

Cover Page

Link to Presentation Slides and code: <https://github.com/roofishaikh/ethos-ares-exprement>

Link to Presentation video:

<https://utexas.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=f93d0005-0798-467c-9fca-b2cc017930ef>

ETHOS-ARES: Replication, Learning, and Extensions

Inspired by "Foundation Model of EMR for Adaptive Risk Estimation" (ETHOS-ARES)

Presenters:

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- **Dataset:** MIMIC-IV v2.2 **Project Repository:** github.com/roofishaikh/ethos-ares-exprement **Date:** April 2025

Introduction

What is our project about?

- Attempted to replicate ETHOS-ARES results: a cutting-edge dynamic risk prediction system built on patient health timelines (PHTs).
- Focused on learning tokenization of EHRs, transformer-based healthcare modeling, and potential future extensions.

Why is it important?

- ETHOS-ARES represents forefront research in healthcare AI, enabling zero-shot dynamic predictions.
- Zero-shot learning allows models to make accurate predictions without task-specific retraining, greatly enhancing scalability and deployment across diverse clinical tasks.
- Understanding and extending such systems can significantly impact patient outcomes and healthcare resource optimization in the U.S. health system.



Methods

Data Source:

- MIMIC-IV v2.2 dataset (PhysioNet)

Environment Setup:

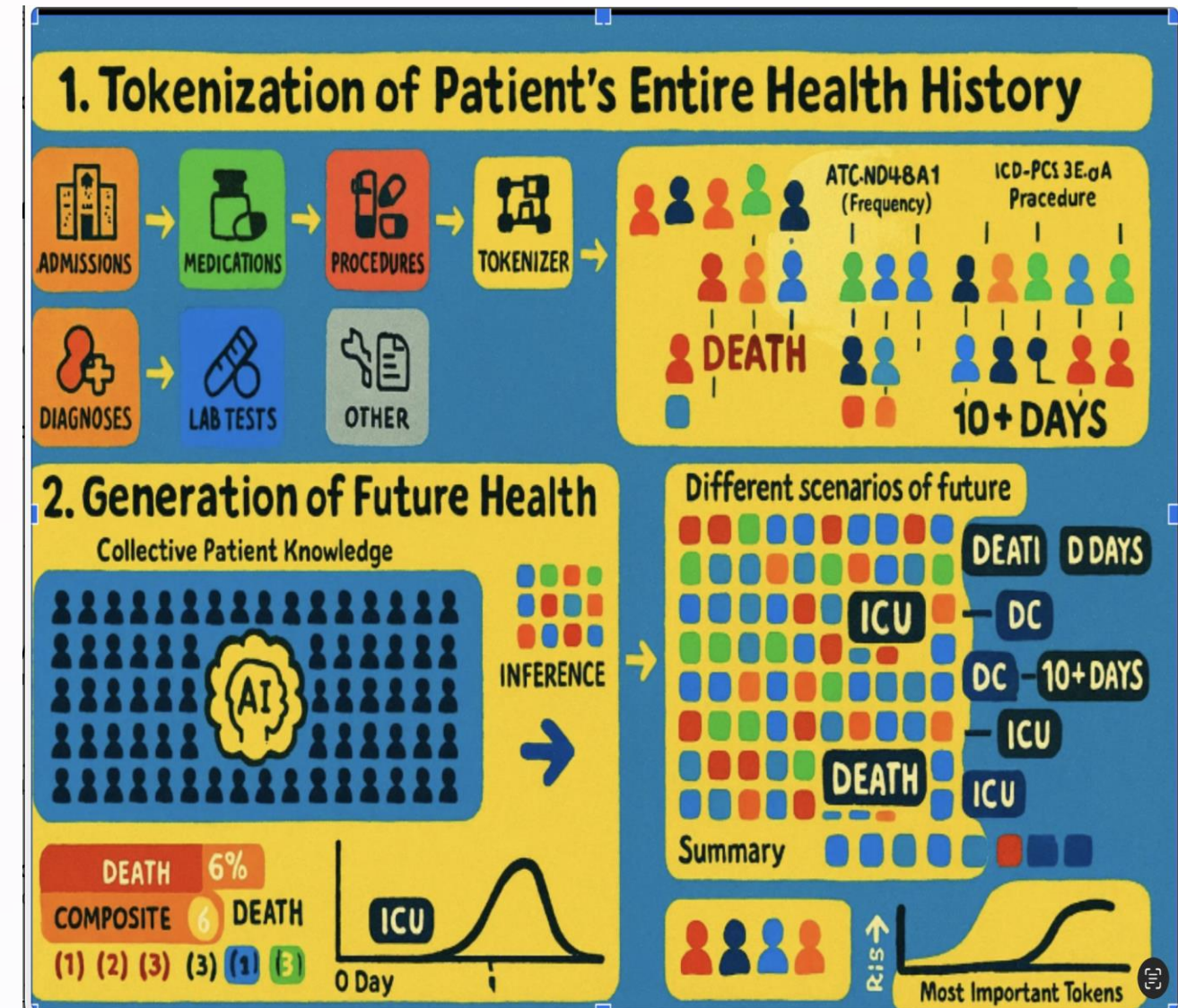
- Tokenization: CPU machine (12 vCPUs, 128GB RAM, 400GB NVMe Disk)
- Training and Inference: GPU machine (H100 GPU, 16 vCPUs, 256GB RAM)
- Cloud Provider: TensorDock

Workflow Followed:

- Followed ethos-ares repository workflow:
 - ethos_tokenize (tokenized raw MIMIC-IV to PHTs)
 - ethos_train (attempted model training)
 - ethos_infer (studied inference pipeline)
- Encountered cost and runtime constraints: partial training attempted, fallback to analyzing paper results

Repository Reference:

- github.com/roofishaikh/ethos-ares-exprement



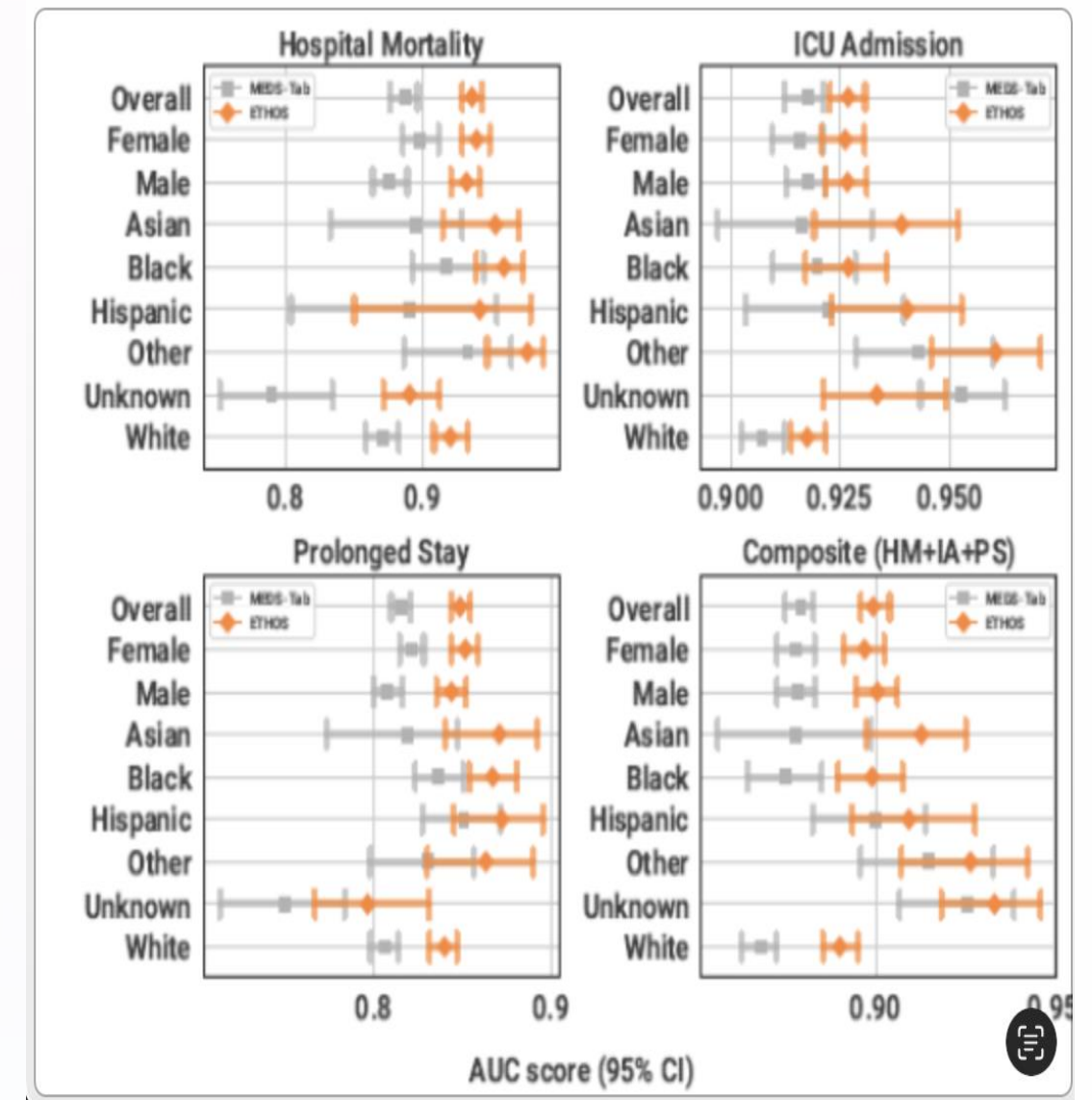
Results

Findings from the ETHOS-ARES Paper:

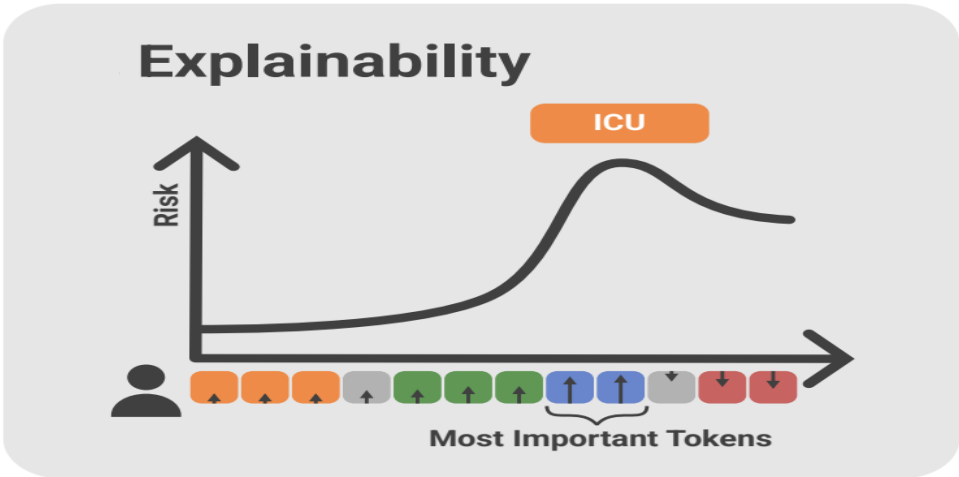
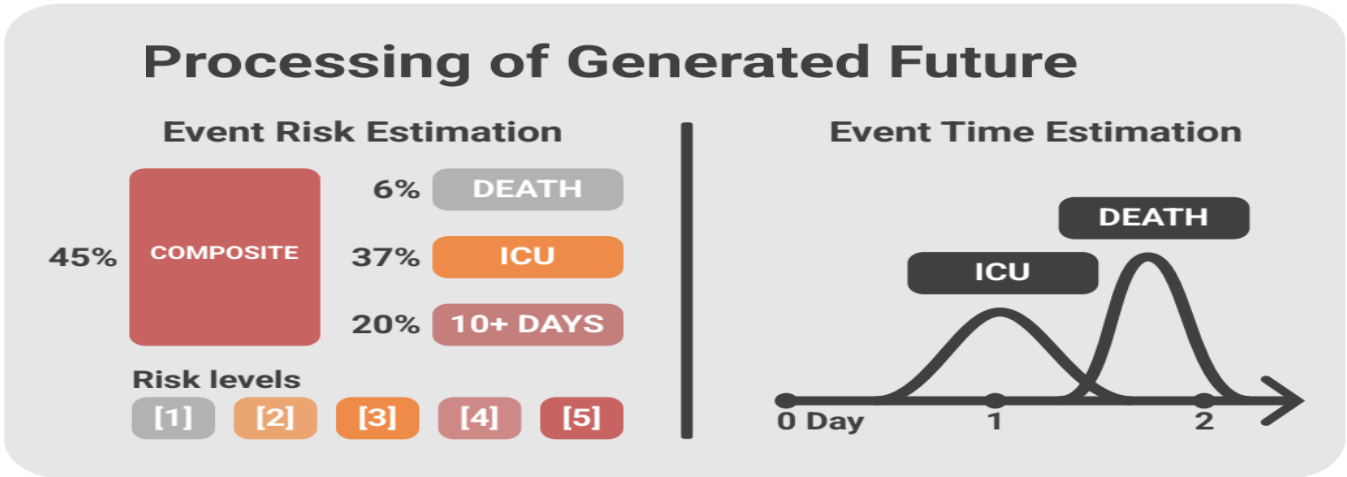
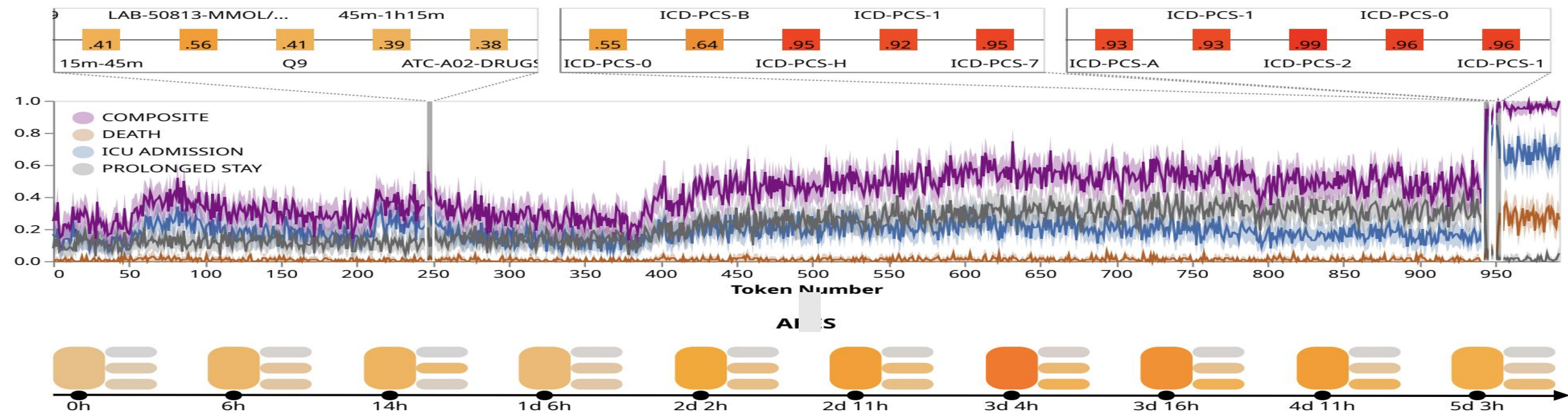
- ETHOS achieved superior AUC scores across tasks:
- Hospital Mortality, ICU Admission, Prolonged Stay, Composite Outcomes.
- Consistent performance across diverse demographic groups (gender, race).
- Dynamic risk trajectories demonstrated real-time prediction power.
- Explainability module highlighted influential clinical factors for individual patients.

Our Observations:

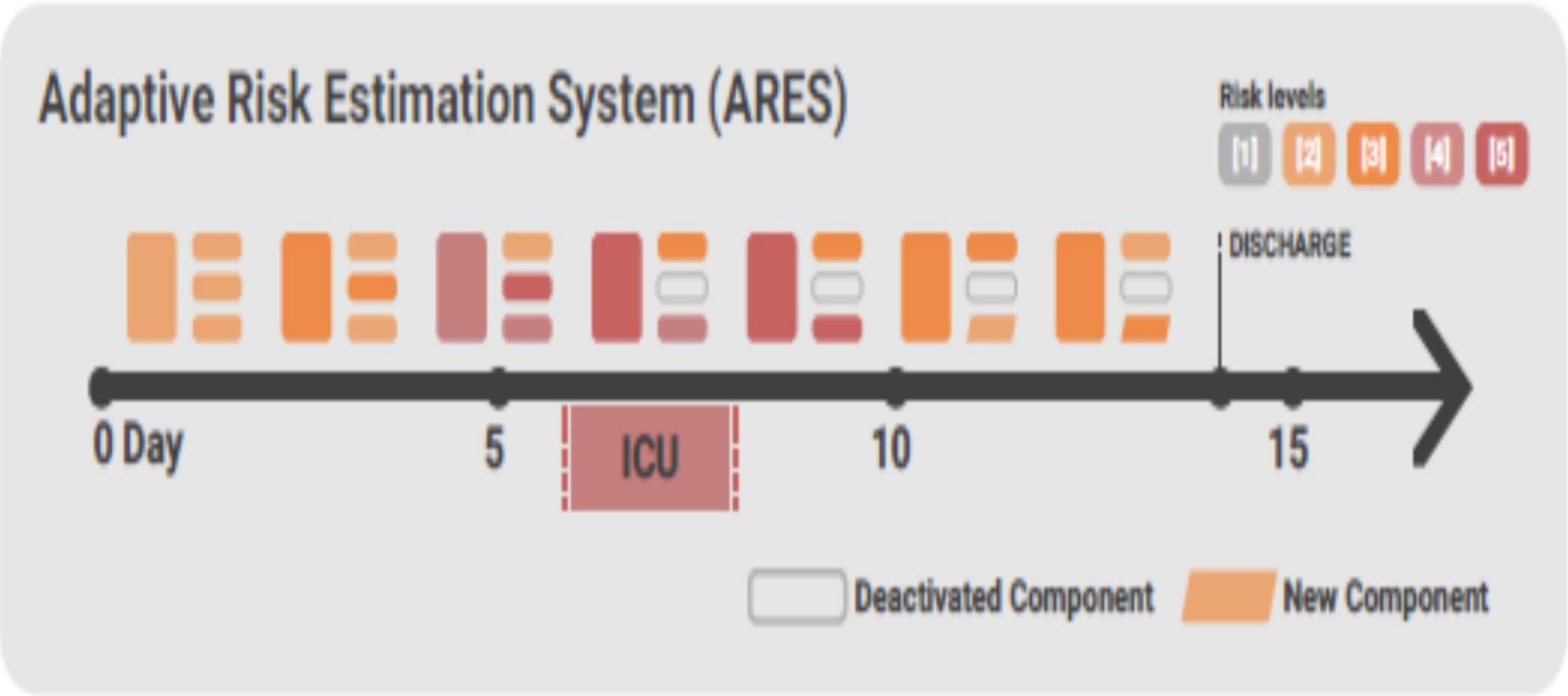
- Tokenization phase was CPU-intensive but achievable within ~4-5 hours.
- Training full ETHOS model is highly cost-intensive (estimated ~\$1000+ for full runs).
- Inference cost is also high: estimating 20–30 hours to generate fPHTs for full MIMIC-IV dataset.
- Model training partially achieved; learned practical constraints in scaling foundation models.
- Zero-shot learning shows promising potential, but compute and data access remain real-world barriers.



Dynamic risk trajectories



Adaptive Risk Estimation System (ARES)





Future Directions



If Redoing the Project:

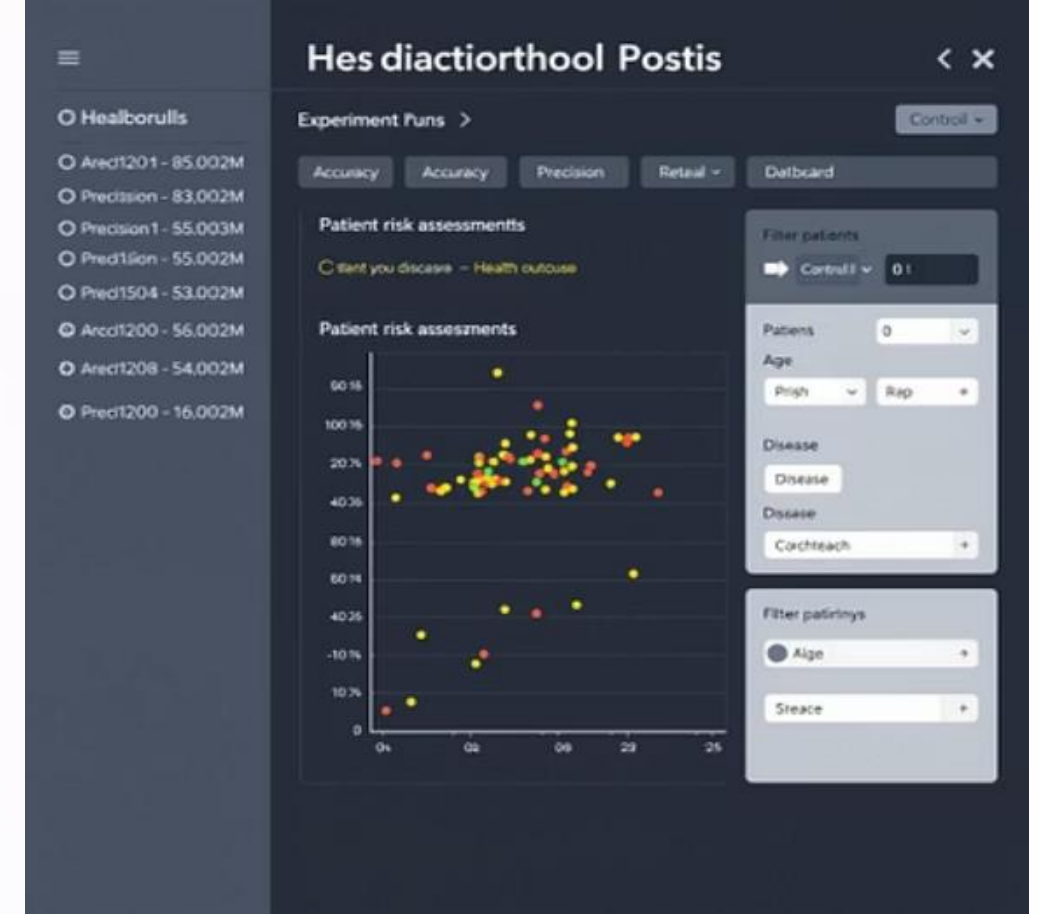
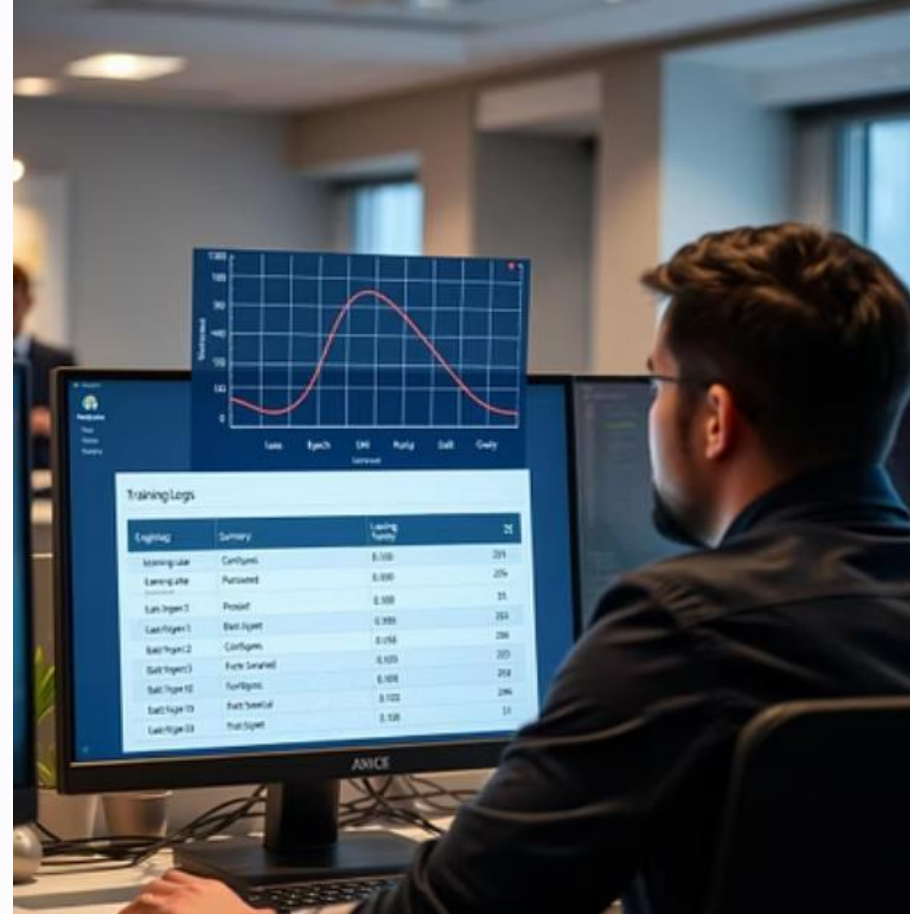
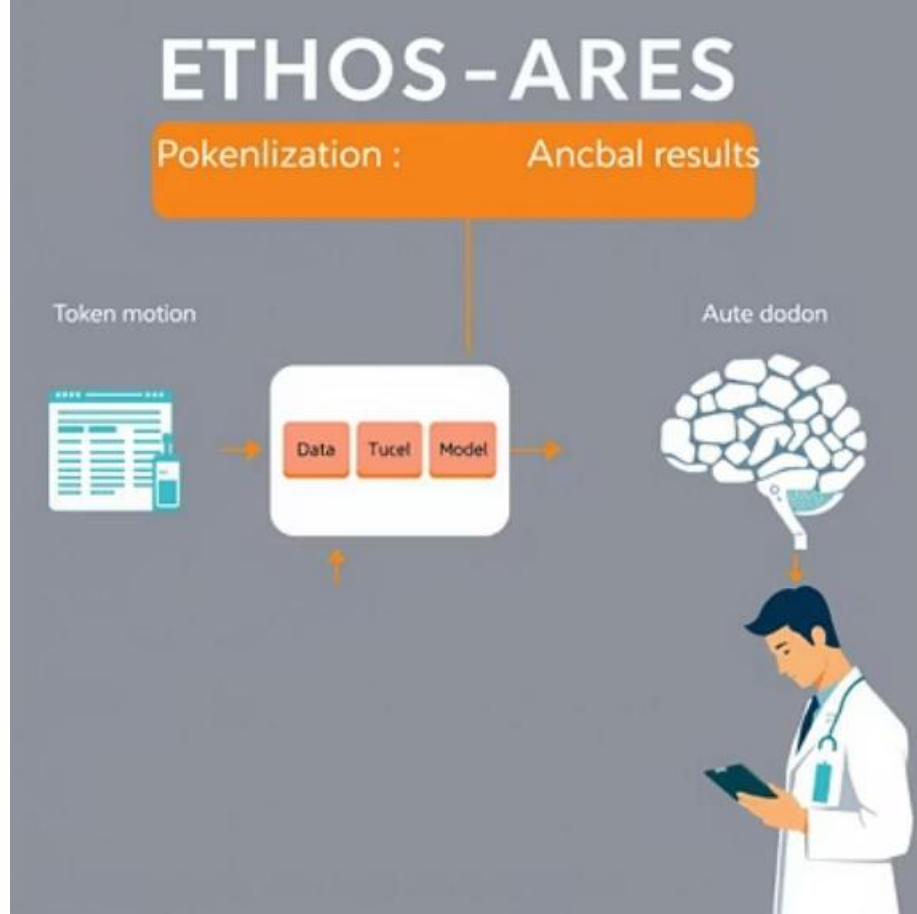
- Plan for cloud infrastructure and cost management earlier.
- Train smaller ETHOS models (2–3 layers) to balance performance and cost.
- Allocate more time for iterative debugging, validation, and optimization.



Future Extensions:

- Integrate additional modalities: clinical notes, waveforms, imaging data.
- Enrich Patient Health Timelines (PHTs) with NLP-driven insights from free-text notes.
- Develop lightweight ETHOS-ARES variant for medium-scale hospital deployments.
- Explore cost-efficient inference strategies (e.g., patient stratification).

Demo



Snapshots:

- ETHOS Overview Diagram (tokenization and model structure)
- Training Logs Snapshot (loss curves, model config summary)
- Results Screenshots from Experiment Runs



Live Demonstration:

- Two server's setup:
 - CPU server for tokenization phase
 - GPU server for training phase



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