# Reinforcement Learning for ICU Treatment Planning


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# Outline of Presentation

# Introduction

Doctors face tough decisions treating critically ill ICU patients with conditions like sepsis. Our AI system learns from ICU data to suggest better plans.
Using reinforcement learning, it builds a "digital twin" simulator to predict patient responses to treatments safely. This enables personalized, safer plans, supporting doctors and reducing risks/costs.

# Problem Statement and Objectives

**Problem:** Timely, personalized ICU treatment decisions are challenging due to dynamic conditions and fragmented data.

- High-stakes, dynamic trajectories.
- Incomplete EHR data.
- AI limited to historical mimicry.

**Objectives:**

- Build patient simulator from EHR data.
- Optimize RL policies safely.
- Provide clinical decision support.

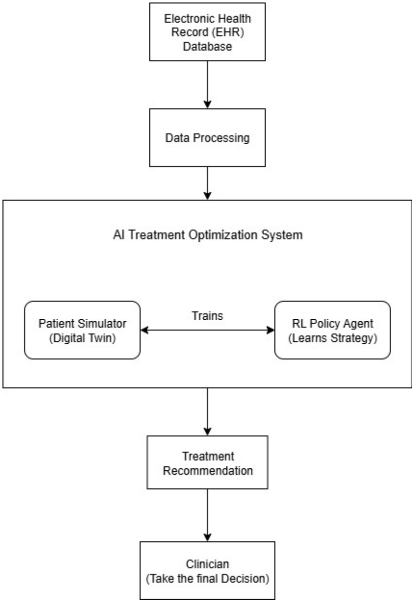
# Design Methodology and Algorithms

This approach is inspired by DreamerV3 and its clinical adaptation in medDreamer.

**Two sequential stages:**

1. Train the **Patient Simulator (World Model)** to predict patient outcomes.
2. Train the **RL Agent (Policy)** using the simulator to discover optimal treatments.

# Design Methodology and Algorithms: Diagrams



# Algorithm 1: Patient Simulator Training

**Goal:** Learn patient health dynamics from EHR data to create a reliable "digital twin".

**Steps:**

1. **Initialization:** Neural network parameters $\phi$
   - Encoder
   - Dynamics predictor
   - Prediction heads (reconstruction, rewards, outcomes)
2. **Training Loop:** For multiple epochs:
   1. Sample patient trajectories (observations, actions, rewards)
   2. Encode observations to latent states $s_t$
   3. Predict next latent state $s_{t+1}$ given $s_t$ and action $a_t$
   4. Reconstruct observations and predict rewards/outcomes
   5. Compute combined loss and update $\phi$ via backpropagation
3. **Output:** Trained Patient Simulator for realistic patient trajectories

# Algorithm 2: RL Agent Training

**Goal:** Train an optimal treatment policy safely in the simulated environment.

**Steps:**

1. Load trained Patient Simulator (weights frozen)
2. Initialize RL Agent: policy network $\theta$ (actor), value network $\psi$ (critic)

**Phase 1: Clinically Grounded Policy Initialization**

- Generate hybrid trajectories (real data + short simulator rollouts)
- Train actor and critic:
  - Critic: evaluate long-term state values
  - Actor: choose actions leading to high-value states

# Algorithm 2 (cont.): Strategic Refinement

**Phase 2: Strategic Refinement through Long-Horizon Imagination**

- Generate fully imagined trajectories using the Patient Simulator
- Fine-tune actor and critic to improve long-term planning

**Output:** Final trained **Optimal Treatment Policy** that recommends actions given a patient's current state

# Implementation Setup Framework

### 4.1 Hardware and Software Requirements

- **Hardware:** GPU-enabled system (RTX 4060/4090 or cloud GPUs).
- **Software:** Python, PyTorch, Ray RLlib, pandas, NumPy, scikit-learn.

### 4.2 Implementation Environment Setup

- Datasets: MIMIC-III, MIMIC-IV, eICU.
- Preprocessing: Clean and structure EHR data into trajectories.
- Frameworks: PyTorch for neural networks, Ray RLlib for RL.

# Implementation Results

**Phase-1 Results:** As this is Phase-1, full implementation is ongoing. Preliminary results include:

- Data preprocessing completed for MIMIC-IV demo.
- Patient Simulator training initiated (e.g., loss curves placeholder).
- Synthetic FHIR Bundle generation for data validation.

# Individual Contributions

- **Goureesh Chandra (TVE22CS069):** Algorithm design and data preprocessing.
- **Ivin Mathew Kurian (TVE22CS075):** Model implementation and simulator training, and notebook development.
- **Muhammed Farhan (TVE22CS094):** RL agent training and evaluation.
- **Rethin Francis (LTVE22CS149):** Data handling and FHIR mapping.

# Future Works (Project Phase-2)

- Complete full RL training and evaluation on larger datasets.
- Extend framework to other diseases (e.g., diabetes, cancer care).
- Incorporate multi-modal data (genomics, imaging).
- Clinician-in-the-loop evaluation and real-world validation.

# Conclusion

- We are developing a **model-based reinforcement learning framework** trained on ICU data for clinical decision support.
- By building a **digital twin of patients**, the system safely explores treatment strategies without direct risk to patients.
- The approach enables **personalized and safer treatment recommendations**, reducing unnecessary interventions and improving patient outcomes.
- Future work includes extending the model to more diverse patient populations and validating in real-world clinical settings.

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Thank You!