Patient Trajectories with AI: from Generation to Insight

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https://mai-research.github.io/


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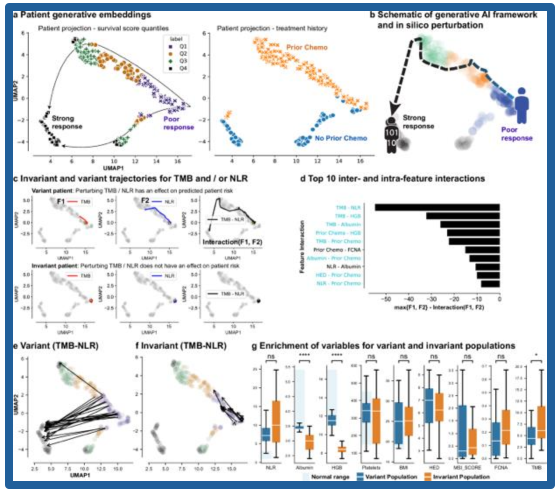
AI In Medicine: Patient Trajectory Prediction

- Trust
- Bias
- Fairness
- Skewed predictions
- Robustness
- Data requirements
- Etc..
- Etc..
- Etc...

IEEE



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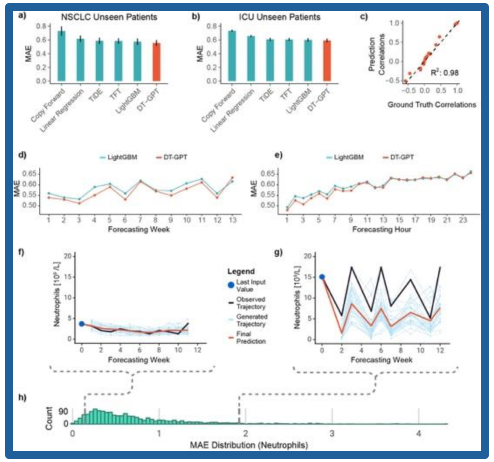

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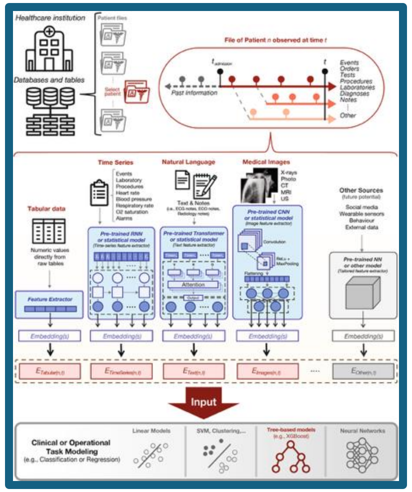
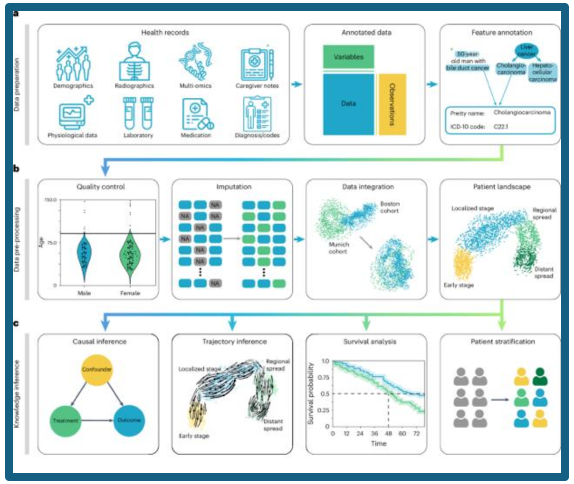


Nature



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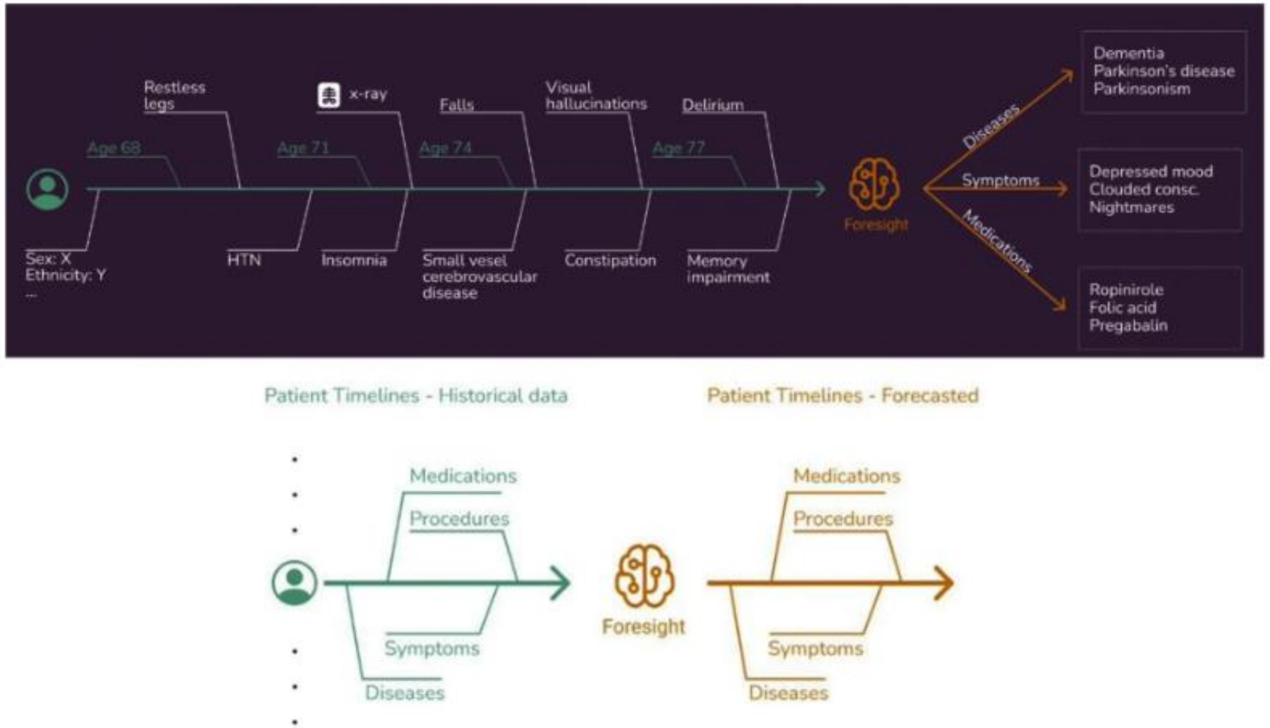
Foresight—a generative pretrained transformer for modelling of patient timelines using electronic health records: a retrospective modelling study

Zeljko Kraljevic, MSc [a,e] · Dan Bean, PhD [a,e] · Anthony Shek, PhD [b,c] · Rebecca Bendayan, PhD [a,e] · Prof Harry Hemingway, PhD [d,f] · Joshua Au Yeung, MBBS [b,c] · et al. Show more

Foresight



Foresight: GPT-based Forecasting Pipeline

Foresight

…oresight: GPT-based Forecasting Pipeline

King's College Hospital NHS Foundation Trust

King's College London

CogStack

Extreme Case: In-hospital Cardiac Arrest (IHCA) Prediction from General Wards

Aim: Evaluate Foresight's ability to serve as a tool for early recognition of IHCA from general wards data.

- IHCA is complex & multifaceted
- General ward patients are diverse
  - Long-term and short-term symptoms, diagnoses, procedures etc…
- General wards are sparsely monitored
  - Vital signs and lab tests (numerical) & observations (text)

Extreme Case: In-hospital Cardiac Arrest (IHCA) Prediction from General Wards

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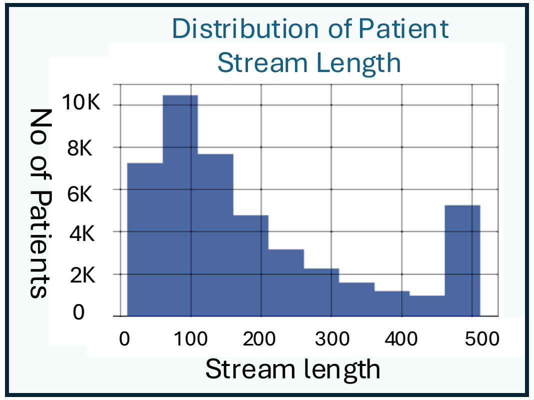
1. **Statistical bias:** Foresight is good with patients with long trails of documents.

Most patients have less documents (younger patients, patients with less comorbidities, etc)



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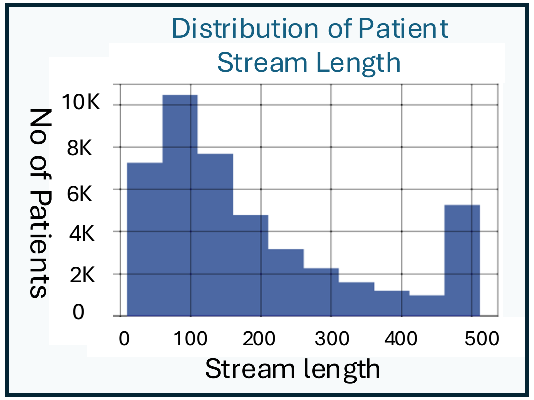

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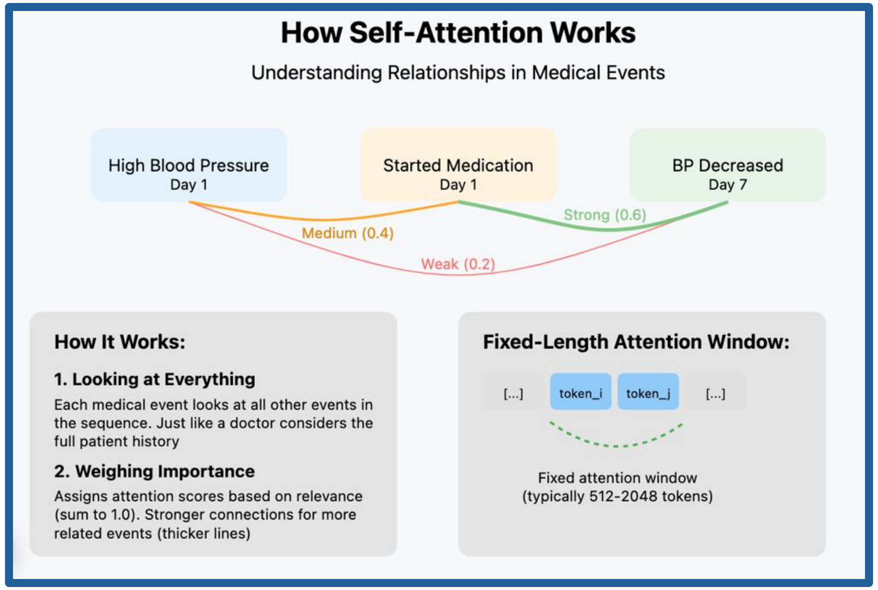

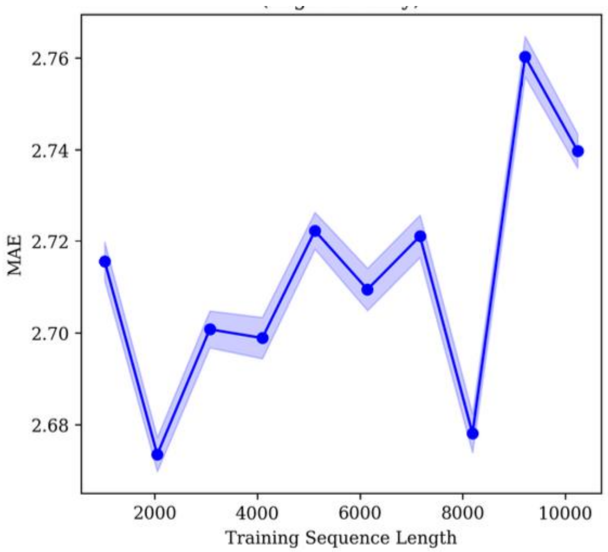

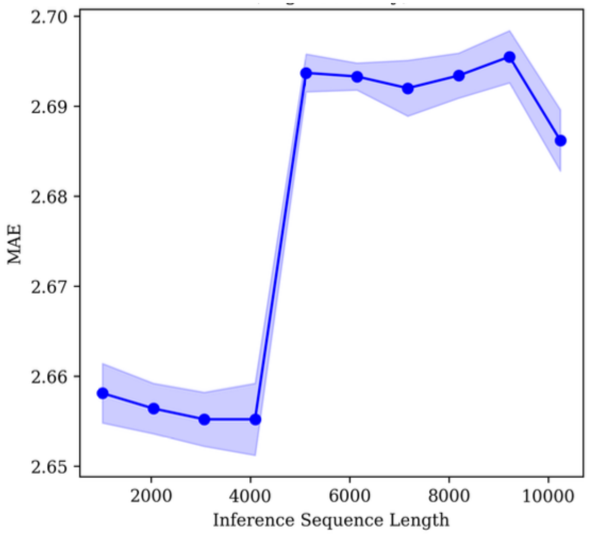

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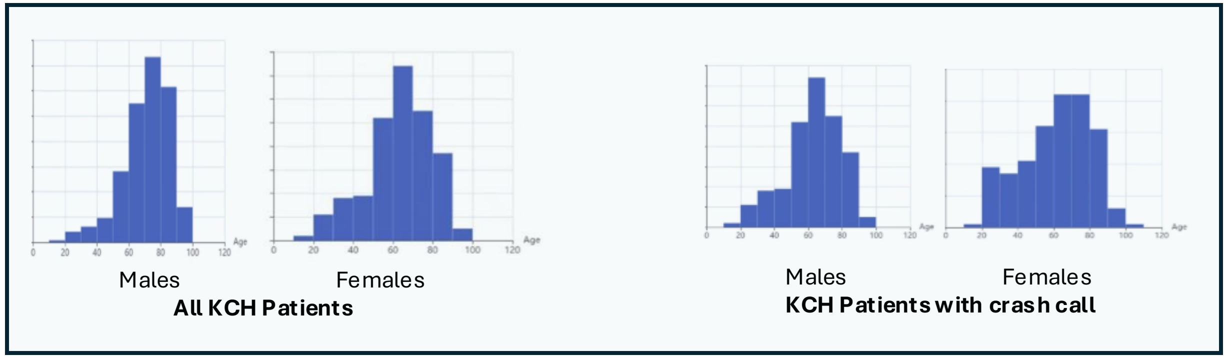
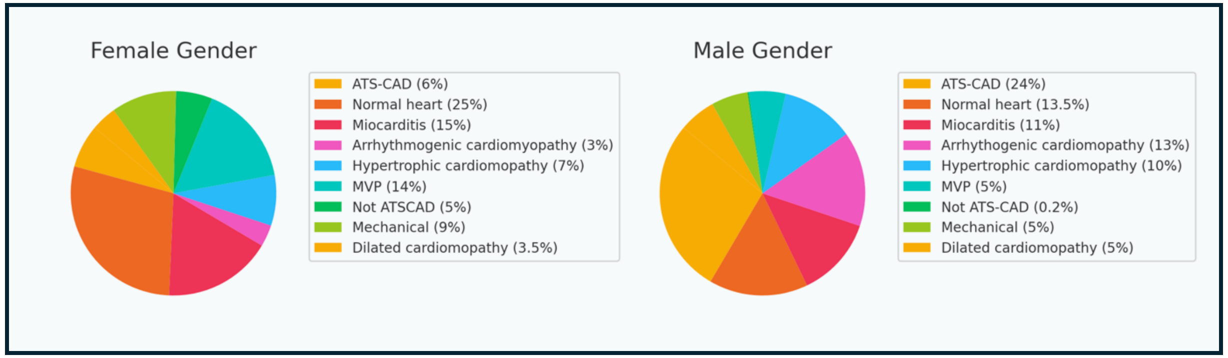
2. **Structural bias:** Foresight's forecasts carry along the clinical and documentation bias within its training data





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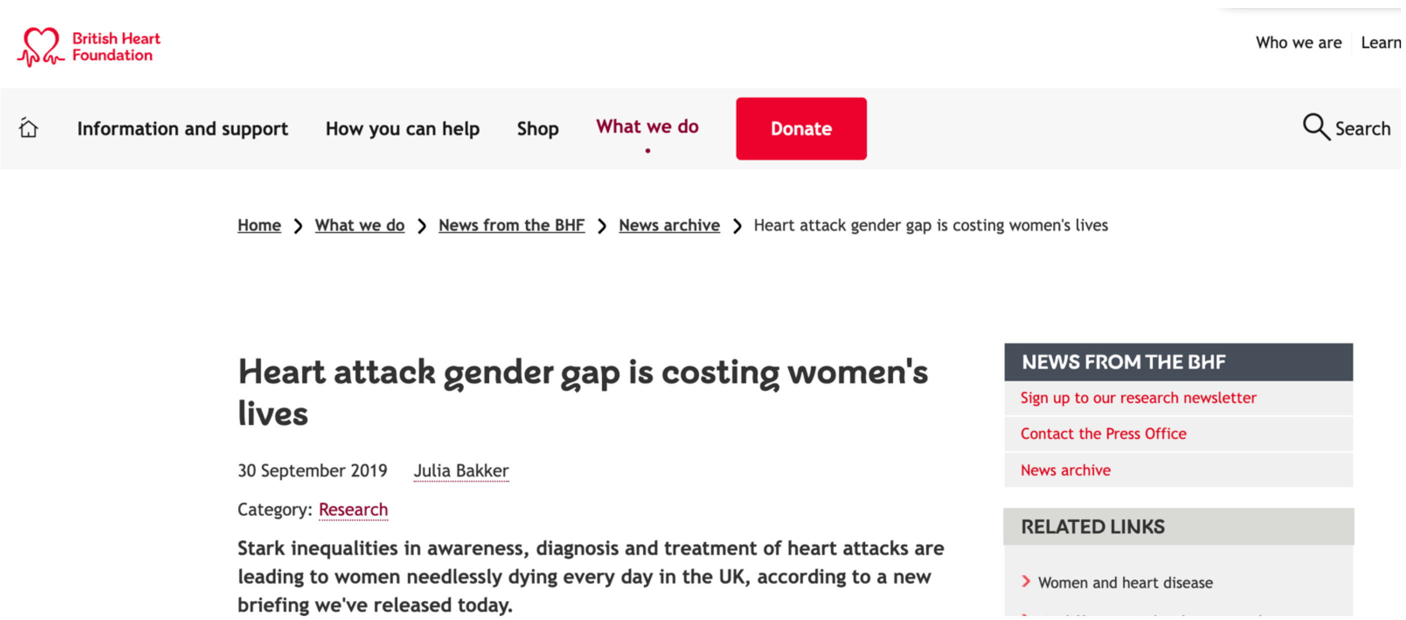
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Heart attack gender gap is costing women's lives

30 September 2019 Julia Bakker

Category: Research

Stark inequalities in awareness, diagnosis and treatment of heart attacks are leading to women needlessly dying every day in the UK, according to a new briefing we've released today.

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Women and heart disease

What we did not do …

- **Train on more data..**
  - The status quo
  - It will not help with structural bias

1. **Statistical bias:** Foresight is good with patients with long trails of documents.
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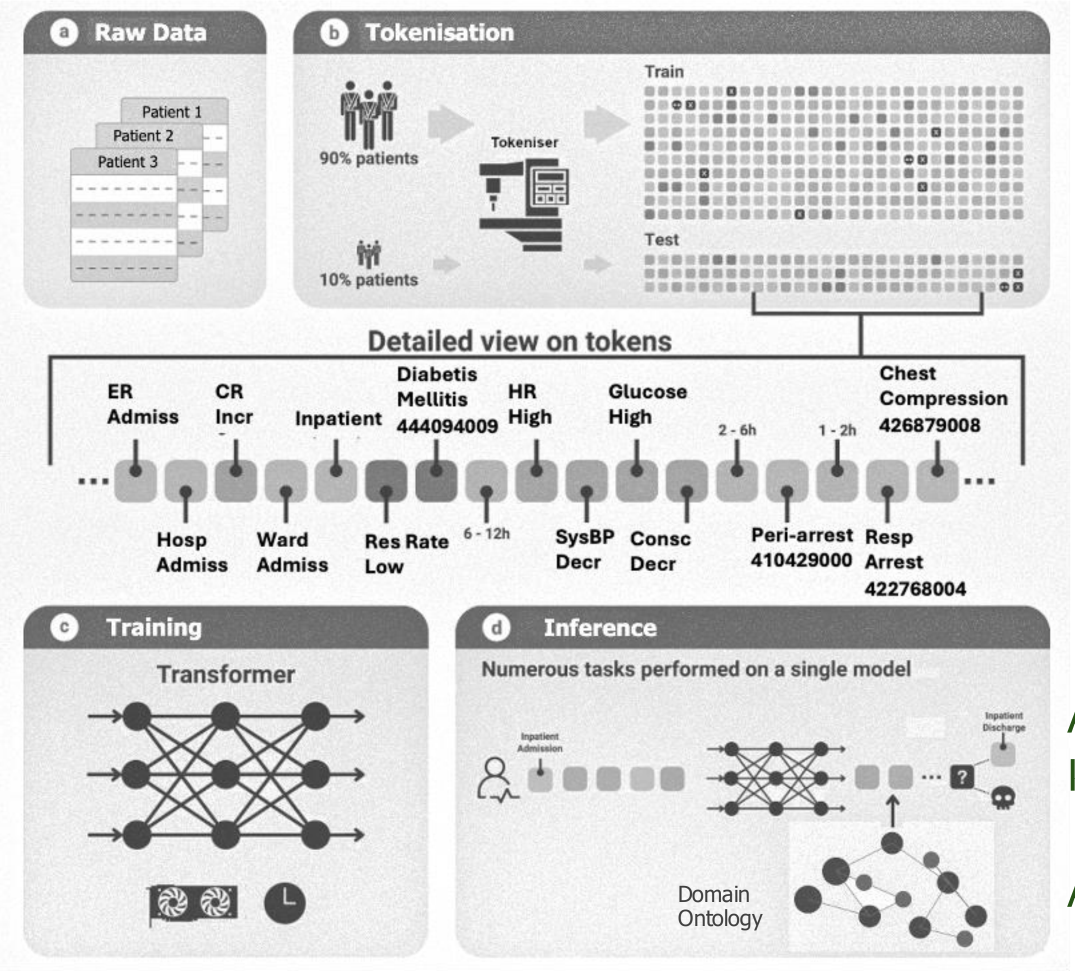
Our Solution – METHOD: Modular Efficient Transformer for Healthcare Outcome Discovery

EHR-oriented representation of medical events

Modified EHR-aligned architecture

Addresses statistical bias



Alignment with medical knowledge/guidelines

Addresses structural bias

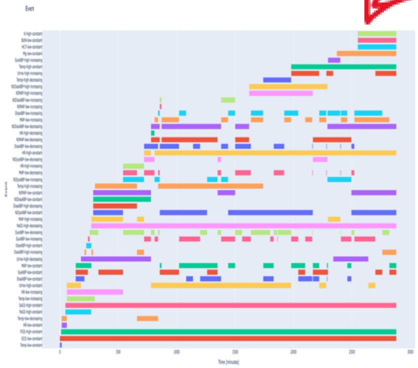
PHASE I **PHASE II**

Our Solution – METHOD: Modular Efficient Transformer for Healthcare Outcome Discovery

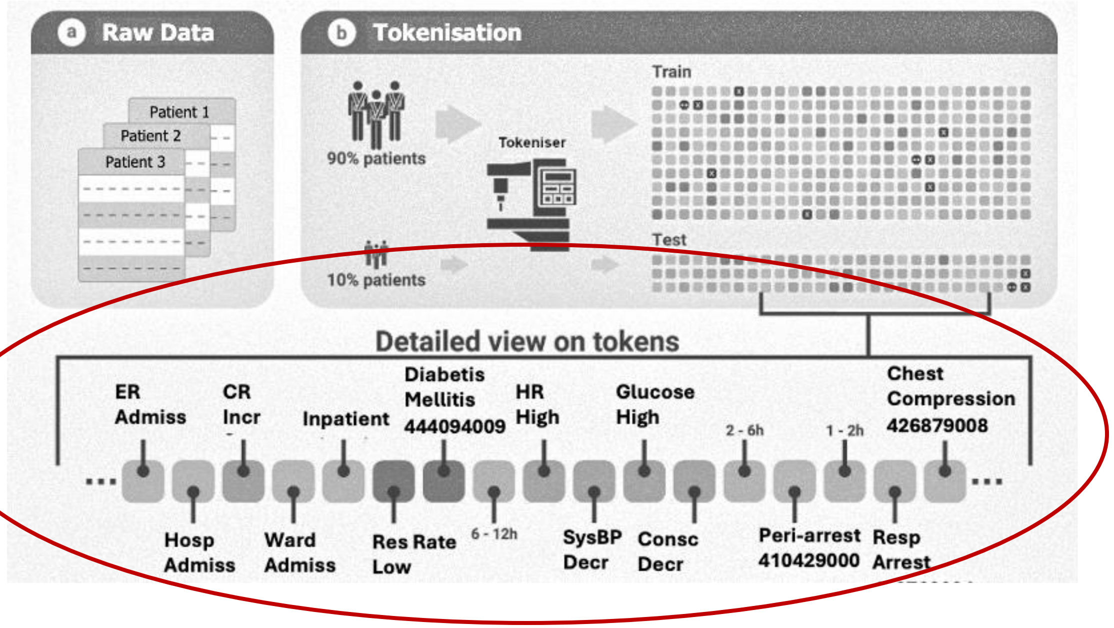
✓ 0.0s

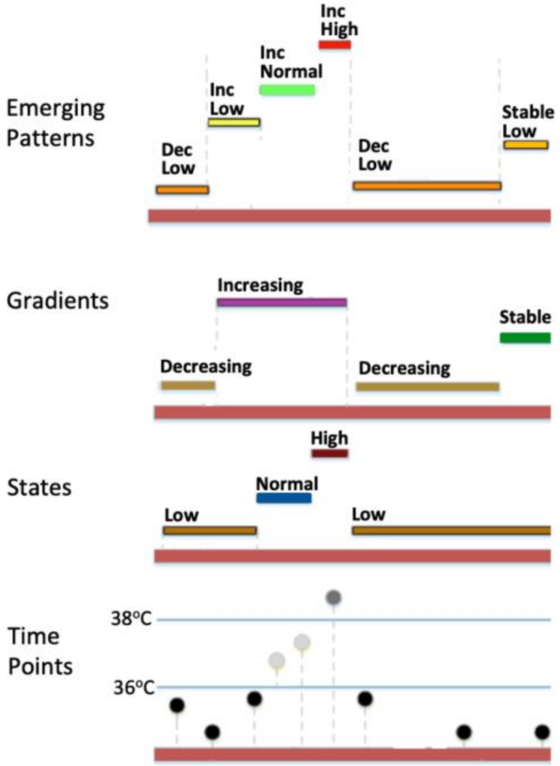
	SUBJECT_ID	ordinal_time_start	VALUENUM	ITEMID	ord
0	3	2101-10-20 16:40:00	3.2	CREATININE	0 days
1	3	2101-10-20 16:40:00	2.4	MAGNESIUM	0 days
2	3	2101-10-20 16:40:00	53.0	BUN	0 days
3	3	2101-10-20 16:40:00	99.0	CHLORIDE	0 days
4	3	2101-10-20 16:40:00	91.0	GLUCOSE	0 days
...	...	...	...	...	
351	3	2101-10-26 17:00:00	103.0	DBP	6 days
352	3	2101-10-26 17:00:00	119.0	MAP	6 days
353	3	2101-10-29 04:45:00	73.0	GLUCOSE	8 day
354	3	2101-10-30 04:30:00	76.0	GLUCOSE	9 day
355	3	2101-10-31 04:55:00	88.0	GLUCOSE	10 day

356 rows × 12 columns



EHR-oriented representation of medical events





1826

ECAI 2020
G.D. Giacomo et al. (Eds.)

doi:10.3233/FAIA200298

Modeling Rare Interactions in Time Series Data Through Qualitative Change: Application to Outcome Prediction in Intensive Care Units

Zina Ibrahim [1] and Honghan Wu [2] and Richard Dobson [3]

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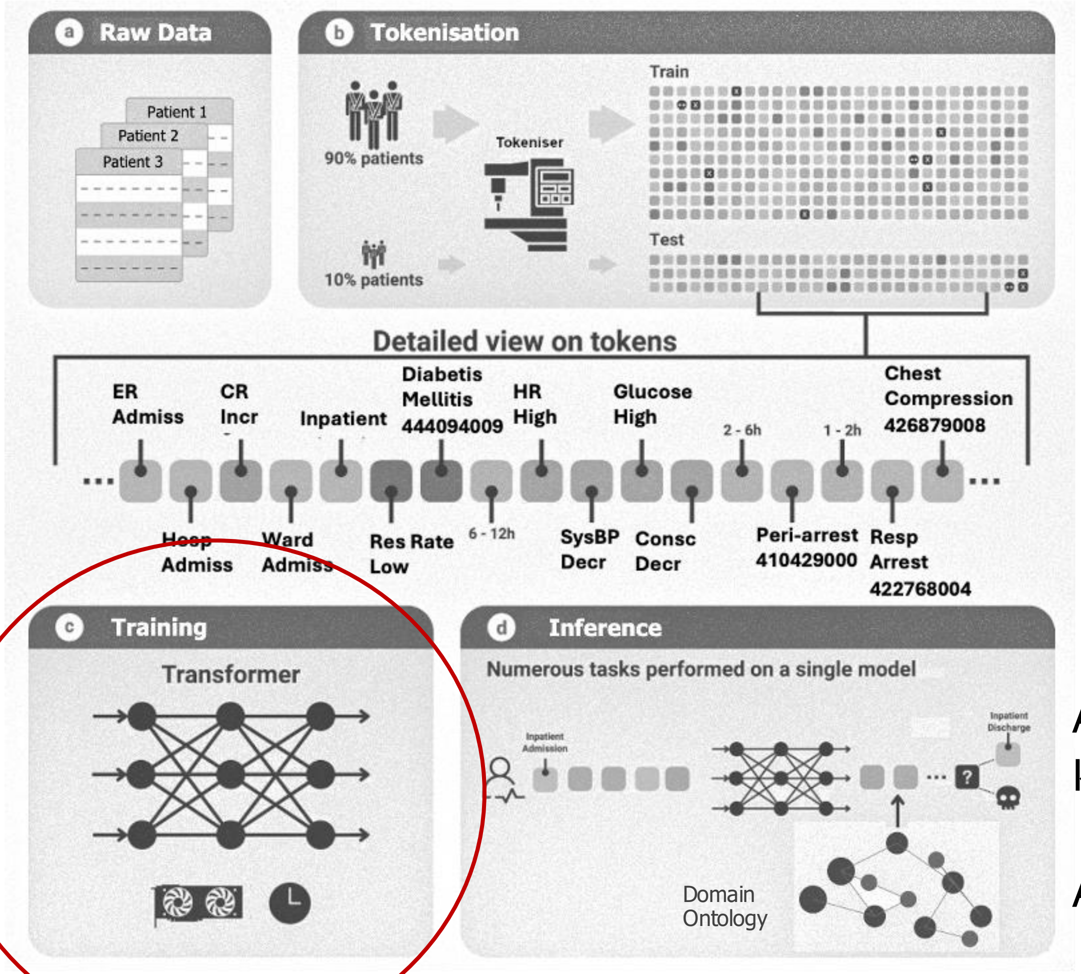


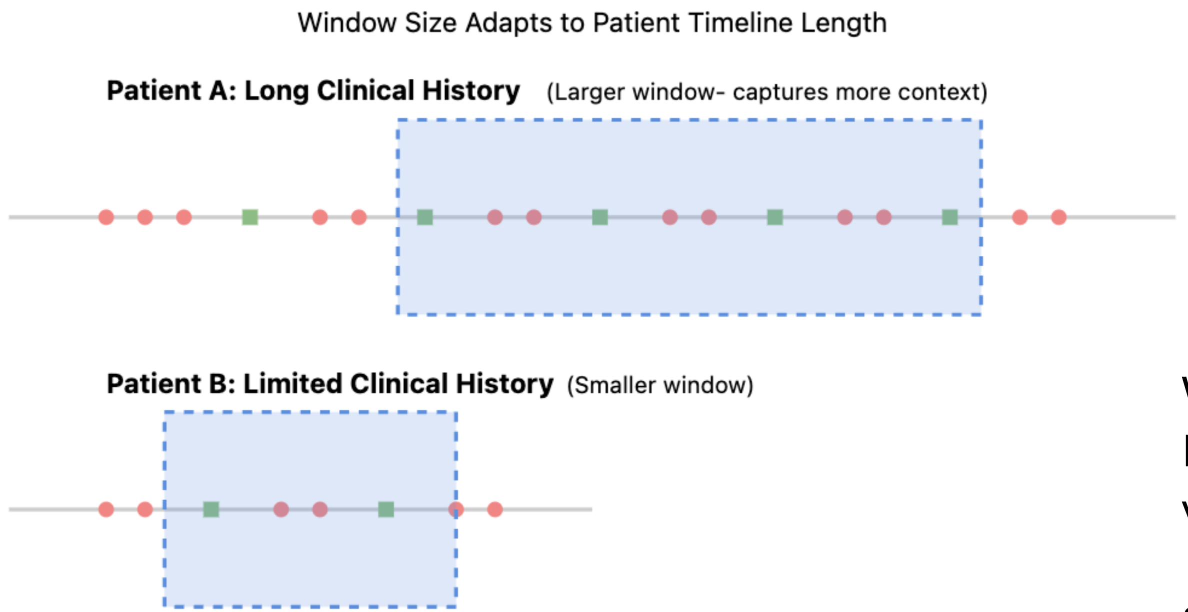
Alignment with medical knowledge/guidelines

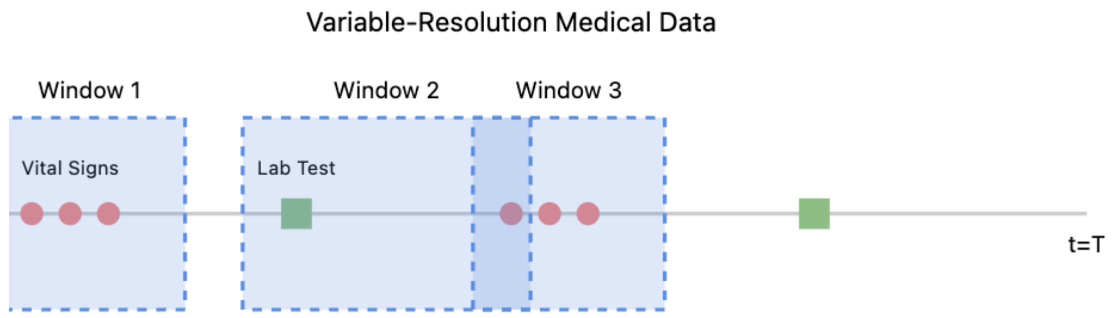
Addresses structural bias

PHASE I

PHASE II

Phase I: METHOD Architecture- Adaptive Sliding Window Attention





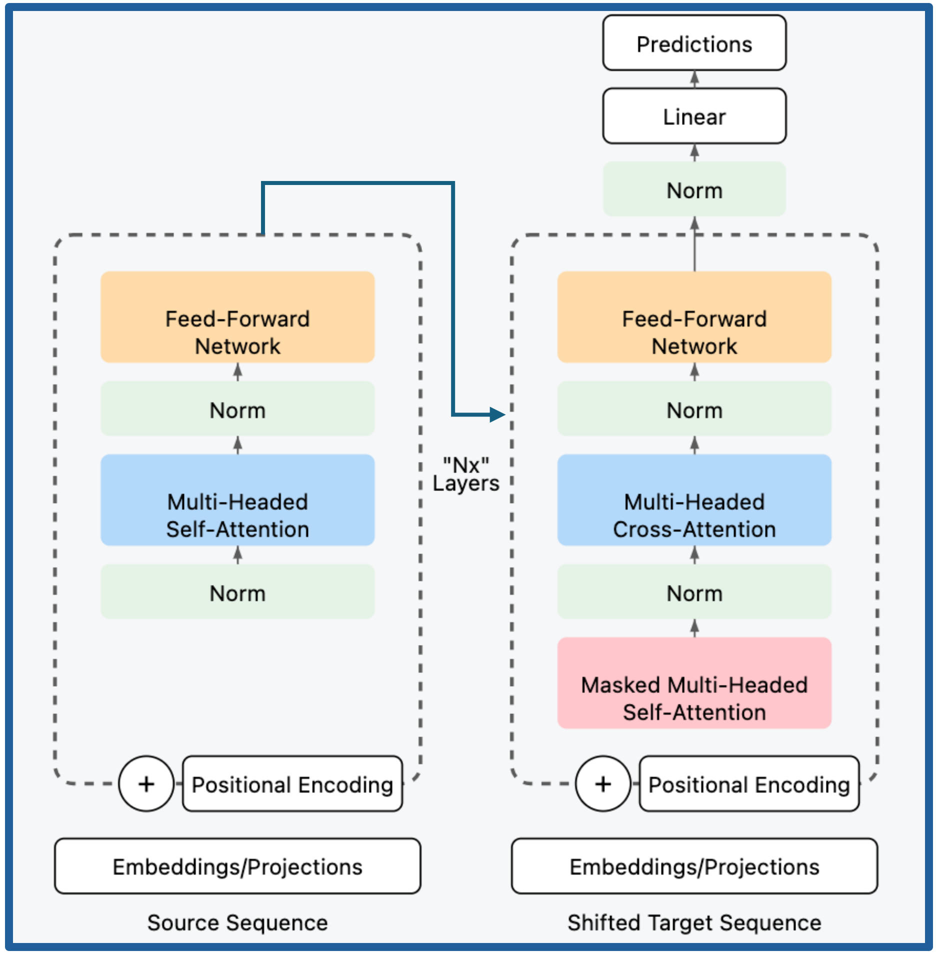
Window size adapts to data density
Handles discrepancies in recording patterns of clinical variables

Slides across timeline to capture local temporal relationships

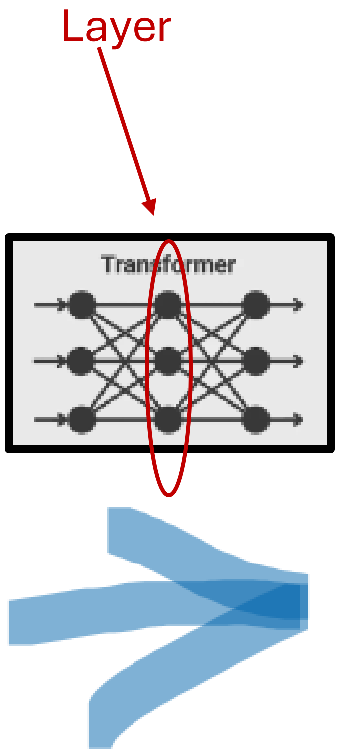
Window size grow with available patient history
Balances local & global dependencies

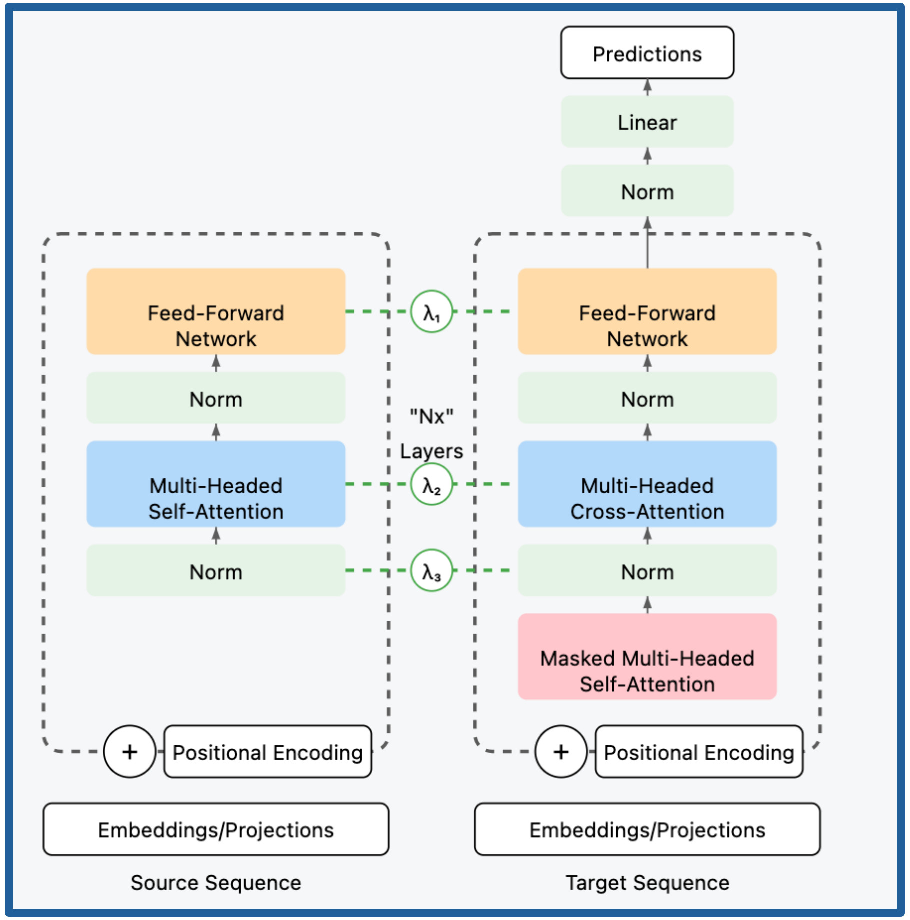
Dr. Linglong Qian

Phase I: Method’s Architecture - U-Net Inspired Skip Attention



Traditional transformer handles information in a sequential fashion



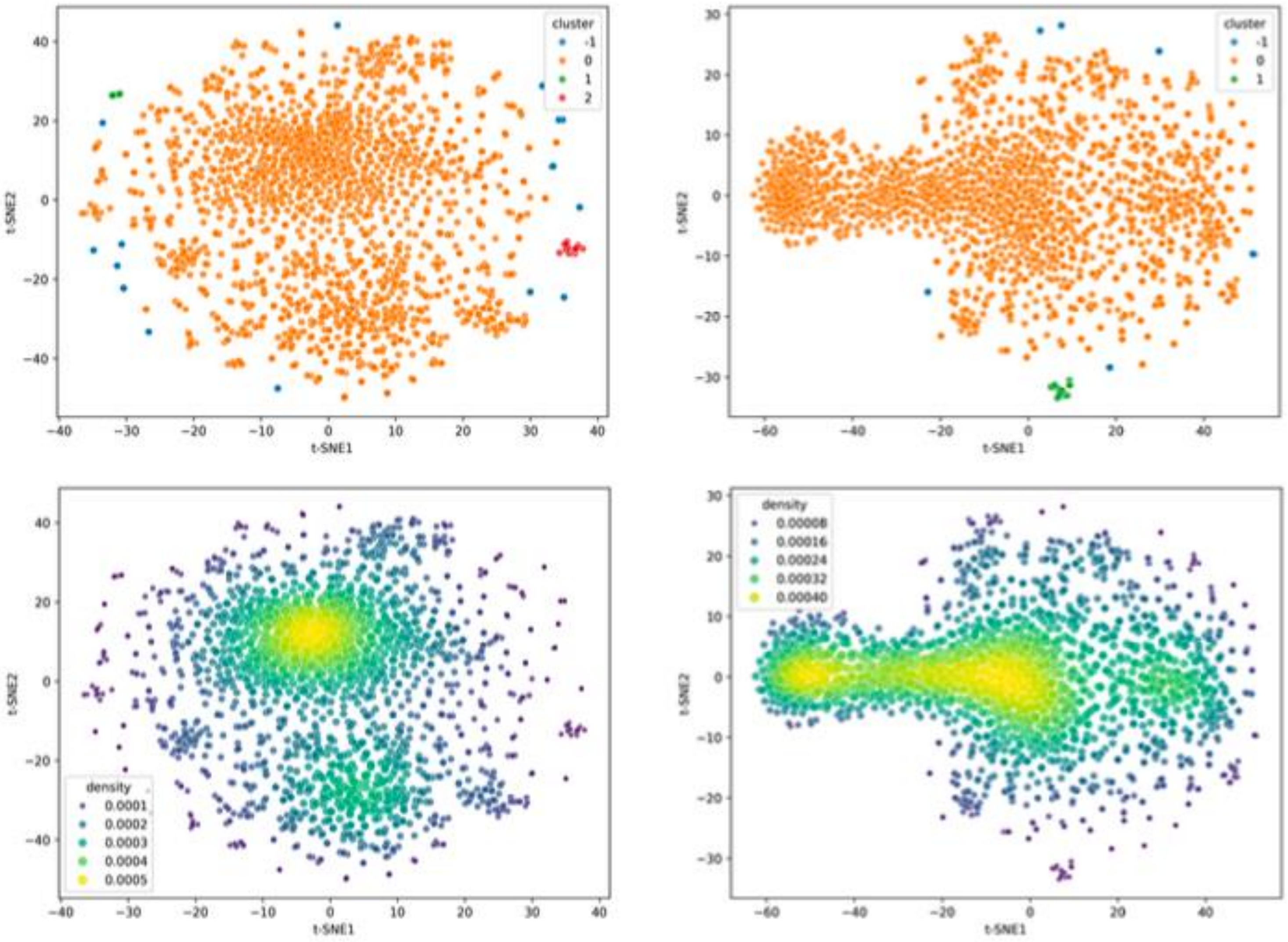


U-Net inspired architecture with dynamically (learnable) stored skip connections: multi-scale feature propagation across layers.

Clustering Results –

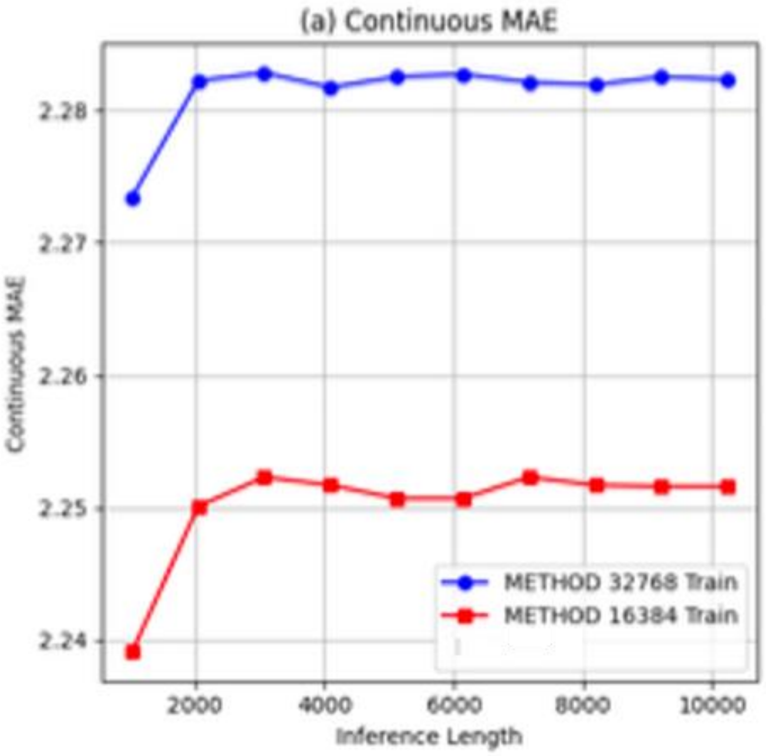
METHOD better separates diversity in CA samples

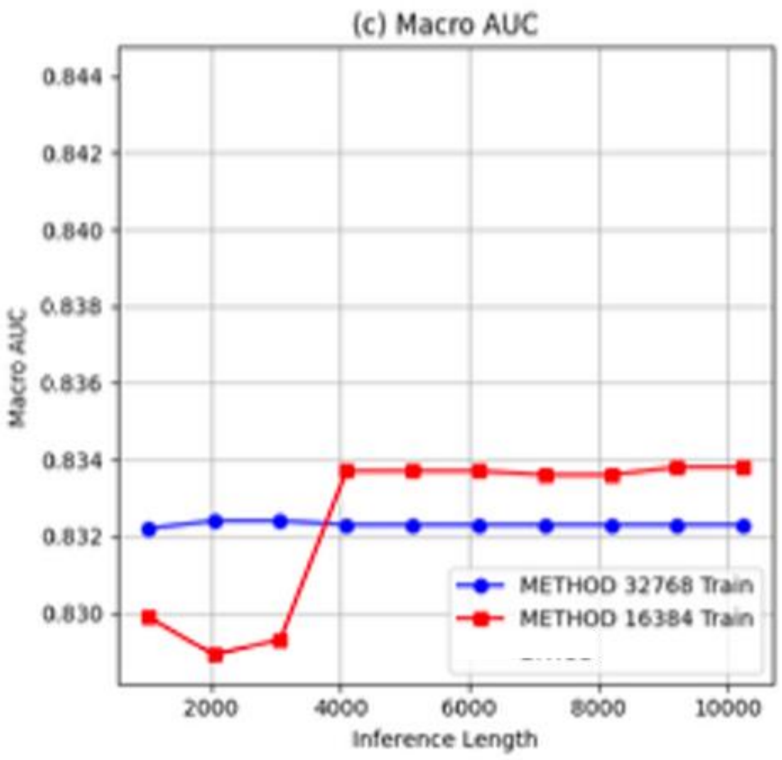
Foresight Clustering

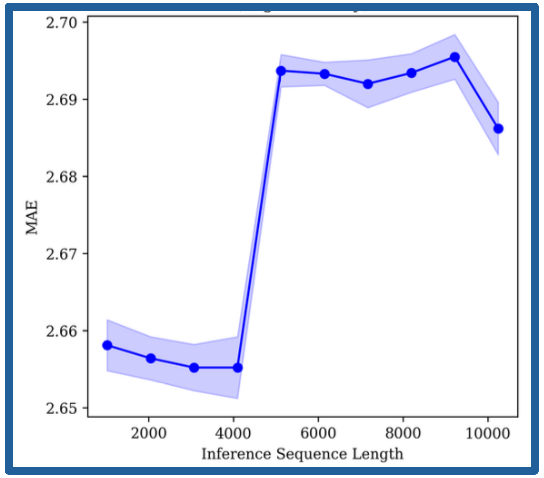


METHOD Clustering

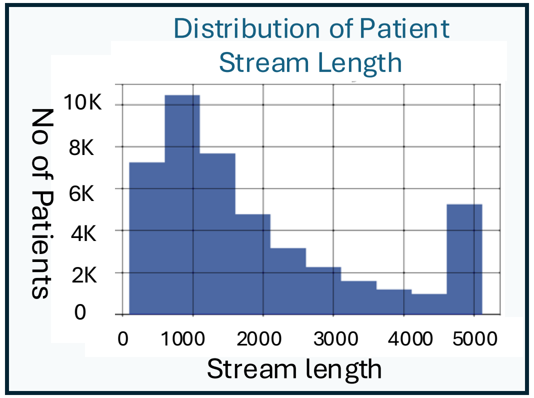
Result: Impressive ability to use ‘short sequence’ data to perform inference







FORESIGHT



Distribution of CUI Streams per Patient @KCH

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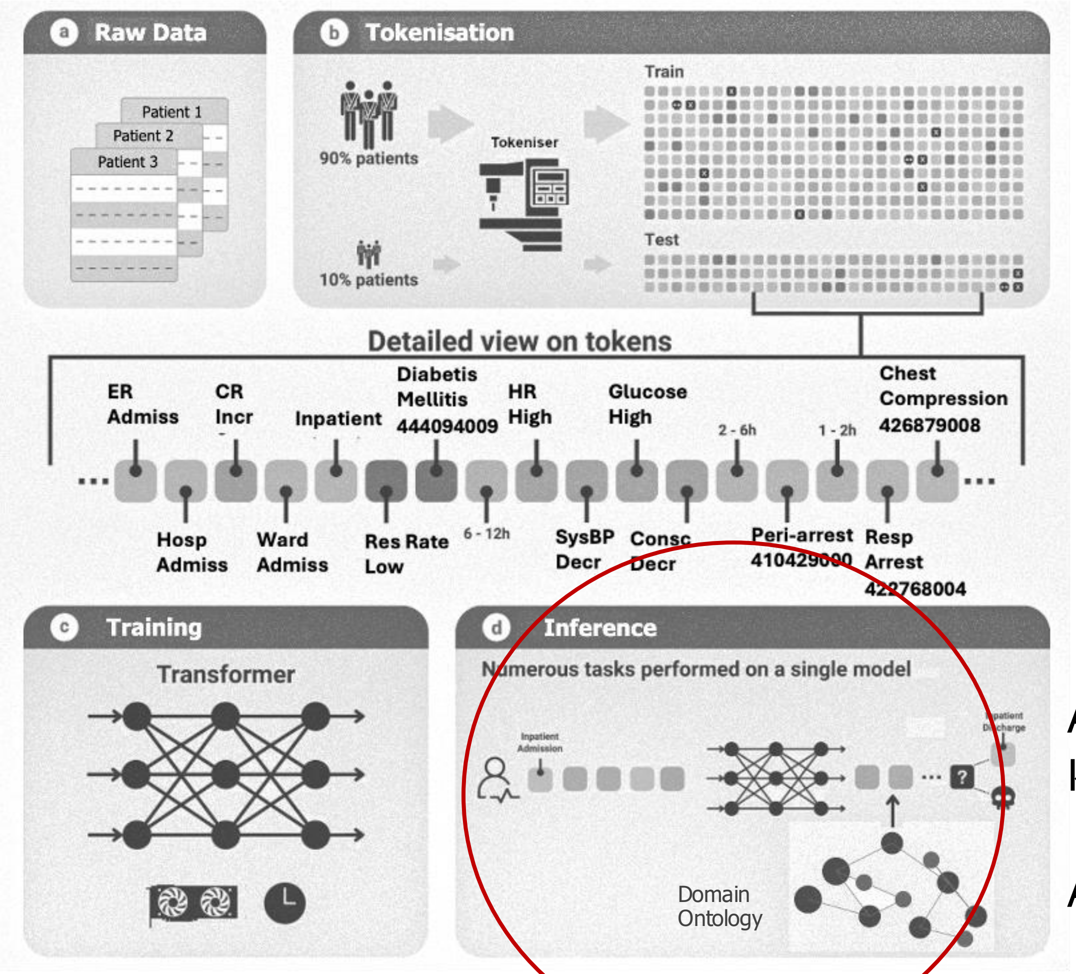

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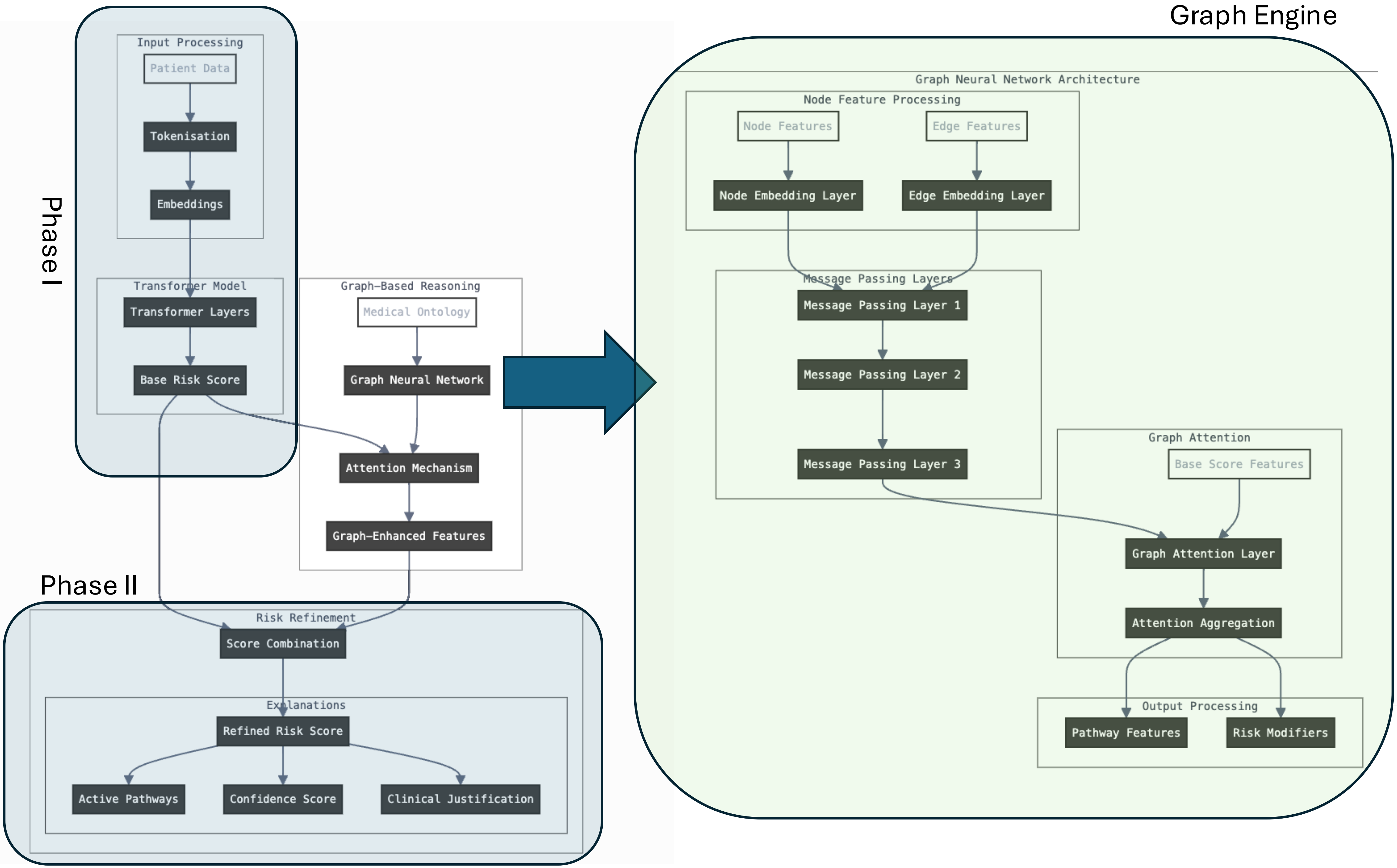
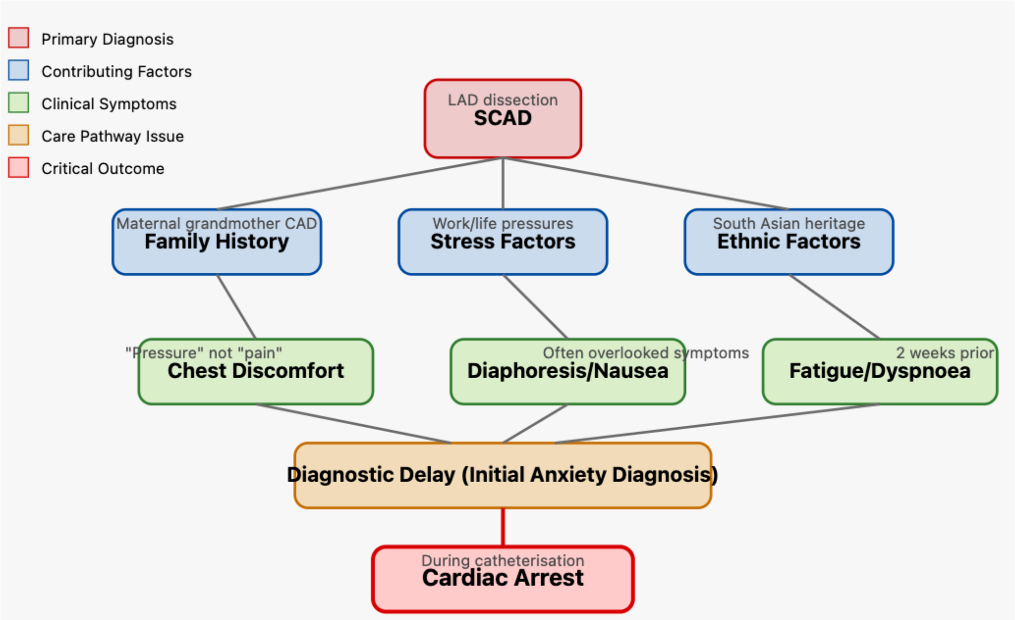
PHASE I

PHASE II




Mr Joseph Arul Raj

Sample Case Analysis



- 32-year-old South Asian female
- No prior cardiovascular history
- BMI: 23.4 (normal range)
- Non-smoker, social alcohol use
- Regular yoga practitioner (3x weekly)
- Family history: Maternal grandmother with premature coronary artery disease (age 49)

- **Presenting Symptoms**
- Sudden onset chest discomfort (described as "pressure" rather than pain)
- Fatigue and dyspnoea for 2 weeks prior
- Initially dismissed by primary care as anxiety/stress
- No classic male-pattern radiation of pain
- Diaphoresis and nausea present
- Initial ECG: Subtle ST-segment elevation in anterior leads
- Initial troponin: Borderline elevated (0.08 ng/ml)

Dr Hugh Logan-Ellis

Take-home Messages

- Off-the-shelf Transformer architectures are less than ideal for EHRs
- Talk to me about:
  - Data-driven (generative) models are not the best we can do!

Thank you!