrics indicate a strong balance between precision and recall, making the model reliable for hospital deployment.

Deployment (10 points)

Integration Steps:

1. Export model as a .joblib file.
2. Build an API using Flask to expose predictions.
3. Connect to the hospital's EHR system.
4. Set up monitoring and retraining schedules.

Compliance Measures:

- Follow HIPAA guidelines: encryption, restricted access, and anonymization.
- Maintain audit logs for all model decisions.
- Implement bias detection reports during deployment.

Optimization (5 points)

To reduce overfitting, apply **early stopping** or **cross-validation** to prevent the model from learning noise in training data.

Part 3: Critical Thinking (20 points)

Ethics & Bias (10 points)

Biased data can lead to unfair patient prioritization and misdiagnosis. For example, if training data underrepresents rural patients, the model might underpredict readmissions for them.

Mitigation Strategy:

- Use stratified sampling.
- Perform fairness checks using demographic parity metrics.
- Include domain experts to review model outputs.

Trade-offs (10 points)

- **Interpretability vs. Accuracy:** Highly interpretable models (like Decision Trees) are easier to explain but may underperform compared to complex models like Neural Networks.
- **Computational Resources:** Limited computing power may force the use of simpler models (e.g., Logistic Regression) instead of deep learning architectures.

Part 4: Reflection & Workflow Diagram (10 points)

Reflection (5 points)

The most challenging stage was ensuring data quality and mitigating bias in healthcare data. With more time, I would implement automated bias detection tools, build explainability dashboards, and integrate SHAP visualizations for transparency.

Workflow Diagram (Text-Style) (5 points)

Problem Definition

↓

Data Collection & Preprocessing

↓

Model Development & Training

↓

Evaluation & Optimization

↓

Deployment & Monitoring

References

- **scikit-learn documentation: https://scikit-learn.org/**
- **WHO Health Data Ethics Framework (2023)**
- **PLP Academy AI for Software Engineering Course Materials (2025)**