Enhancing Clinical Informatics through Foundation AI Models and Automated Machine Learning Techniques.

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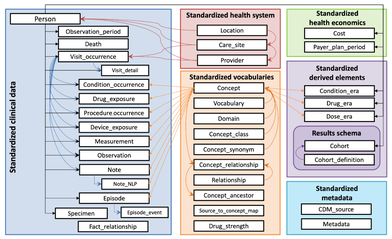
Motivation

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

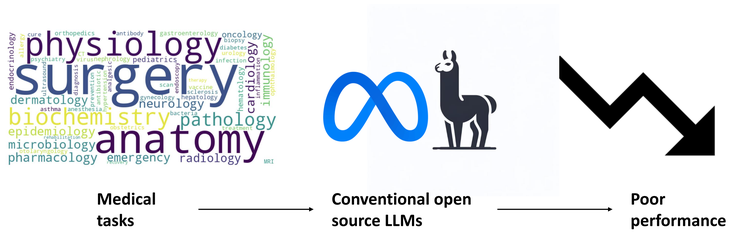
1.1 Texas Children's Hospital Electronic Health Records use OMOP standard



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.



Medical tasks → Conventional open source LLMs → Poor performance

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

Texas Children's Hospital >2.5 m patients

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~180,000 patients MIMIC

References

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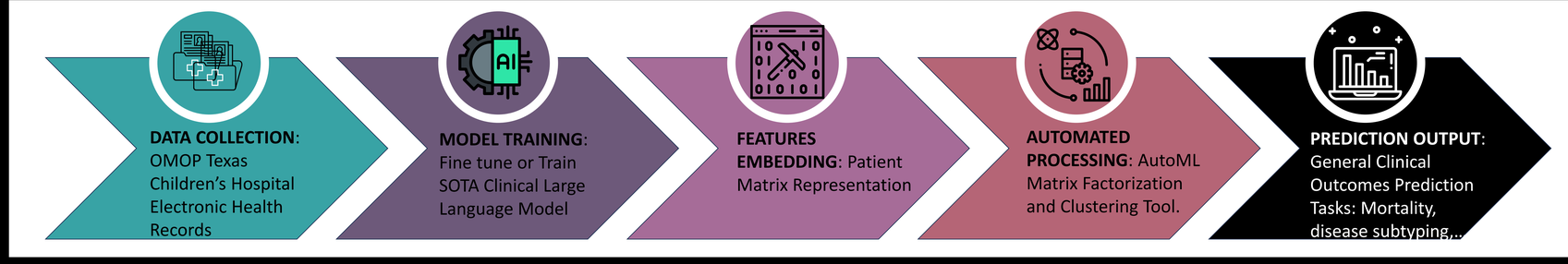
Gulf Coast Consortia
QUANTITATIVE BIOMEDICAL SCIENCES

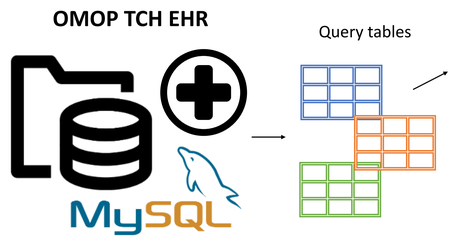


Large Language Models and AutoML

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

Electronic Health Records: structured and unstructured data. → Large Language Models + Automated Machine Learning → Facilitating medical analysis and clinical predictions

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

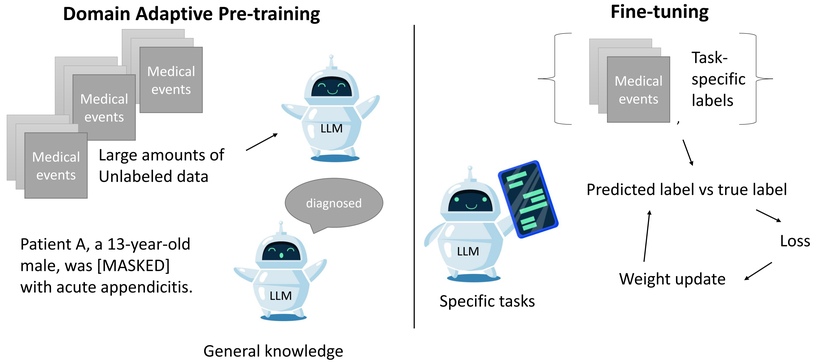


Medical Event

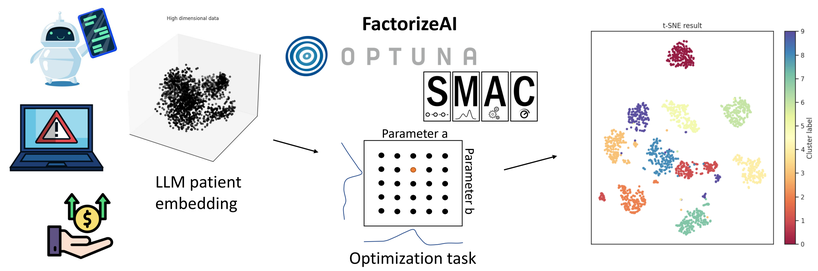
Patient A, a 13-year-old male, was diagnosed with acute appendicitis. He was administered intravenous ceftriaxone at a dose of 50 mg/kg, along with metronidazole at 7.5 mg/kg.

Toy example not actual medical records

2.3 Fine tuning Clinical Large Language Models for mortality prediction.

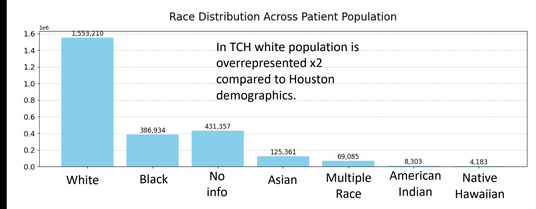


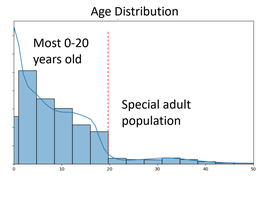
2.4 FactorizeAI: AutoML tool for matrix factorization and clustering.



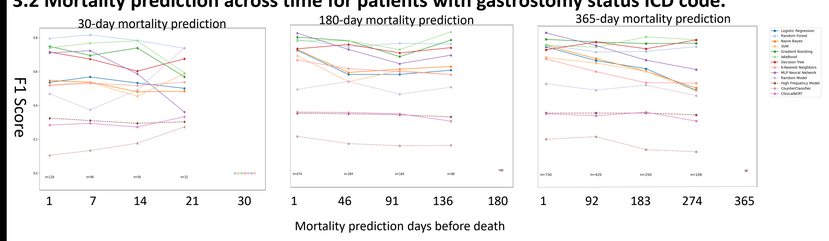
Stratified Sampling, Mortality Predictions, and AI-Driven Analysis

3.1 Addressing health care disparities with stratified sampling.

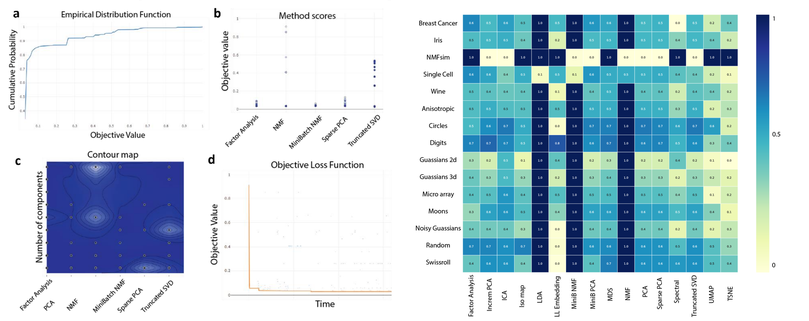




3.2 Mortality prediction across time for patients with gastrostomy status ICD code.

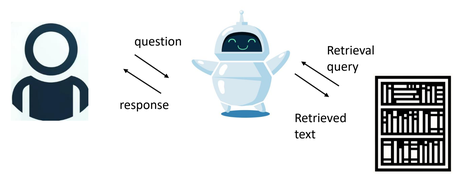


3.3 FactorizeAI Optuna visualizations and early results.



Conclusion and future directions

- **Task Expansion**: We will extend our efforts to potentially preventable readmissions and disease subtyping tasks.
- **Model Advancement**: Deployment of advanced transformer models, such as Gatortron S.
- **Methodological Enhancements**: Enhancements to FactorizeAI are planned, incorporating methods like Retrieval-Augmented Generation (RAG) and cosine similarity to improve integration with patient embeddings.



FactorizeAI github page