Part 1: Short Answer Questions

1. Problem Definition (6 points)

- **Problem:** Predicting employee turnover in a medium-sized company.

- **Objectives:**

    1. Identify employees at high risk of leaving within the next 6 months.

    2. Reduce turnover rate by enabling early intervention strategies.

    3. Improve retention policies based on data-driven insights.

- **Stakeholders:**

    1. Human Resources (HR) managers.

    2. Employees and team leaders.

- **Key Performance Indicator (KPI):**
  Turnover prediction accuracy (percentage of correctly predicted employee departures).

2. Data Collection & Preprocessing (8 points)

- **Data Sources:**

    1. Internal HR databases containing employee demographics, job roles, performance reviews, and exit interviews.

    2. Employee engagement survey results.

- **Potential Bias:**
  Historical turnover data may reflect past managerial biases or specific department issues, causing the model to unfairly target or ignore certain groups.

- **Preprocessing Steps:**

    1. Handling missing data by imputing employee survey responses with the median or using domain-informed defaults.

    2. Encoding categorical variables such as department and job title using one-hot encoding.

    3. Normalizing numeric features like salary and tenure to a common scale for model stability.

3. Model Development (8 points)

- **Model Chosen:** Random Forest
  Justification: Robust to overfitting, handles mixed data types well, provides feature importance for interpretability.

- **Data Splitting:**
  Split the dataset into 70% training, 15% validation, and 15% test sets to train the model, tune hyperparameters, and assess generalization.

- **Hyperparameters to Tune:**

  1. Number of trees, to balance bias and variance.

  2. Maximum tree depth, to control model complexity and prevent overfitting.

4. Evaluation & Deployment (8 points)

- **Evaluation Metrics:**

  1. Precision - important to minimize false positives (predicting turnover when it won't happen) and avoid unnecessary interventions.

  2. Recall - critical to identify as many true departures as possible for timely action.

- **Concept Drift:**
  Changes in employee behavior or company policies over time that cause the model's performance to degrade. To monitor it, implement periodic model evaluations and retrain with updated data.

- **Technical Challenge during Deployment:**
  Ensuring scalability to handle real-time predictions with low latency as employee data grows and HR systems integrate continuously.

Part 2: Case Study Application

Problem Scope (5 points)

- **Problem:**
  The hospital aims to predict the risk of patient readmission within 30 days after discharge to enhance post-discharge care, minimize unnecessary return visits, and improve resource allocation.journals.plos

- **Objectives:**

  - Accurately identify patients most likely to be readmitted within 30 days.academic.oup

  - Enable targeted intervention to reduce readmissions and associated costs.academic.oup

  - Improve overall patient care quality by delivering post-discharge support to high-risk individuals.medinform.jmir

- **Stakeholders:**

  - Hospital management and administrators.

  - Frontline clinicians, nurses, and discharge coordinators.

Data Strategy (10 points)

- **Data Sources:**

  - Electronic Health Records (EHRs) with patient demographics, diagnoses, procedures, length of stay, and comorbidity indices.journals.plos+1

  - Social determinants of health and insurance claims (if available), such as housing status, income, and previous hospitalizations.academic.oup

- **Ethical Concerns:**

  - Patient privacy and confidentiality, especially when handling sensitive medical and personal information.medinform.jmir

  - Risk of algorithmic bias affecting vulnerable groups (e.g., underrepresented minorities, elderly).journals.plos

- **Preprocessing Pipeline:**

  - Clean and standardize structured EHR data; handle missing values using statistical imputation or domain knowledge.

  - Engineer features such as Charlson Comorbidity Index, recent medication changes, and previous readmissions.academic.oup

  - Encode categorical variables (admission source, discharge disposition) and normalize continuous features for modeling.

Model Development (10 points)

- **Model Selection and Justification:**

  - Random Forest or an ensemble method (e.g., LightGBM) to handle complexity and class imbalance, as proven effective in recent hospital readmission studies.academic.oup

- **Confusion Matrix (Hypothetical Data):**

Actual / Predicted	Readmit	No Readmit
Readmit	30	15
No Readmit	10	45

- **Precision:** 30/30+10 =0.75

- **Recall:** 30/30+15=0.67

Deployment (10 points)

- **Integration Steps:**

    - Develop an API for the model and embed it into the hospital's EHR or discharge workflow.

    - Enable real-time risk scores for discharged patients at the point of care.medinform.jmir

    - Train staff on interpreting and acting upon the risk predictions in clinical decision-making.medinform.jmir

- **Regulatory Compliance:**

    - Ensure encryption and access controls for all patient data in accordance with HIPAA.

    - Conduct regular privacy audits and ensure transparent patient consent procedures for AI deployment.medinform.jmir

Optimization (5 points)

- **Method to Address Overfitting:**

    - Employ cross-validation (e.g., k-fold) and regularization (e.g., limiting tree depth in Random Forest or LGBM) to ensure the model generalizes well to unseen patient cases.journals.plos+1

Part 3: Critical Thinking

Ethics & Bias (10 points)

- Impact of Biased Training Data on Patient Outcomes:
  Biased training data can cause an AI model to predict readmission risk inaccurately for specific groups. For example, underrepresented populations—such as minorities or patients with rare conditions—may receive less accurate predictions, leading to poorer post-discharge follow-up, missed early interventions, and in some cases preventable complications or inequitable care. Biases introduced from historical healthcare inequalities, incomplete records, or sampling errors deepen health disparities.emjreviews+4

- Strategy to Mitigate Bias:
  Implement collection and use of large, diverse datasets that accurately represent all patient populations served. This includes targeted sampling to ensure minority and high-risk groups are sufficiently represented, combined with statistical debiasing methods (such as reweighting and fairness constraints) and routine bias audits with subgroup validation before deployment.nature+2

Trade-offs (10 points)

- Model Interpretability vs. Accuracy in Healthcare:
There is often a trade-off between accuracy and interpretability in AI models. Complex models such as deep neural networks might deliver higher predictive accuracy but are difficult for clinicians to understand and trust, making it challenging to justify decisions and trace errors or biases. Interpretable models (like logistic regression or decision trees) are more transparent and easier to validate, but may not capture intricate patterns in the data as well, potentially limiting performance.learn.hms.harvard+2

- Impact of Limited Computational Resources on Model Choice:
If the hospital has limited computational resources, it may be necessary to favor simpler models that require less processing power and memory. This often rules out intensive models (such as large neural networks or ensembles) and favors logistic regression, decision trees, or small-scale Random Forests, which can run efficiently on basic hardware—though potentially at the cost of accuracy or the ability to process very large feature sets.

Reflection & Workflow Diagram

Reflection (5 points)

The most challenging part of the AI development workflow is data collection and preprocessing. Hospital data is often incomplete, comes from varied sources, and may have missing or inconsistent records—addressing these issues is time-consuming and critical to model performance. With more time and resources, the approach could be improved by investing in better data integration systems, expanding data collection (including more patient-reported and social factors), and automating cleaning and feature engineering tasks for greater accuracy and scalability.pmc.ncbi.nlm.nih+2

Diagram (5 points)

Below is a flowchart visualizing the key stages of the AI Development Workflow. It includes Problem Definition, Data Collection & Preprocessing, Model Development, Evaluation, and Deployment & Monitoring, connected in a sequential flow

AI Development Workflow

Start

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Problem Definition

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Data Collection
& Preprocessing

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Model Development

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Evaluation

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Deployment
& Monitoring

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End