Importance of Free-Text in EHR and Role of Artificial Intelligence

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National Academies of Science, Engineering, and Medicine

Workshop on Health Disparities in the Medical Record and Disability Determinations, Session 6

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Department of Learning Health Sciences

Disclosures

- I do not have any financial or personal conflicts of interest to disclose at this time.

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Unstructured Data = Iceberg Under Water

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(2022)

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Over 400M “documents” within Michigan Medicine!

(2020)

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Books, Journals, Peer-reviewed literature

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Medical Records

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Prescriptions

6.7B retail prescriptions filled at US pharmacies in 2022

(IQVIA Institute, May 2023)

Medical Natural Language Processing

Published literature

Electronic Medical Records

Pharmacies

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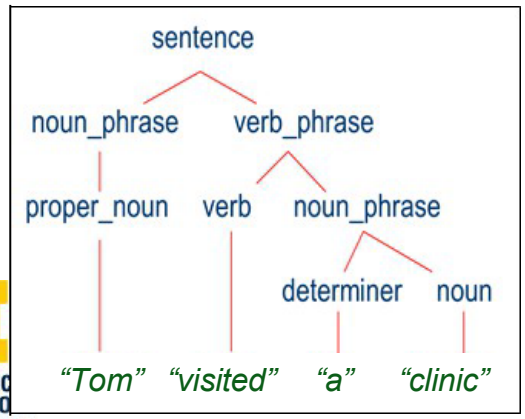

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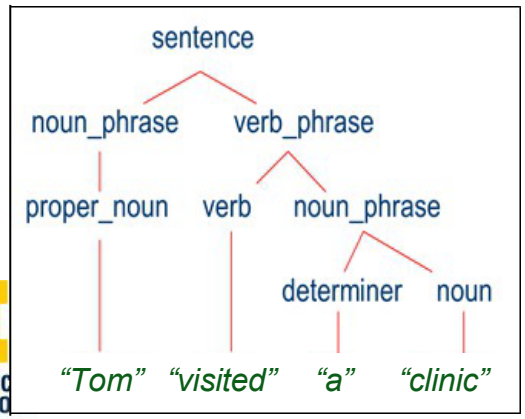

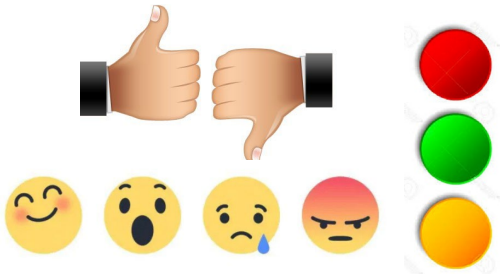

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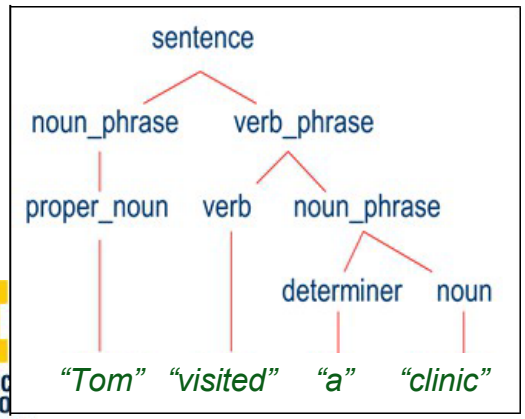

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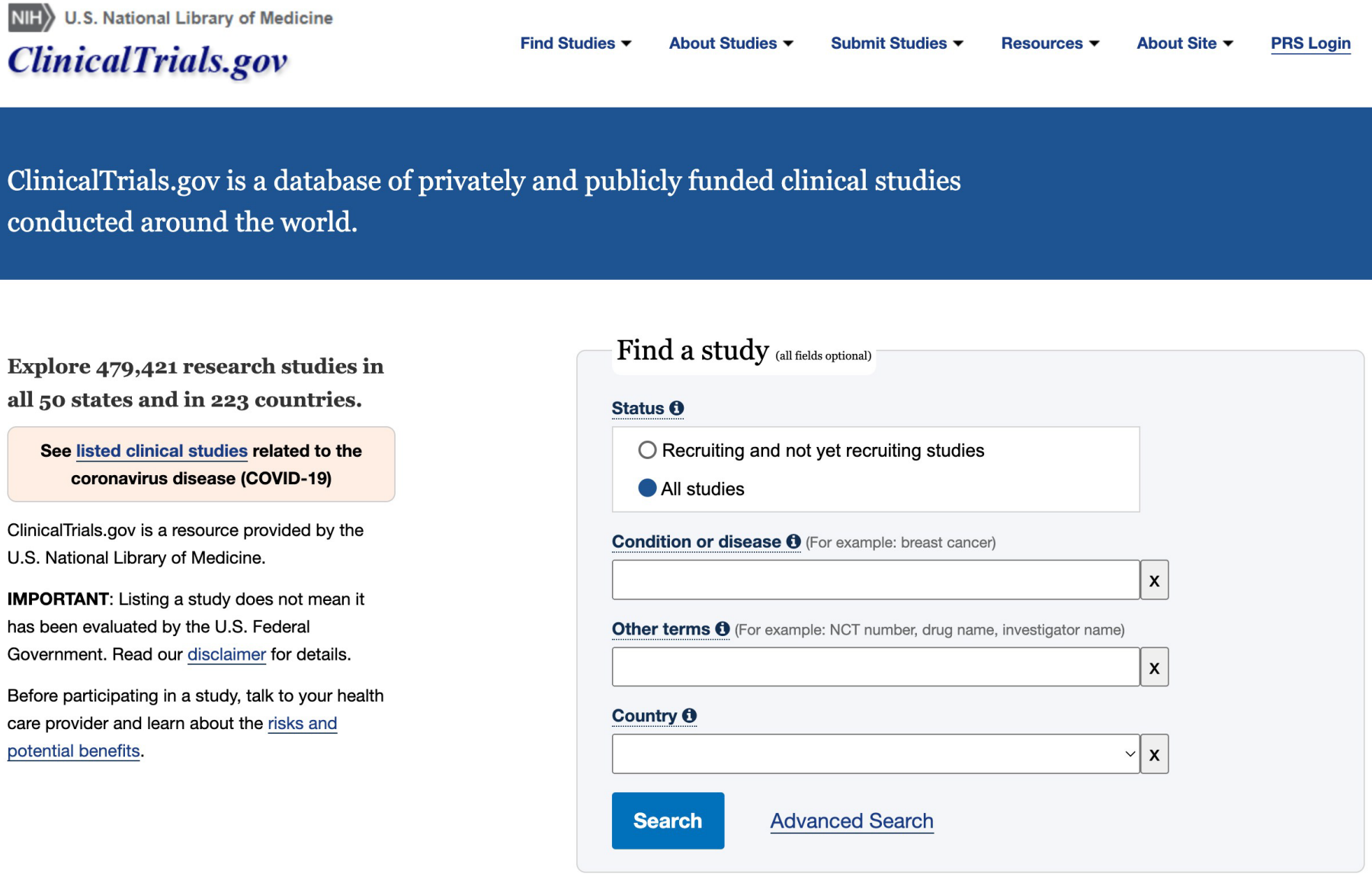
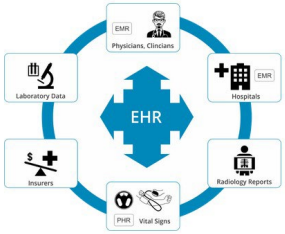
Case study: Cohort Identification



https://classic.clinicaltrials.gov/ Accessed Jan 21, 2024. Expected to retire soon.

Cohort Identification from EHRs



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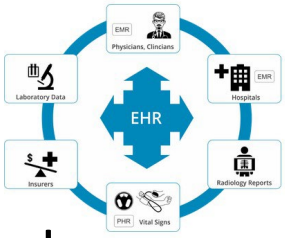

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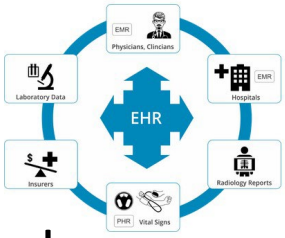

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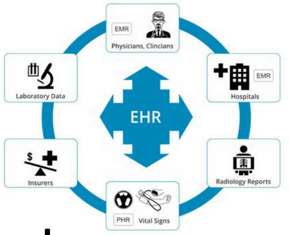

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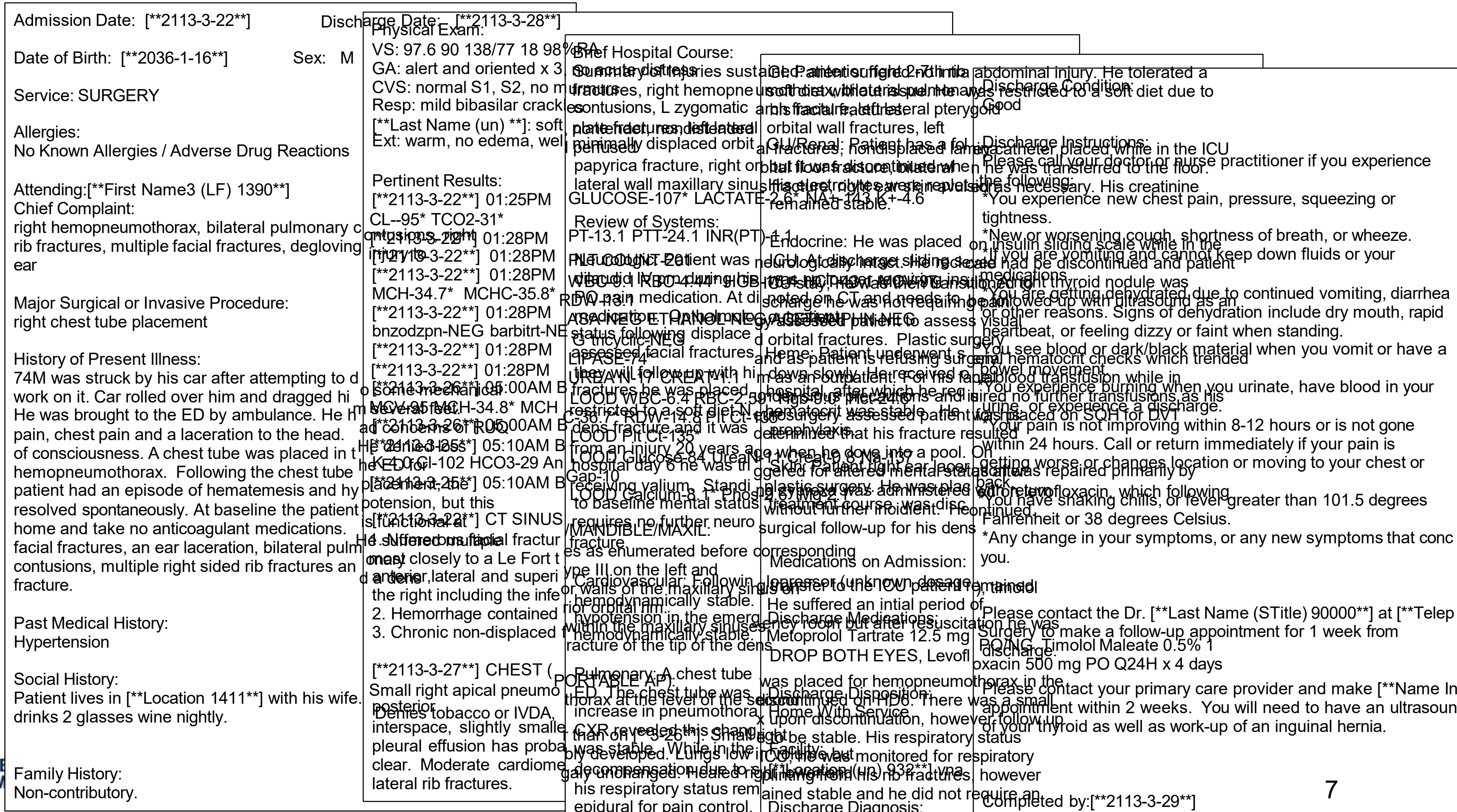

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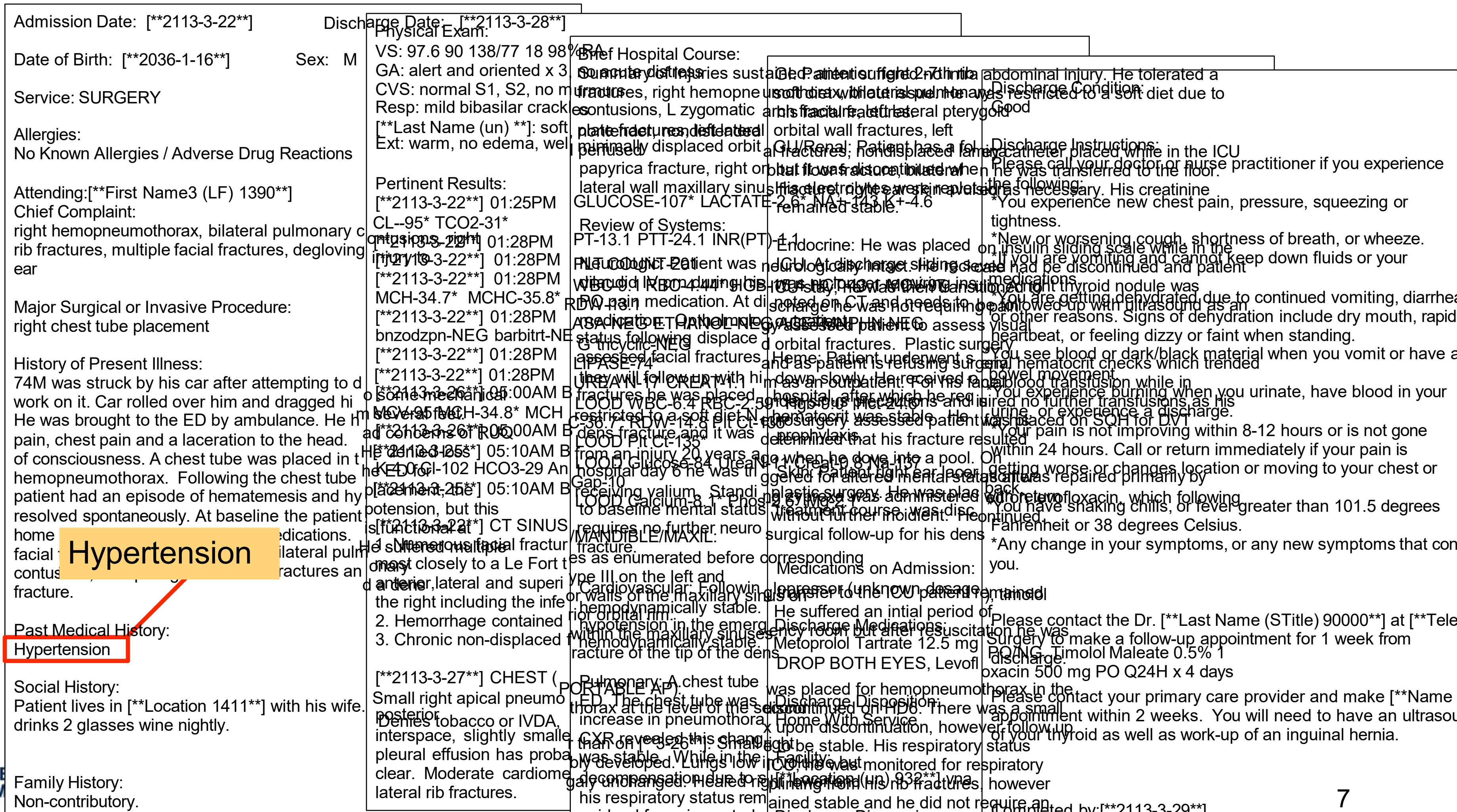

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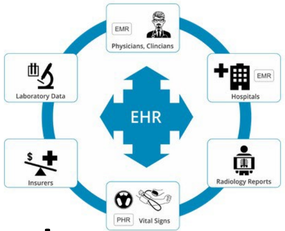

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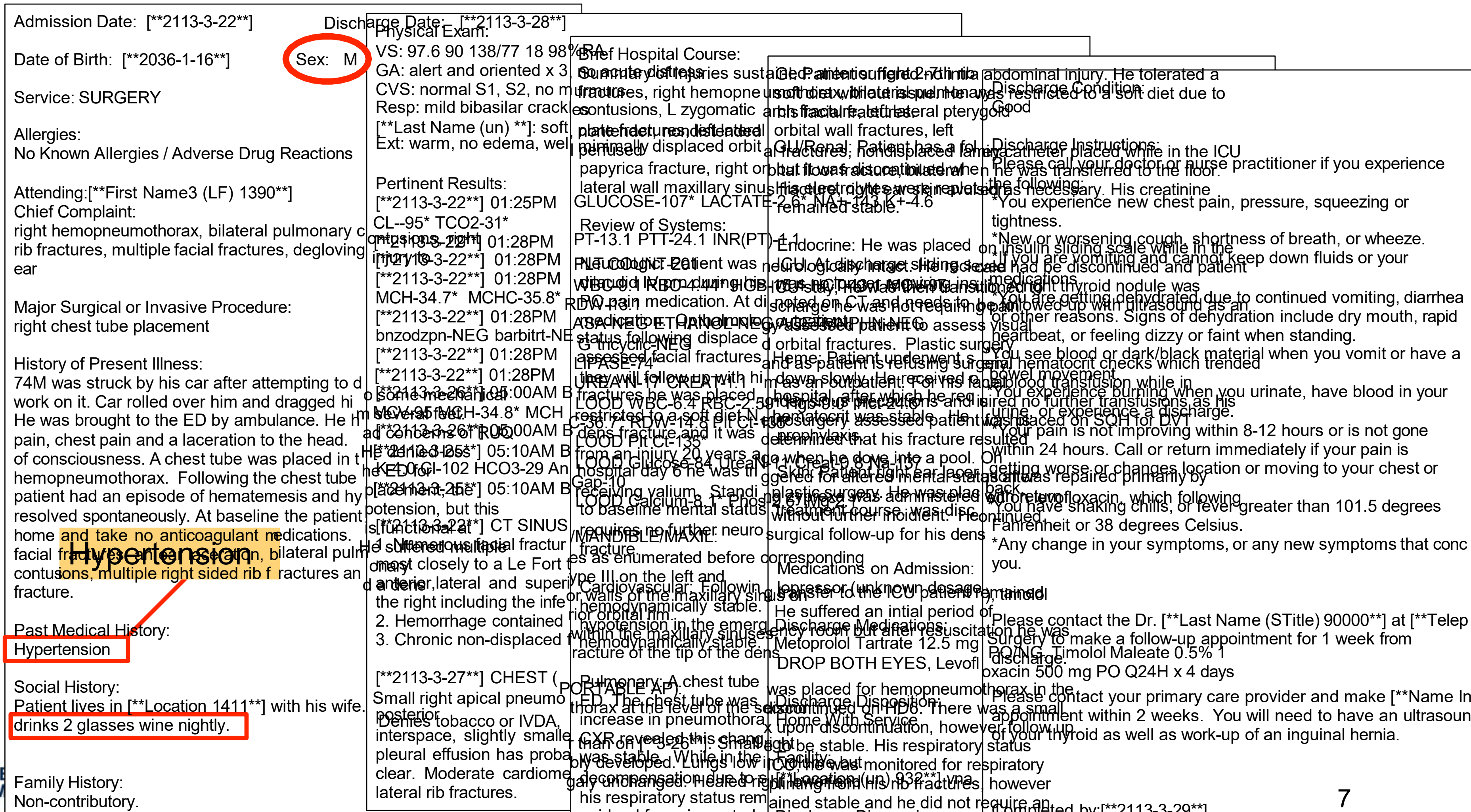

Admission Date: [**2113-3-22**] Discharge Date: [**2113-3-28**]

Date of Birth: [**2036-1-16**] Sex: M

Service: SURGERY

Allergies:
No Known Allergies / Adverse Drug Reactions

Attending:[**First Name3 (LF) 1390**]
Chief Complaint:
right hemopneumothorax, bilateral pulmonary c
rib fractures, multiple facial fractures, degloving
ear

Major Surgical or Invasive Procedure:
right chest tube placement

History of Present Illness:
74M was struck by his car after attempting to d
work on it. Car rolled over him and dragged hi
He was brought to the ED by ambulance. He h
pain, chest pain and a laceration to the head.
of consciousness. A chest tube was placed in t
hemopneumothorax. Following the chest tube
patient had an episode of hematemesis and hy
resolved spontaneously. At baseline the patient
home and take no anticoagulant medications.
facial fractures, ... bilateral pulm
contusions, multiple right sided rib fractures an
fracture.

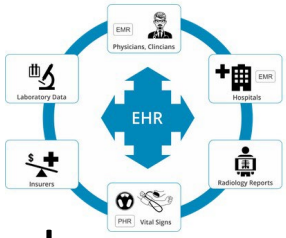
Hypertension

Past Medical History:
Hypertension

Social History:
Patient lives in [**Location 1411**] with his wife.
drinks 2 glasses wine nightly.

Family History:
Non-contributory.

Cohort Identification from EHRs



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Physical Exam:
VS: 97.6 90 138/77 18 98
GA: alert and oriented x 3
CVS: normal S1, S2, no m
Resp: mild bibasilar crack
[**Last Name (un) **]: soft
Ext: warm, no edema, wel

Pertinent Results:
[**2113-3-22**] 01:25PM
CL--95* TCO2-31*
[**2113-
[**2113-
[**2113-
MCH-34
[**2113-3-22**] 01:28PM
bnzodzpn-NEG barbitrt-NE
[**2113-3-22**] 01:28PM
[**2113-3-22**] 01:28PM
[**2113-3-26**] 05:00AM B
MCV-95 MCH-34.8* MCH
[**2113-3-26**] 05:00AM B
[**2113-3-25**] 05:10AM B
K-4.0 Cl-102 HCO3-29 An
[**2113-3-25**] 05:10AM B

[**2113-3-22**] CT SINUS
1. Numerous facial fractur
most closely to a Le Fort t
anterior,lateral and superi
the right including the infe
2. Hemorrhage contained
3. Chronic non-displaced f

[**2113-3-27**] CHEST (P
Small right apical pneumo
posterior
interspace, slightly smalle
pleural effusion has proba
clear. Moderate cardiome
lateral rib fractures.

Brief Hospital Course:
Summary of Injuries susta
fractures, right hemopne
contusions, L zygomatic
plate fractures, left lateral
minimally displaced orbit
papyrica fracture, right or
lateral wall maxillary sinu

Review of Systems:

gic: Patient was
IV prn during his
medication. At di
medication. Opthalmolo
status following displace
assessed facial fractures
they will follow up with hi
fractures he was placed
restricted to a soft diet.N
dens fracture and it was
from an injury 20 years a
hospital day 6 he was tri
receiving valium. Standi
to baseline mental status
requires no further neuro
fracture.

Cardiovascular: Followin
hemodynamically stable.
hypotension in the emerg
hemodynamically stable.

Pulmonary: A chest tube
ED. The chest tube was
increase in pneumothora
CXR revealed this chang
was stable. While in the
decompensation due to s
his respiratory status rem
epidural for pain control.

GI: Patient suffered no intra
soft diet without issue. He
his facial fractures.

GU/Renal: Patient has a fol
but it was discontinued whe
His electrolytes were replet
remained stable.

Endocrine: He was placed
ICU. At discharge sliding s
was no longer requiring ins
noted on CT and needs to
outpatient,

Heme: Patient underwent s
down slowly. He received o
hospital, after which he req
hematocrit was stable. He
prophylaxis.

Skin: Patient right ear lacer
plastic surgery. He was plac
treatment course, was disc

Medications on Admission:
lopressor (unknown dosage

Discharge Medications:
Metoprolol Tartrate 12.5 mg
DROP BOTH EYES, Levofl

Discharge Disposition:
Home With Service

Facility:
[**Location (un) 932**] vna

Discharge Diagnosis:

Discharge Condition:
Good

Discharge Instructions:
Please call your doctor or nurse practitioner if you experience the following:
*You experience new chest pain, pressure, squeezing or tightness.
*New or worsening cough, shortness of breath, or wheeze.
*If you are vomiting and cannot keep down fluids or your medications.
*You are getting dehydrated due to continued vomiting, diarrhea or other reasons. Signs of dehydration include dry mouth, rapid heartbeat, or feeling dizzy or faint when standing.
*You see blood or dark/black material when you vomit or have a bowel movement.
*You experience burning when you urinate, have blood in your urine, or experience a discharge.
*Your pain is not improving within 8-12 hours or is not gone within 24 hours. Call or return immediately if your pain is getting worse or changes location or moving to your chest or back.
*You have shaking chills, or fever greater than 101.5 degrees Fahrenheit or 38 degrees Celsius.
*Any change in your symptoms, or any new symptoms that conc you.

Please contact the Dr. [**Last Name (STitle) 90000**] at [**Telep Surgery to make a follow-up appointment for 1 week from discharge.

Please contact your primary care provider and make [**Name In appointment within 2 weeks. You will need to have an ultrasoun of your thyroid as well as work-up of an inguinal hernia.

Completed by:[**2113-3-29**]

Hypertension

Low Risk Alcohol Use

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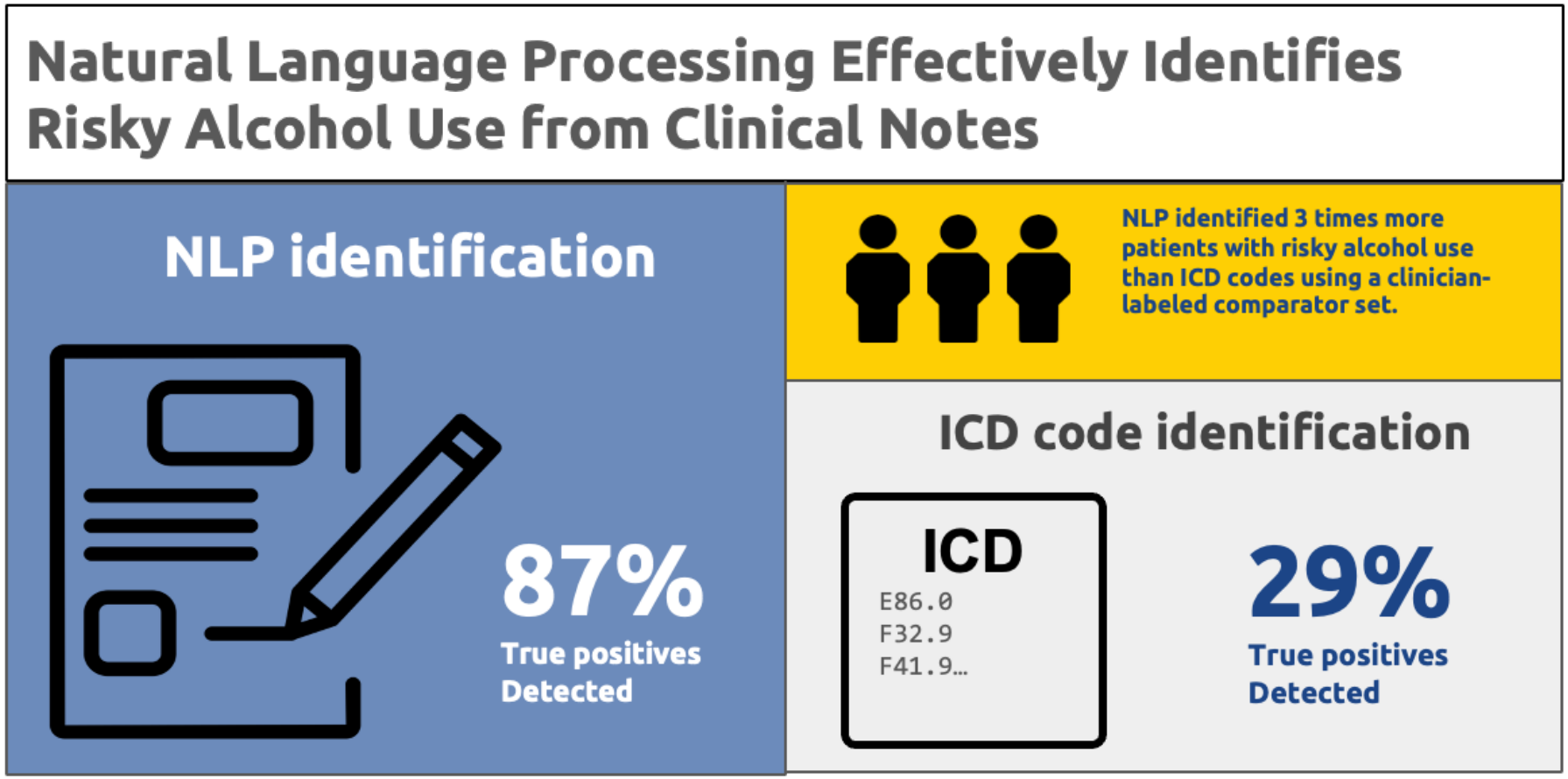

Vydiswaran, et al. Automated-detection of risky alcohol use prior to surgery using natural language processing. *Alcohol, Clinical and Experimental Research*, 2024 Jan; Volume 48, Issue 1 p.153-163. DOI: 10.1111/acer.15222

Extracting SDoH from EHRs

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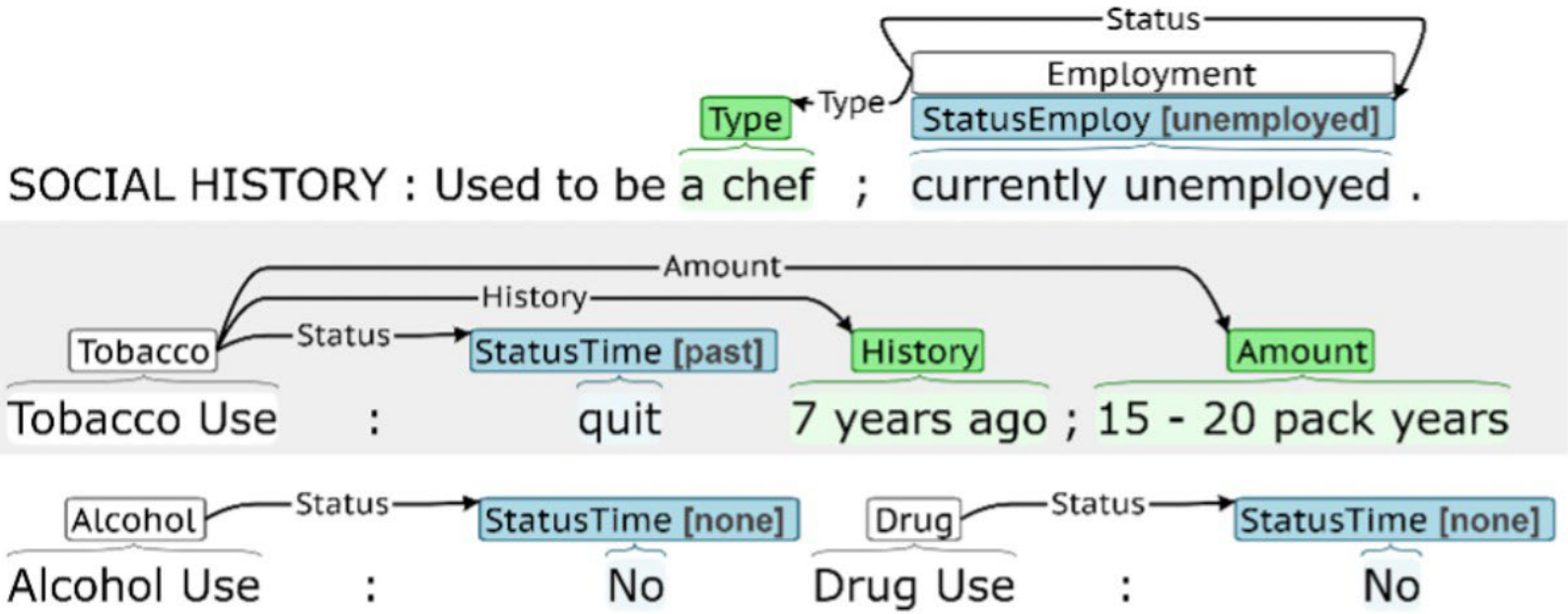

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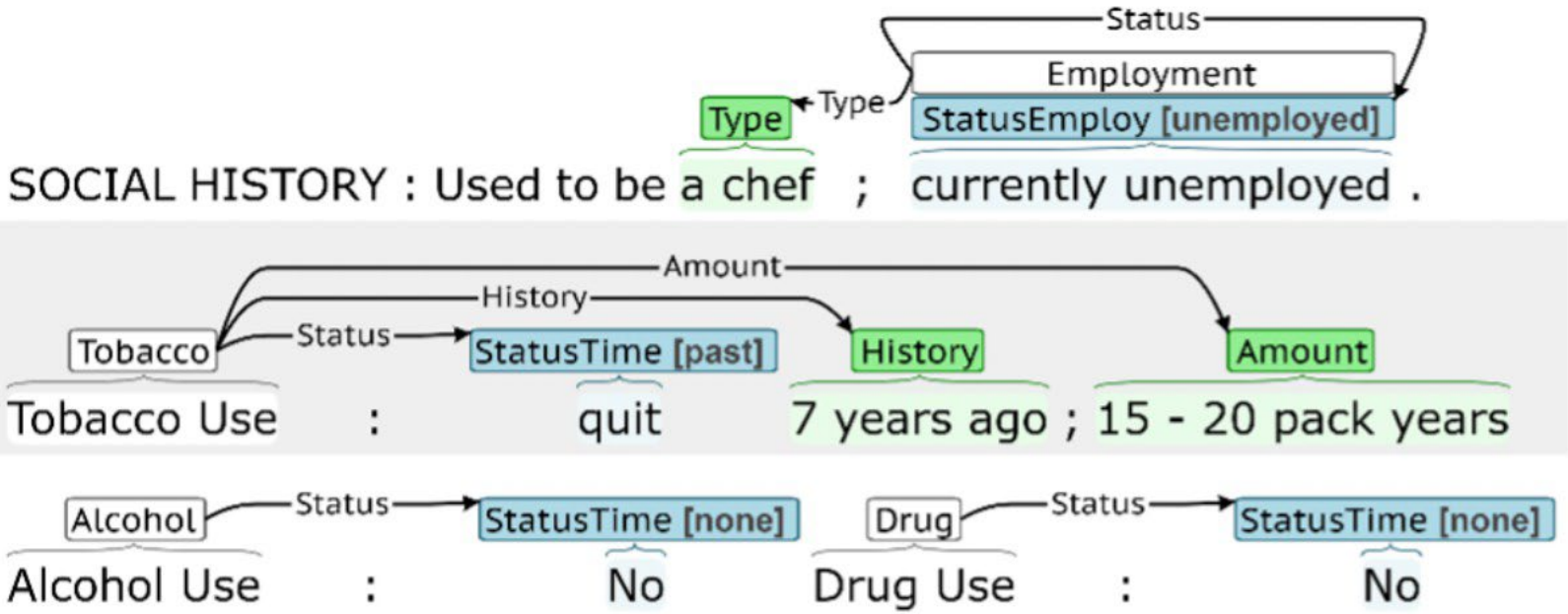

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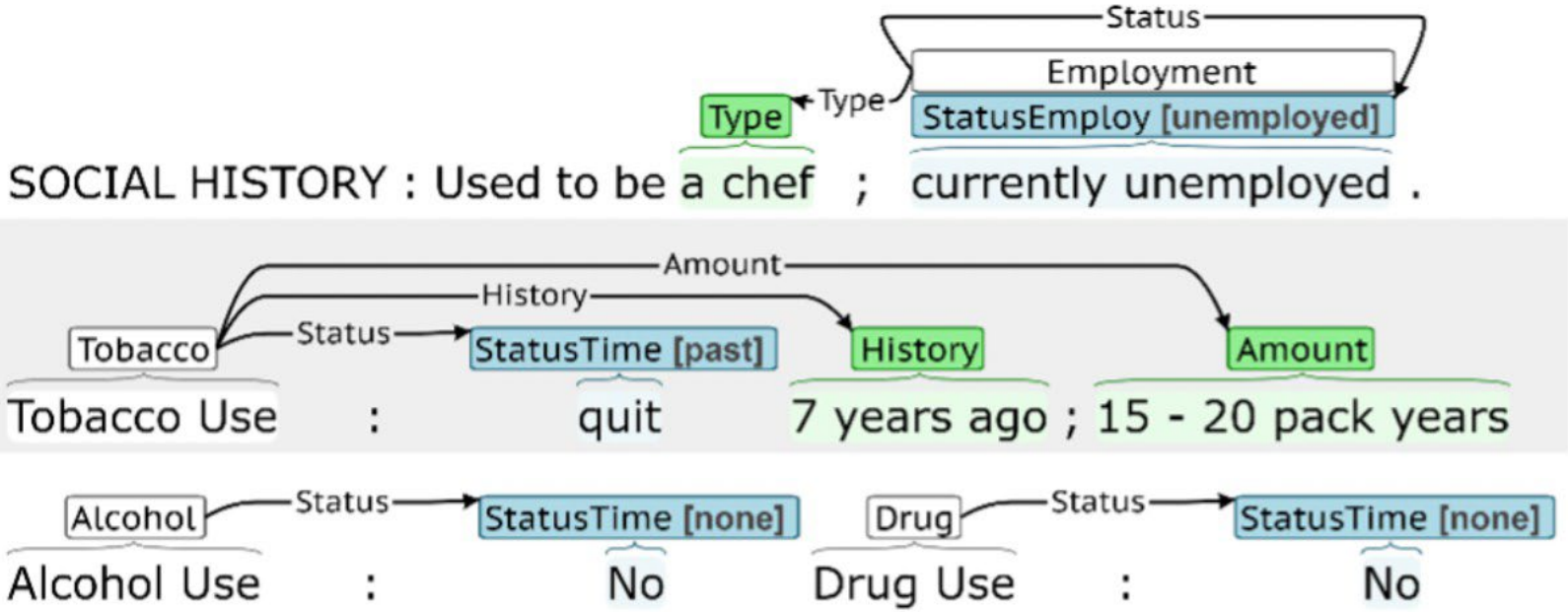
  - Current state-of-the-art systems use **deep neural network models**



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Patients with completed encounters were more likely to be **younger than 65 years old** (71.8%-74.1%), be **female** (58.8%-61.8%), be **White** (75.6%-76.7%), and have **no significant comorbidities** (63.2%-66.8%) or **no disabilities** (53.2%-61.1%) in all time periods than those who had only canceled or missed encounters

Buis LR, et al. Identifying inequities in video and audio telehealth services for primary care encounters during COVID-19: Repeated cross-sectional, observational study. *J Med Internet Res*. 2023 Sep 29;25:e49804. DOI: 10.2196/49804.

Identifying inequities via EHR analyses (2)

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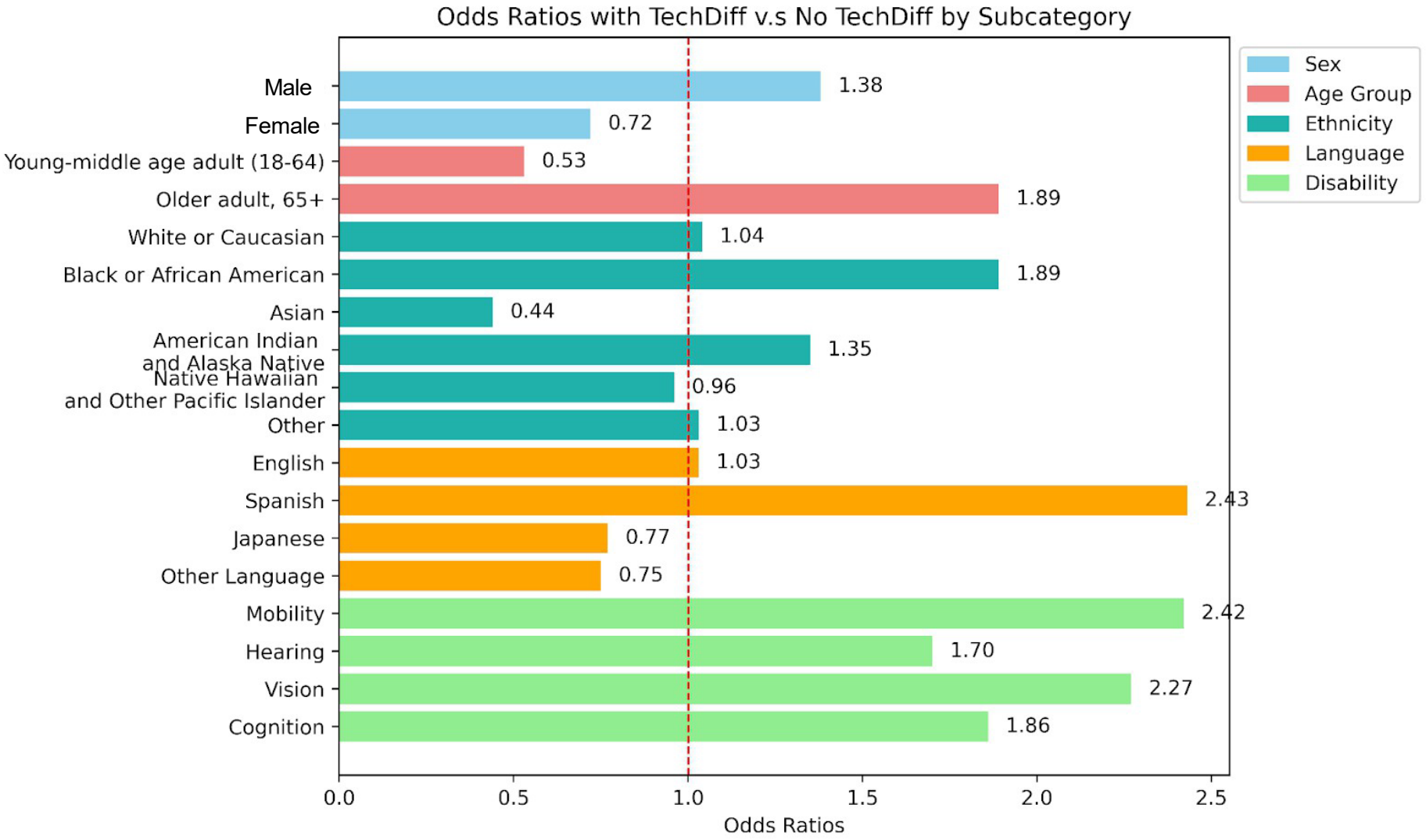

Li J, et al. Active learning to identify patients encountering technical difficulties during care virtualization. Under preparation.

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Questions, Comments: vgvinodv@umich.edu

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- Computable biomedical knowledge objects and a Learning Health System Infrastructure are **essential** to scale it up!

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