



# HCT Survival Equity System

## From Analysis to Design

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Sergio Nicolás Mendivelso Martínez • Sergio Leonardo Moreno Granado • Juan Manuel Otálora Hernández • Juan Diego Moreno Ramos

**Professor:** Ing. Carlos Andrés Sierra, M.Sc.

# 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.

### → 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.

## Variable Assessment

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



# 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.

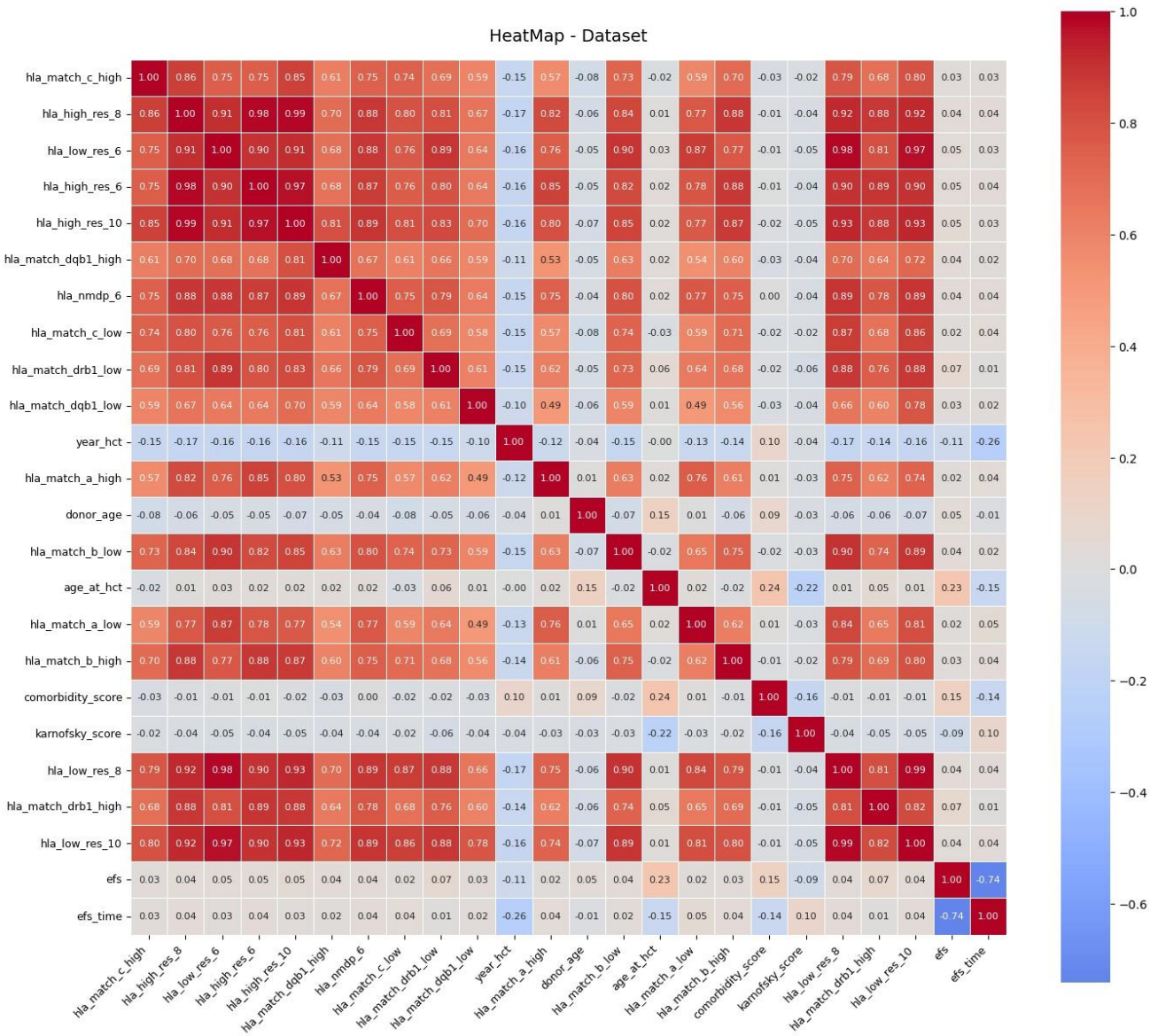
## Chaotic Effects

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



# 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

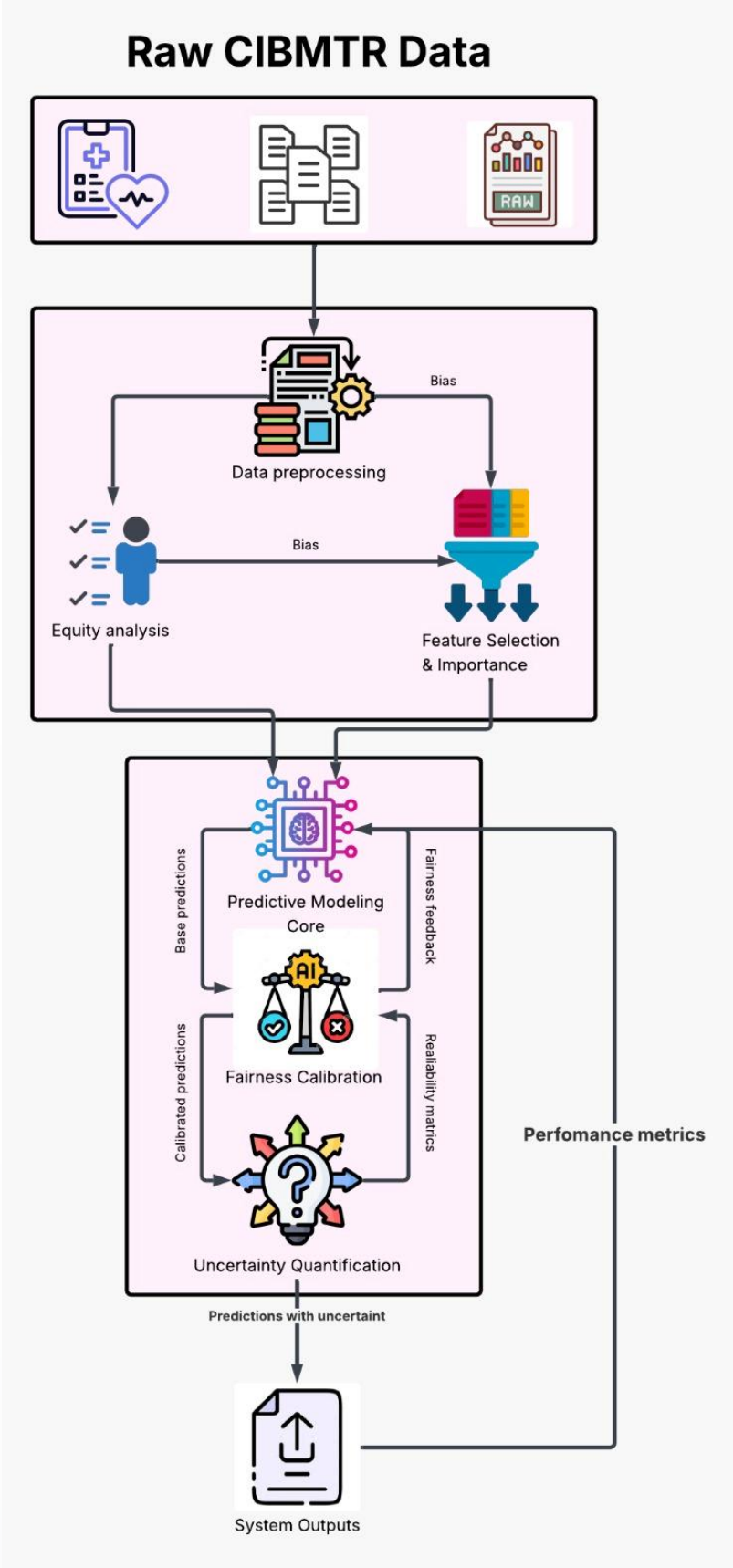
Uncertainty Quantification

Confidence intervals and prediction reliability metrics.
- 7

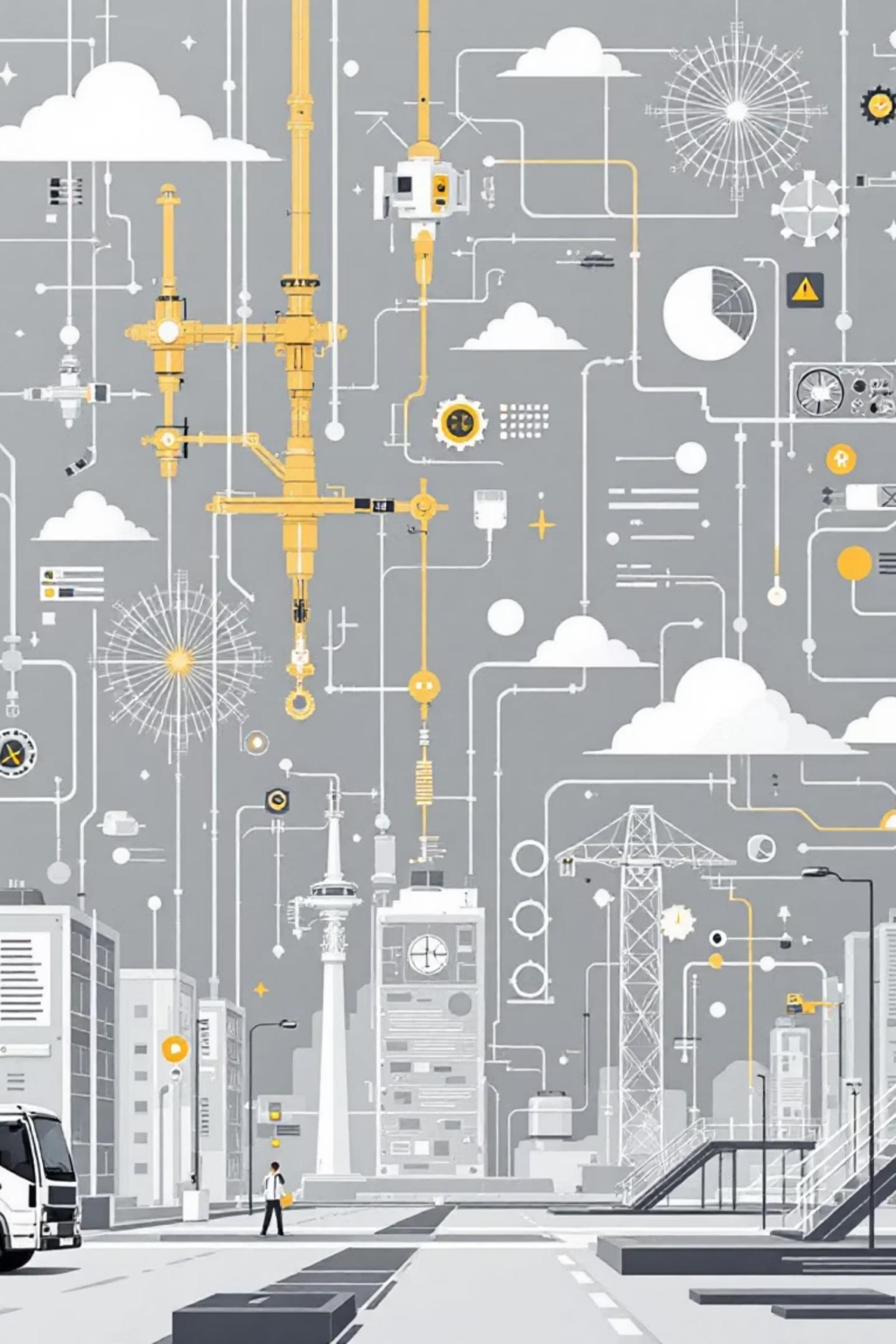
Output & Metrics

Results reporting and clinical decision support.

# System Diagram







## 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.

