HCT Survival Equity System
From Analysis to Design

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General Objective

Build a Predictive System

Develop an advanced survival prediction model specifically for post-HCT outcomes.

Ensure Fairness

Guarantee precision and equity across diverse demographic groups in predictive models.

Apply Engineering Principles

Integrate systems engineering and fair machine learning methodologies.

System Analysis

Exploration & Identification

Deep examination of the medical context surrounding hematopoietic cell transplantation, including clinical protocols, treatment variations, and patient outcomes across different healthcare settings.

Variable Assessment

Comprehensive identification and evaluation of clinical, genetic, and demographic variables that influence survival trajectories post-transplant.

→ **Sensitivity Analysis**

Evaluate system responsiveness to variable changes.

→ **Chaos in Clinical Outcomes**

Investigate nonlinear dynamics affecting results.

→ **Stratified C-Index Measurement**

Apply fairness metrics across demographic groups.

Key Analysis Findings

High Complexity
Medical systems exhibit strong nonlinearity and interdependencies that traditional linear models cannot capture effectively.

Critical Variables Identified
Patient age, HLA compatibility, and comorbidities emerge as primary drivers of post-HCT survival outcomes.

Chaotic Effects
Small variations in initial conditions produce dramatically different clinical trajectories, requiring robust modeling approaches.

Model Requirements
Systems must be robust, interpretable, and fair—balancing accuracy with explainability and equity across populations.

Heat Map

HeatMap - Dataset
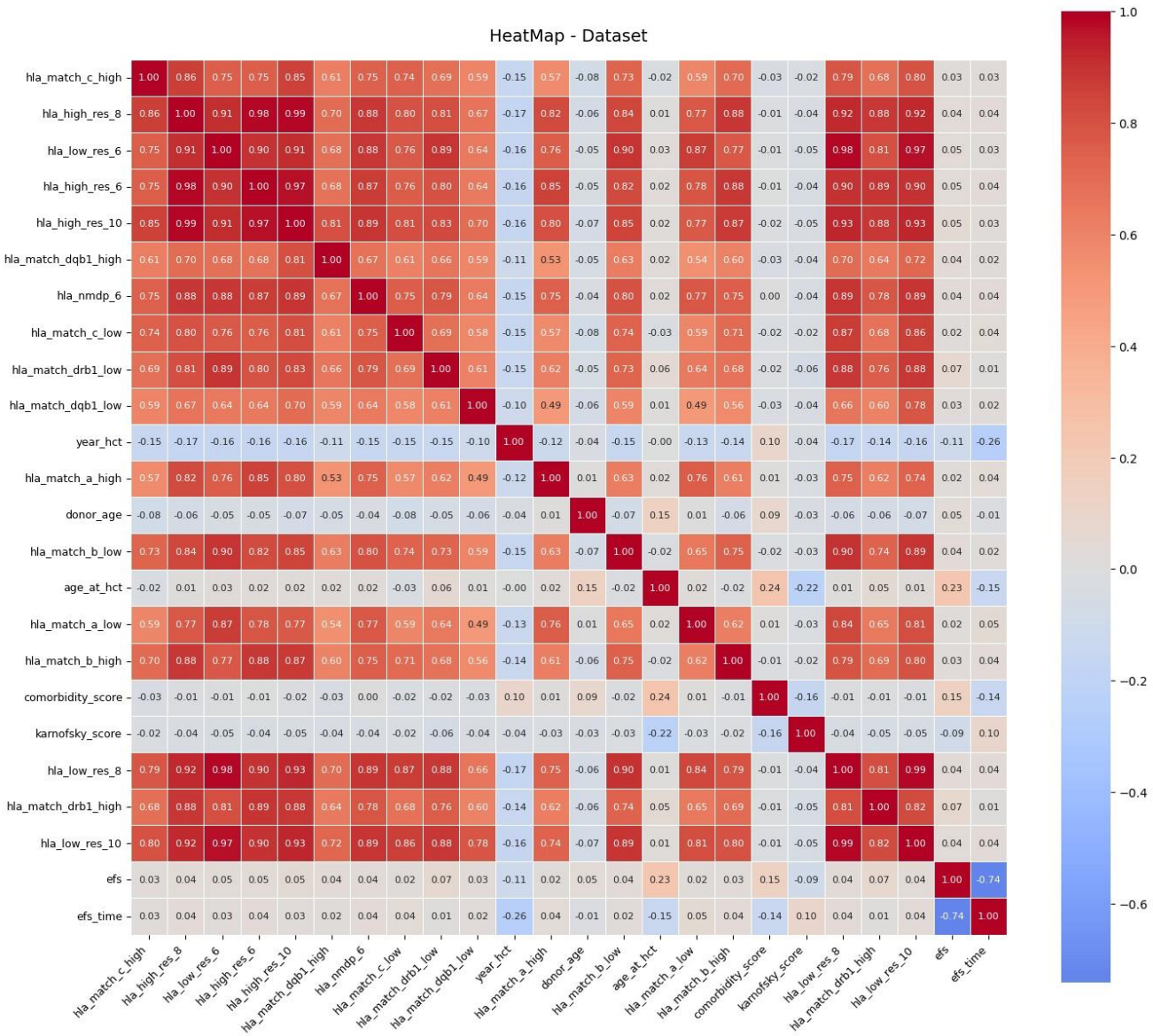
System Design Architecture

The proposed HCT Survival Equity System implements a modular, scalable architecture designed to handle medical complexity while maintaining fairness and transparency.

Data Pipeline

- Patient intake and clinical data ingestion
- Preprocessing and quality validation
- Feature extraction and transformation

Evaluation Framework

- Fairness calibration modules
- Uncertainty quantification
- Performance monitoring

Core System Modules

1 — **Data Preprocessing**
Standardization, cleaning, and validation of clinical datasets.

2 — **Equity Analysis**
Detection and quantification of demographic disparities.

3 — **Feature Selection**
Identification of clinically relevant predictive variables.

4 — **Predictive Core**
Machine learning models for survival outcome forecasting.

5 — **Fairness Calibration**
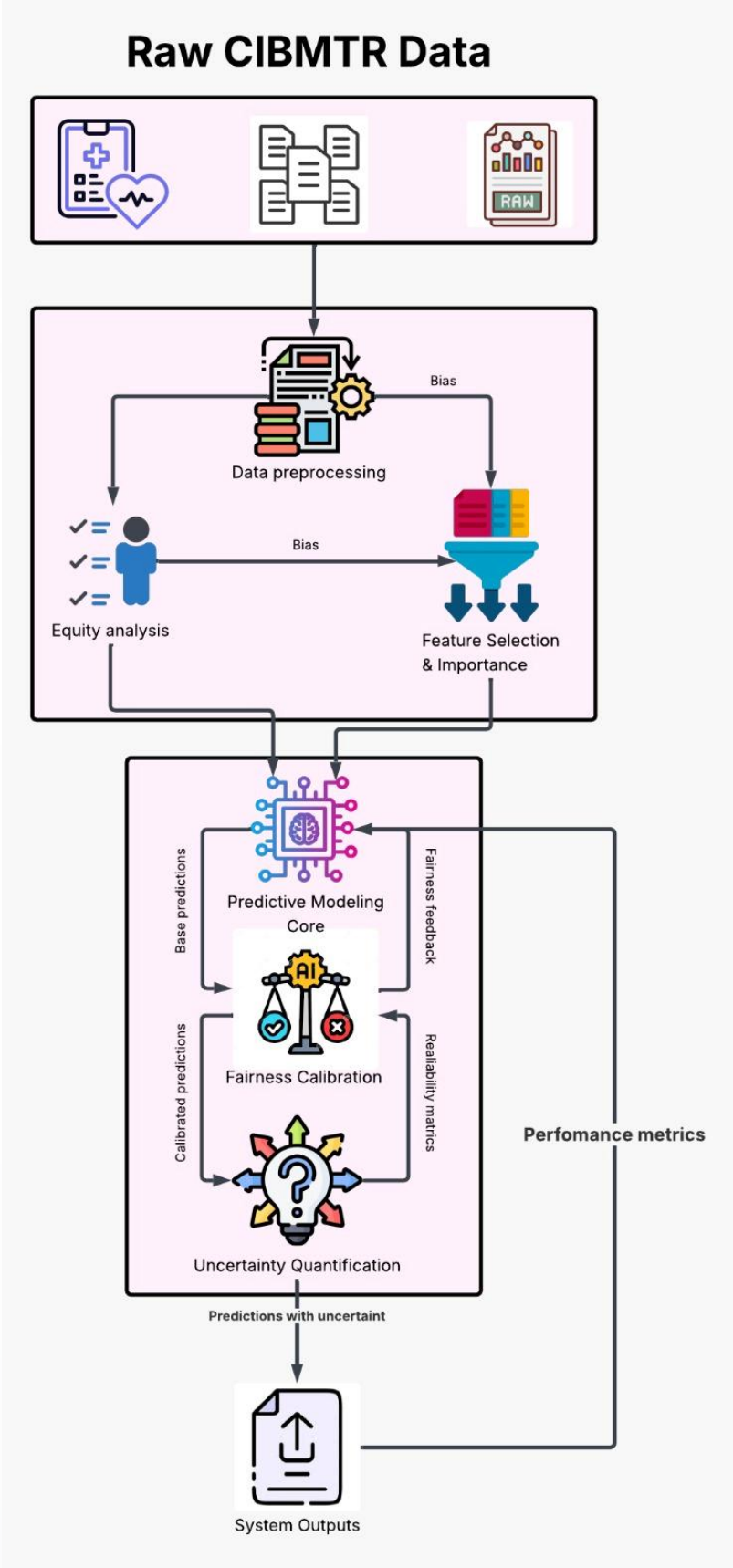Adjustment mechanisms to ensure equitable predictions.
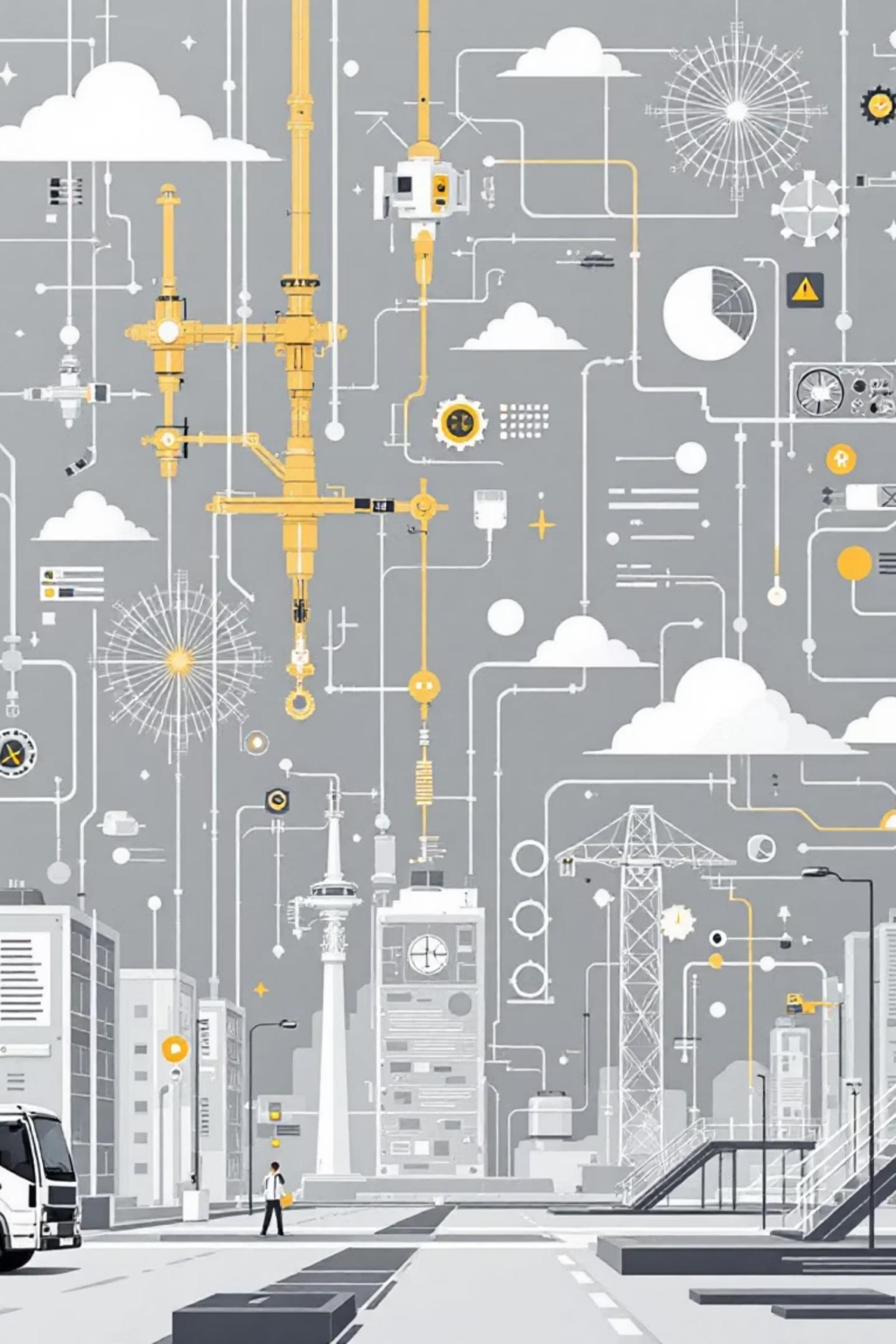
6 — **Uncertainty Quantification**
Confidence intervals and prediction reliability metrics.

7 — **Output & Metrics**
Results reporting and clinical decision support.

System Diagram

Raw CIBMTR Data

Data preprocessing

Bias

Equity analysis

Bias

Feature Selection & Importance

Base predictions

Fairness feedback

Predictive Modeling Core

Calibrated predictions

Reliability metrics

Fairness Calibration

Performance metrics

Uncertainty Quantification

Predictions with uncertain

System Outputs

Design Principles Applied

Modularity
Decoupled components enable independent updates and scalability across different healthcare systems.

Robustness
Designed to handle chaotic medical data while maintaining performance stability under real-world conditions.

Reproducibility
MLflow and Docker containerization ensure complete traceability and reproducible results across environments.

Balanced Trade-offs
Intentional optimization across precision, interpretability, and fairness metrics.

Expected Results

Demographic Stability

Models demonstrate consistent performance across all demographic groups without significant disparity.

Improved Stratification

Enhanced stratified C-Index metrics enable better patient risk segmentation and personalized treatment planning.

Clinical Confidence

Explainability features and fairness metrics increase clinician trust and adoption in real hospital settings.

Conclusion

This system represents a comprehensive engineering approach to resolving the fundamental tension between predictive accuracy and algorithmic fairness in clinical applications. By integrating rigorous technical analysis, medical sensitivity, and ethical principles, we advance the field toward more transparent and equitable clinical artificial intelligence.

Technical Excellence

Sophisticated modeling addresses medical complexity and nonlinearity effectively.

Ethical Foundation

Fairness-first design ensures equitable outcomes across diverse patient populations.

Clinical Impact

Stepping stone toward transparent, accountable, and equitable clinical decision support systems.