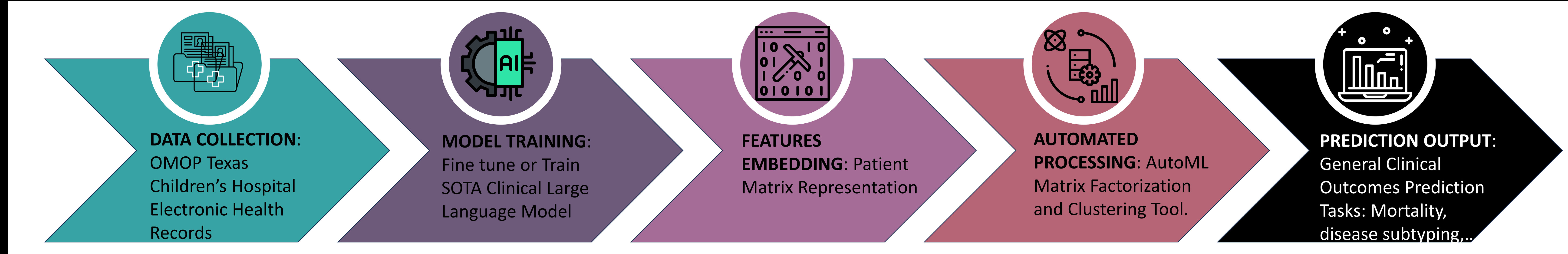
Foundation AI models and AutoML approaches for clinical informatics.

Daniel Palacios[1,2], Zhandong Liu[1,2] Elmer V. Bernstam[3,4]

[1]Baylor College of Medicine, Houston, TX. [2]Dan Duncan Neurological Research Institute at Texas Children's Hospital, Houston, TX [3]McWilliams School of Biomedical Informatics, the University of Texas Health Science Center, Houston, TX. [4]McGovern Medical School, the University of Texas Health Science Center, Houston, TX.



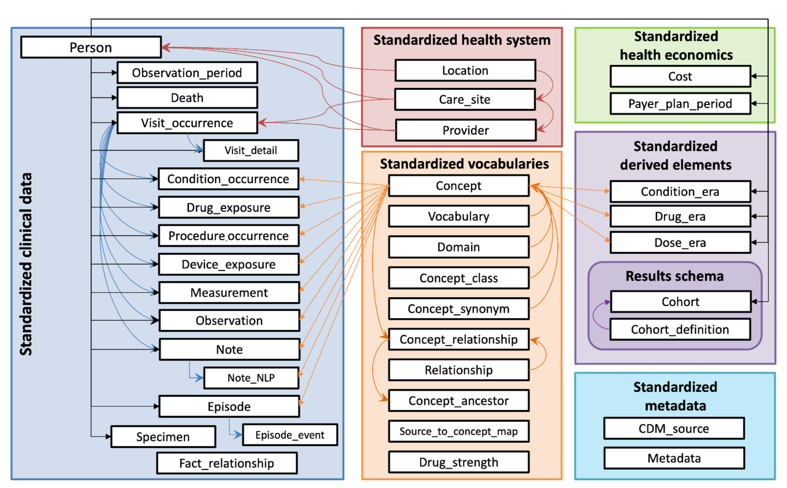
Motivation

This study proposes the use of Foundation AI models and automated machine learning with pediatrics data to facilitate general clinical outcome predictions.

- Predictive analytics leads to reduction in emergency room and specialist visits.
- Improves service delivery and patient outcomes by identifying potential patient issues early.
- Lack of pediatric training data in Clinical Large Language Models.

OMOP TCH Data

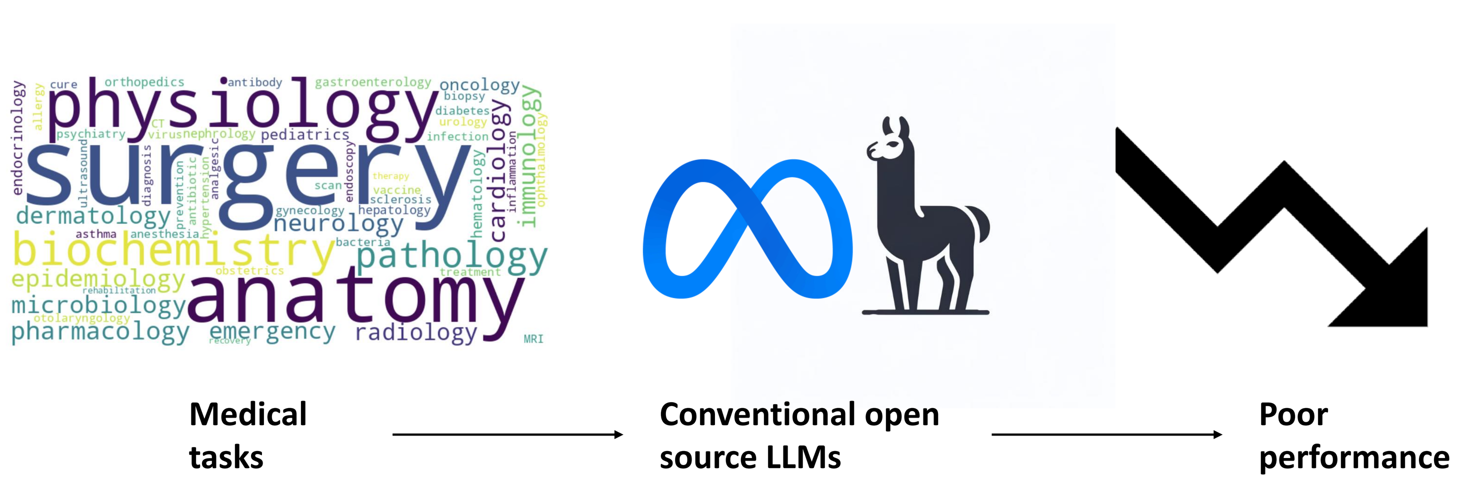
1.1 Texas Children's Hospital Electronic Health Records use OMOP standard



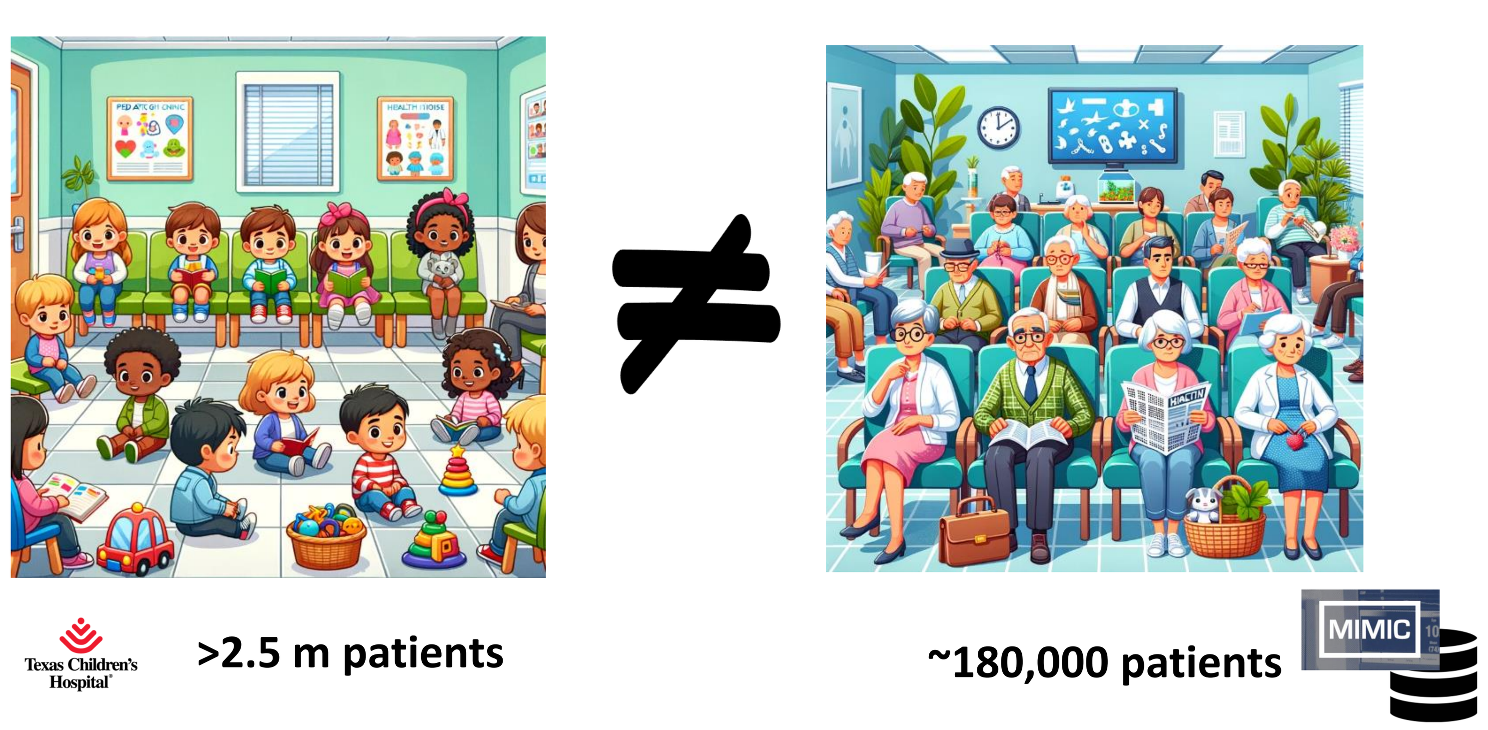
source OHDSI.org

Unique Patients	2,578,481
Unique care sites	1,389
Unique ICD codes	48,748
Unique medication	12,393
Total number of CPT codes	163,879,646
Unique CPT codes	26,258
Total number of visits	151,729,310
Total number of providers	143,970
Average visits instances per patient	58.84

1.2 Conventional Large Language Models are not trained with Medical data.

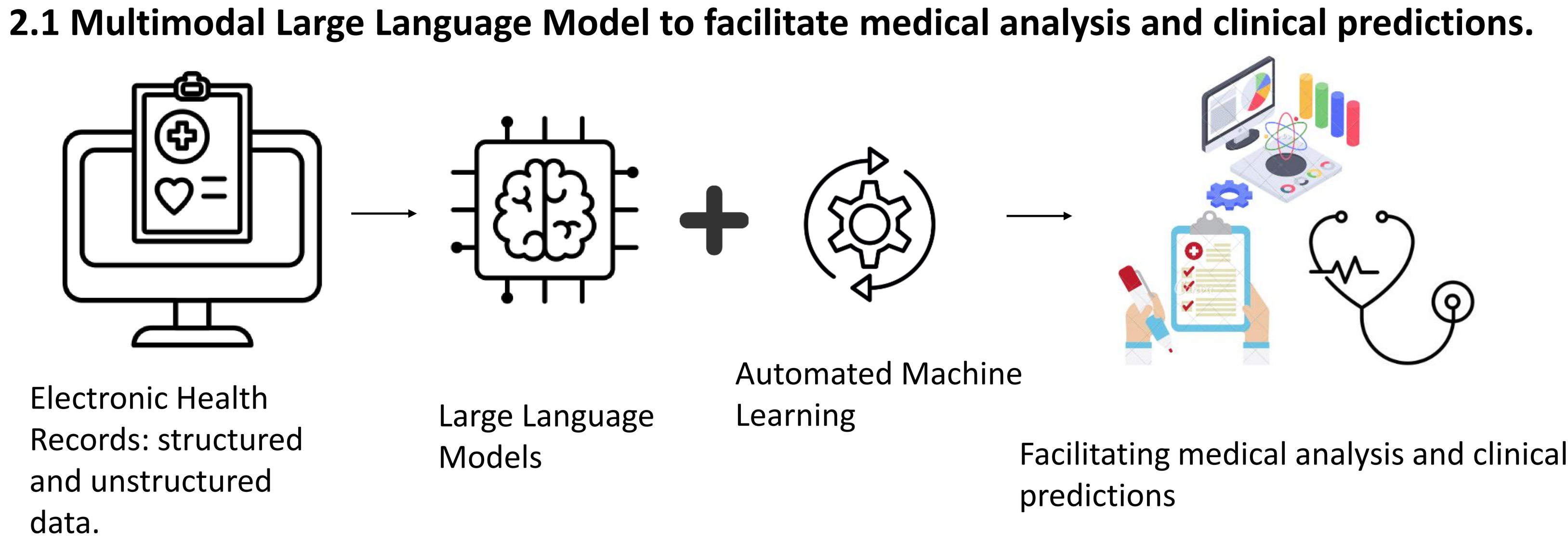


1.3 Clinical Large Language Models are usually trained in adult data only.

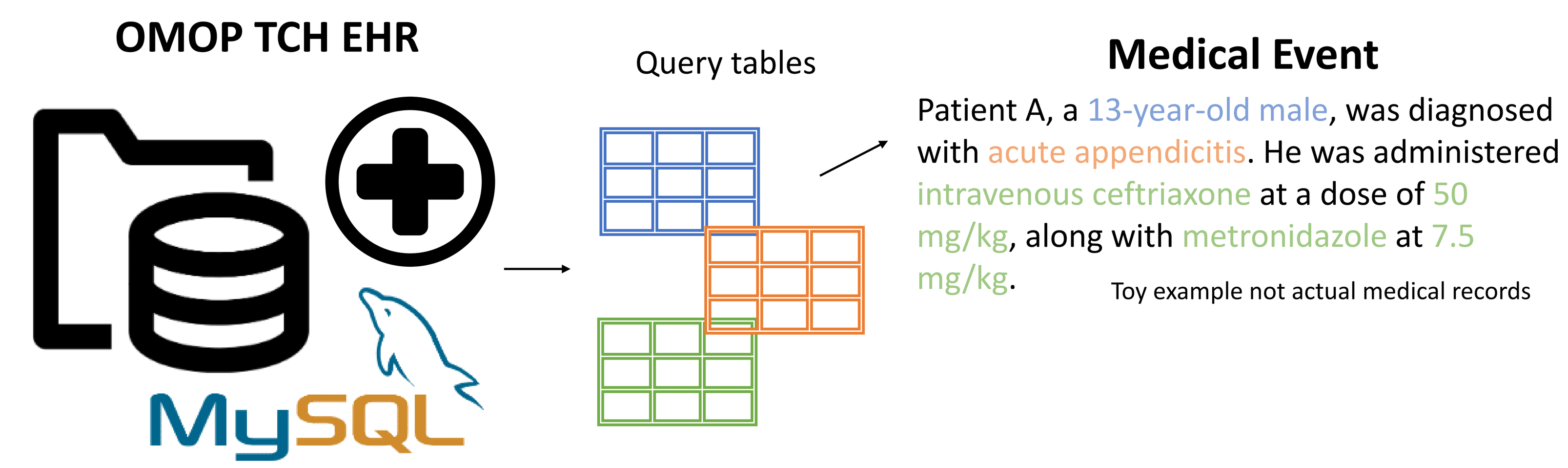


Large Language Models and AutoML

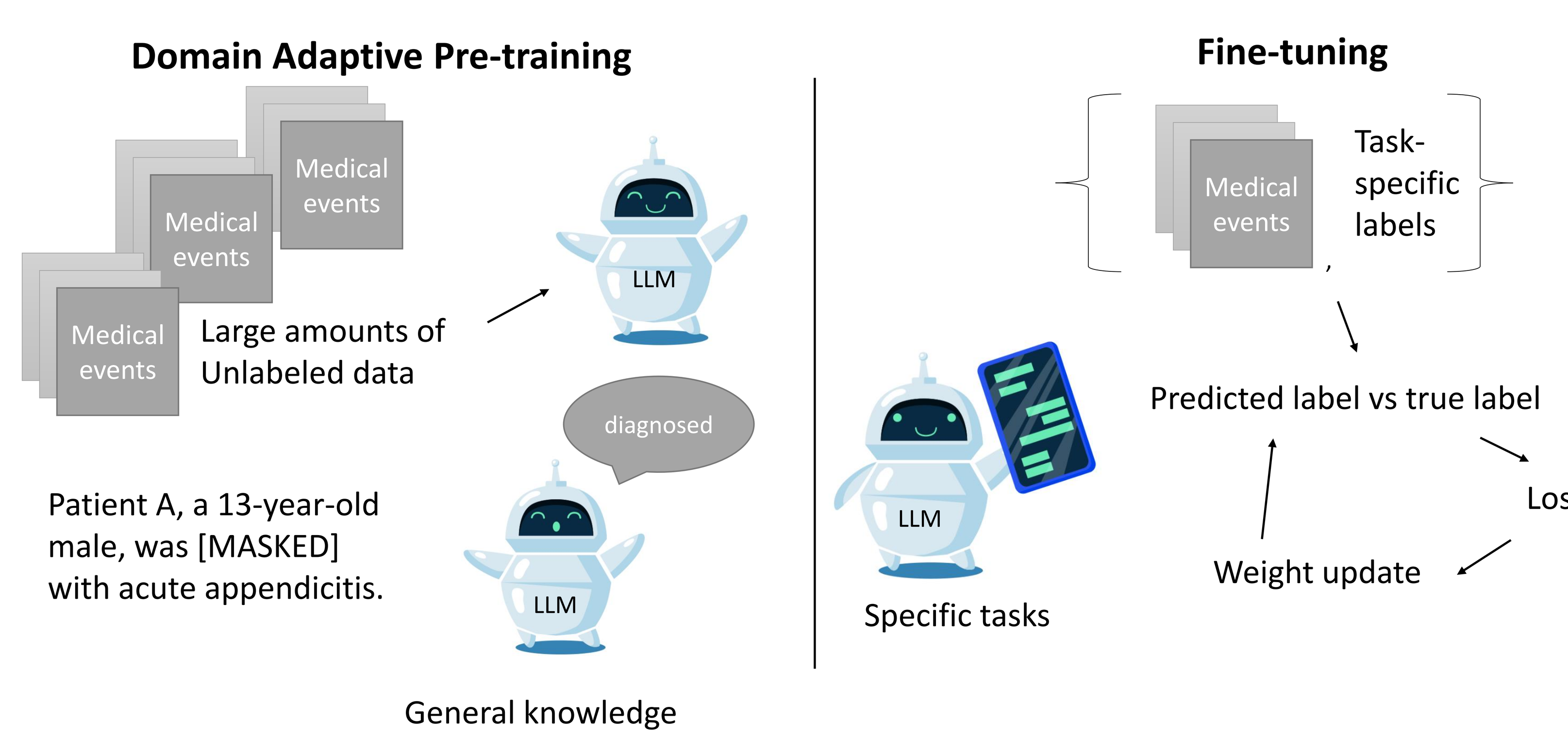
2.1 Multimodal Large Language Model to facilitate medical analysis and clinical predictions.



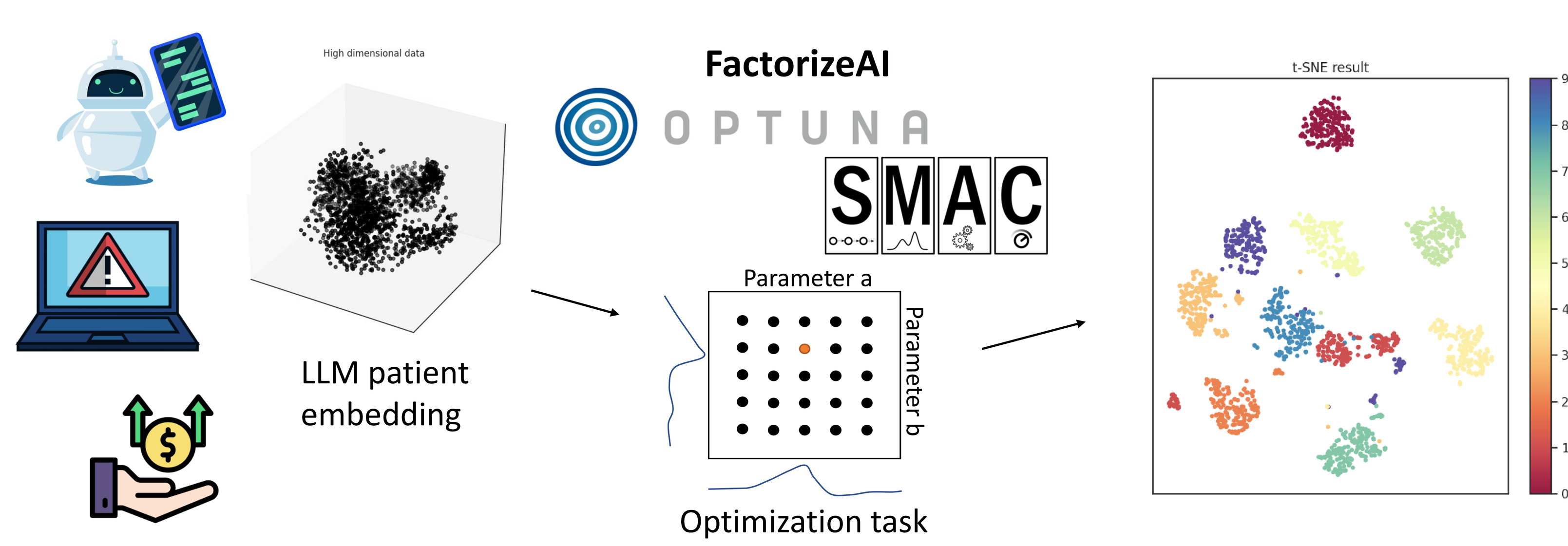
2.2 Creating synthetic medical events from OMOP TCH Electronic Health Records.



2.3 Fine tuning Clinical Large Language Models for mortality prediction.

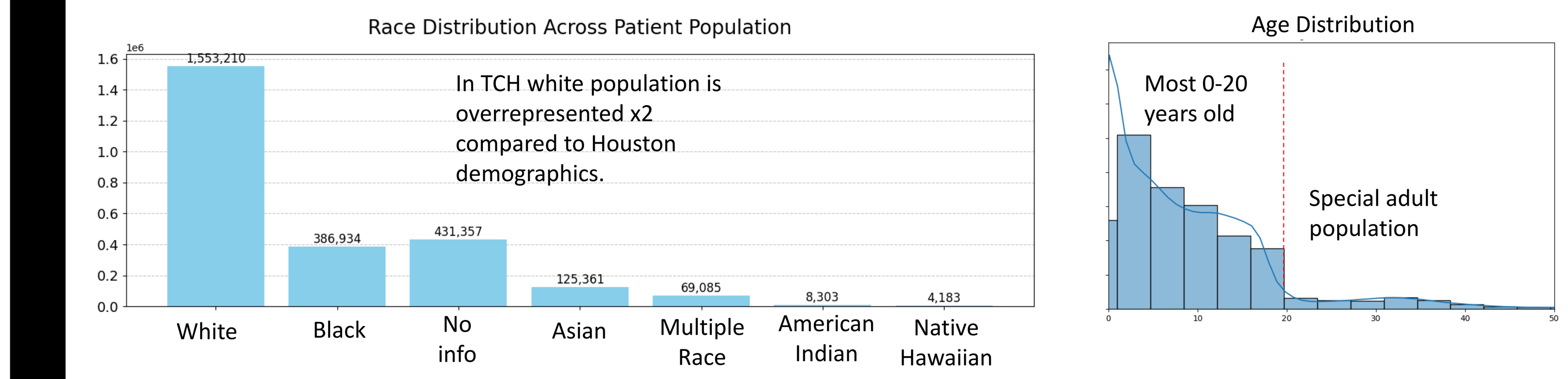


2.4 FactorizeAI: AutoML tool for matrix factorization and clustering.

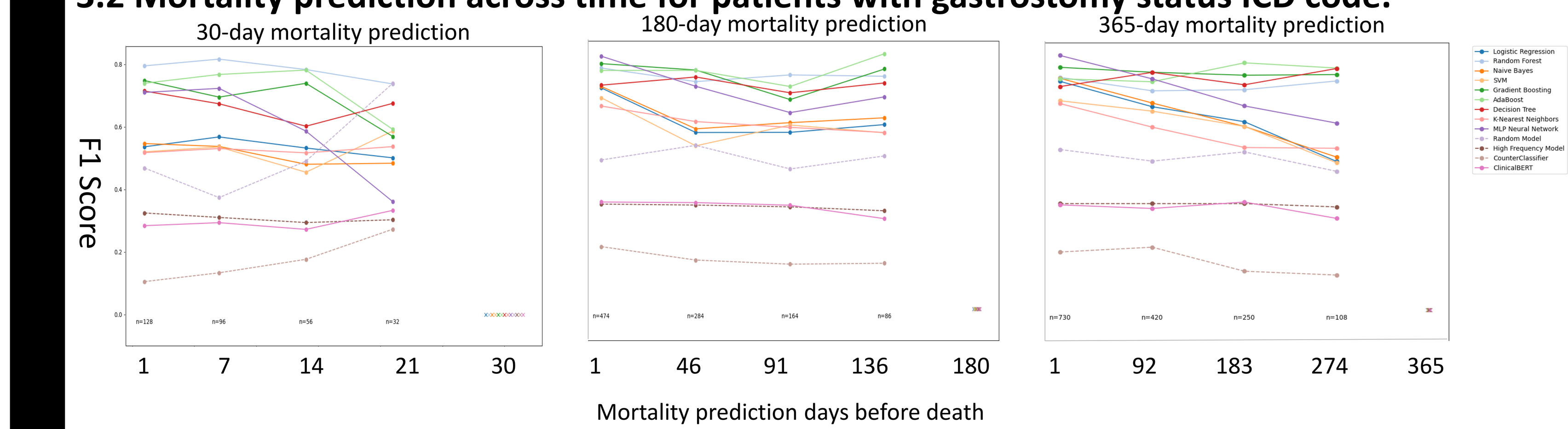


Stratified Sampling, Mortality Predictions, and AI-Driven Analysis

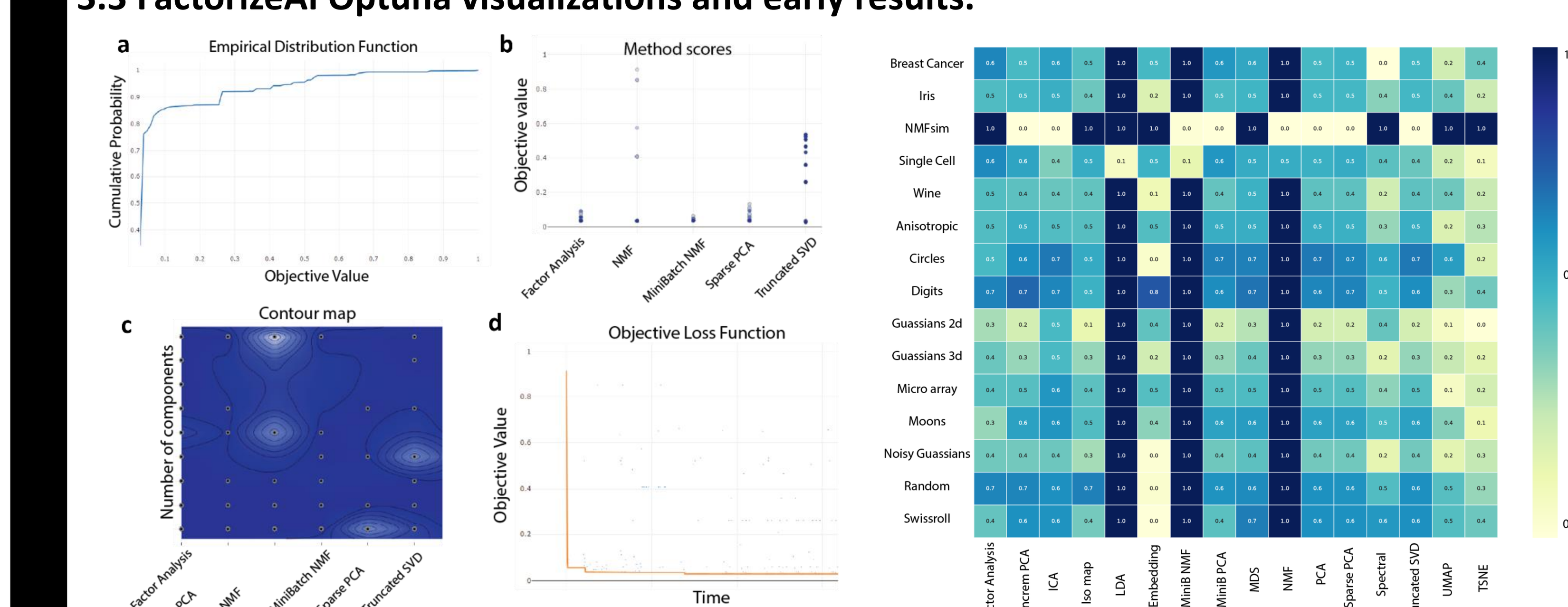
3.1 Addressing health care disparities with stratified sampling.



3.2 Mortality prediction across time for patients with gastrostomy status ICD code.

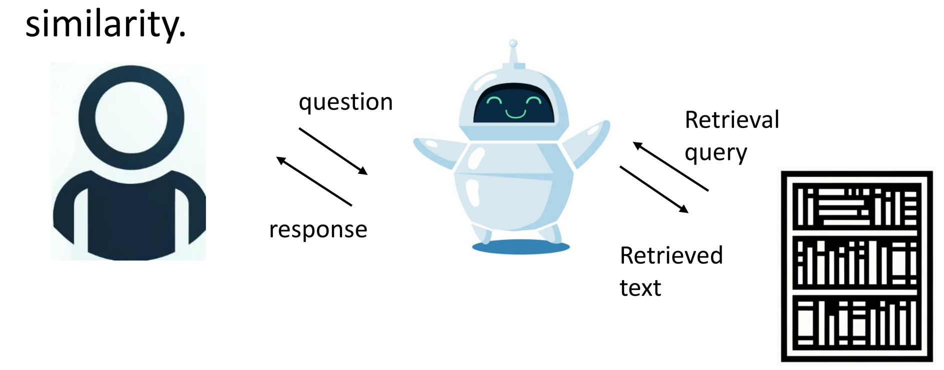


3.3 FactorizeAI Optuna visualizations and early results.



Conclusion and future directions

- **Clinical LLM Fine-Tuning:** Performance in pediatric scenarios remains limited. Tree methods (e.g., random forests) and boosting methods tend to overfit with small sample sizes.
- **Task Expansion:** We will extend our efforts to potentially preventable readmissions and disease subtyping tasks.
- **Methodological Enhancements:** Enhancements to FactorizeAI are planned, incorporating methods like Retrieval-Augmented Generation (RAG) with cosine similarity.



FactorizeAI github page

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