OHDSI
Observational Health Data Sciences and Informatics

Next Steps in Evidence Dissemination

OHDSI Community Call
Nov. 12, 2024 • 11 am ET

Upcoming Community Calls

Date	Topic
Nov. 12	Next Steps in Evidence Dissemination
Nov. 19	Evidence Network in Action: Semiglutide Study
Nov. 26	Collaborator Showcase Honorees
Dec. 3	Recent OHDSI Publications
Dec. 10	How Did We Do In 2024?
Dec. 17	Holiday-Themed Final Call of 2024

Three Stages of The Journey

Where Have We Been?

Where Are We Now?

Where Are We Going?

Upcoming Workgroup Calls

Date	Time (ET)	Meeting
Tuesday	12 pm	Common Data Model Vocabulary Subgroup
Tuesday	12 pm	Gener
Wednesday	9 am	Patient-Level Prediction
Wednesday	12 pm	Health Equity
Wednesday	4 pm	Joint Vulcan/OHDSI Meeting
Wednesday	7 pm	Medical Imaging
Thursday	10:30 am	Evidence Network
Thursday	12 pm	Strategus HADES Subgroup
Thursday	6 pm	Eyecare and Vision Research
Thursday	7 pm	Dentistry
Friday	10 am	GIS-Geographic Information System
Friday	10:30 am	Open-Source Community
Friday	11:30 am	Steering
Monday	9 am	Vaccine Vocabulary
Monday	10 am	Healthcare Systems Interest Group
Monday	11 am	Data Bricks User Group
Monday	2 pm	Electronic Animal Health Records

NEI Eye Care and Ocular Imaging Challenge

NIH

NEI Expand OHDSI Initiative for Eye Care and Ocular Imaging Challenge

Submit your innovative ideas related to eye care and vision research for leveraging OHDSI.

This challenge seeks to expand the OHDSI network for vision research by incentivizing innovative ideas for leveraging real-world evidence. Prizes can support winner's integration into the network.

Key Dates and Challenge Timeline:

- Registration Period Open: August 26, 2024
- Mandatory Registration (intent to participate) Due: November 12, 2024
- Submission Period Open: December 1, 2024
- Submission Deadline: January 31, 2025
- Judging Start: February 10, 2025
- Judging End: March 24, 2025
- Winners Announced: April 2025

ENCePP Guide Survey Due Nov. 18

The 12th revision of the ENCePP Guide on Methodological Standards in Pharmacoepidemiology will be published next year, and the editorial team seek feedback from the ENCePP community and users of the Guide.

Deadline is Nov. 18.

EMA/95098/2010 Rev.11

The European Network of Centres for Pharmacoepidemiology and Pharmacovigilance (ENCePP) Guide on Methodological Standards in Pharmacoepidemiology

(Revision 11)

Next CBER Best Seminar: Nov. 20

Topic: Statistical methods for improving post-licensure vaccine safety surveillance

Presenter: Jennifer Clark Nelson, PhD, Director of Biostatistics & Senior Investigator, Biostatistics Division, Kaiser Permanente Washington Health Research Institute.

Date/Time: Nov. 20, 11 am ET

ohdsi.org/cber-best-seminar-series

The Center for Advanced Healthcare Research Informatics (CAHRI) at Tufts Medicine welcomes:

Agnes Kiragga, PhD

Lead - Data Science Program, African Population and Health Research Center (APHRC)

'Promoting Data Science and Data Harmonization in Africa '

November 21, 2024, 11am-12pm EST
Virtually via [Zoom]

Please contact Marty Alvarez at malvarez2@tuftsmedicalcenter.org for calendar invite or questions.

TuftsMedicine
Tufts Medical Center

2024 APAC Symposium

Dec. 4-8 • Marina Bay Sands & National University of Singapore (NUS)

Dec. 4: Tutorial at NUS

Dec. 5-6: Main Conference at Marina Bay Sands

Dec. 7-8: Datathon at NUS

ohdsi.org/APAC2024

#OHDSISocialShowcase This Week

Monday

Process of Conversion of Ukrainian Medical Data to OMOP CDM Format

(**Bohdan Khilchevskyi**, Denys Kaduk, Maksym Trofymenko, Polina Talapova, Tetiana Nesmiian, Max Ved, Inna Ageeva, Pavlova Olga, Holovko Tetiana, Shevchenko Natalia)

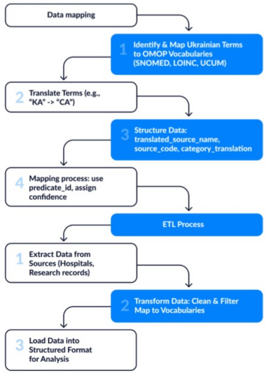
UKRDATA: Process of Conversion of Ukrainian Medical Data to OMOP CDM Format

PRESENTER:
Polina Talapova
polina.talapova@sciforce.tech

INTRO:

If we don't standardize and integrate Ukrainian medical data, it stays siloed, disconnected, and useless for international research. By converting it into the OMOP CDM format, we unlock the potential for global collaboration, real-world evidence generation, and ultimately, better patient outcomes. This project matters because it's about making Ukrainian health data count on the world stage, and ensuring it contributes to life-saving discoveries.

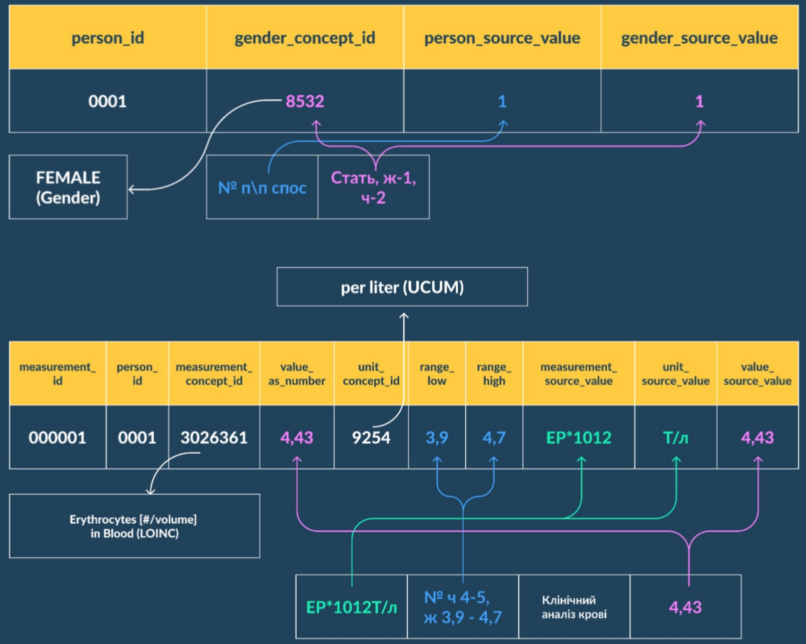
METHODS

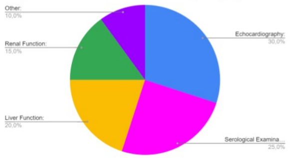


RESULTS

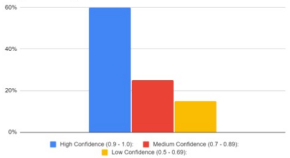
The conversion process successfully standardized a dataset of Ukrainian medical data, including patient demographics, diagnoses, and procedures. The mapping relied on SNOMED and other vocabularies, utilizing SSSOM exact matches where possible and broad or narrow terms when necessary. Over 85% of the mappings achieved high confidence, ensuring accurate integration into OMOP standards. Lab tests were mapped to LOINC, using "in blood" for hematology and "in serum or plasma" for biochemical tests. The data is now ready for analysis using tools like ATLAS and is suitable for international presentation.

Enable global research collaboration via **standardization of Ukrainian medical data** through **OMOP CDM** and **SSSOM**





This diagram 1 highlights the diversity of medical concepts included in the dataset and shows which categories are most prevalent. It helps stakeholders understand areas with rich data and those that may require further exploration or additional mapping.



The diagram 2 summarizes the confidence levels associated with the mappings from Ukrainian medical terms to OMOP standardized vocabularies. It categorizes the mappings based on their accuracy and reliability, providing a clear view of how confident the team is in each mapping.

CONCLUSION

This case study successfully demonstrates the potential of converting regional healthcare data, such as Ukrainian medical records, into the OMOP CDM format, thereby enhancing data interoperability and facilitating international collaborative research within the OHDSI network.

Bohdan Khilchevskyi, Denys Kaduk, Maksym Trofymenko, Polina Talapova, Tetiana Nesmiian, Max Ved, Inna Ageeva, Olga Pavlova, Tetiana Holovko, Natalia Shevchenko

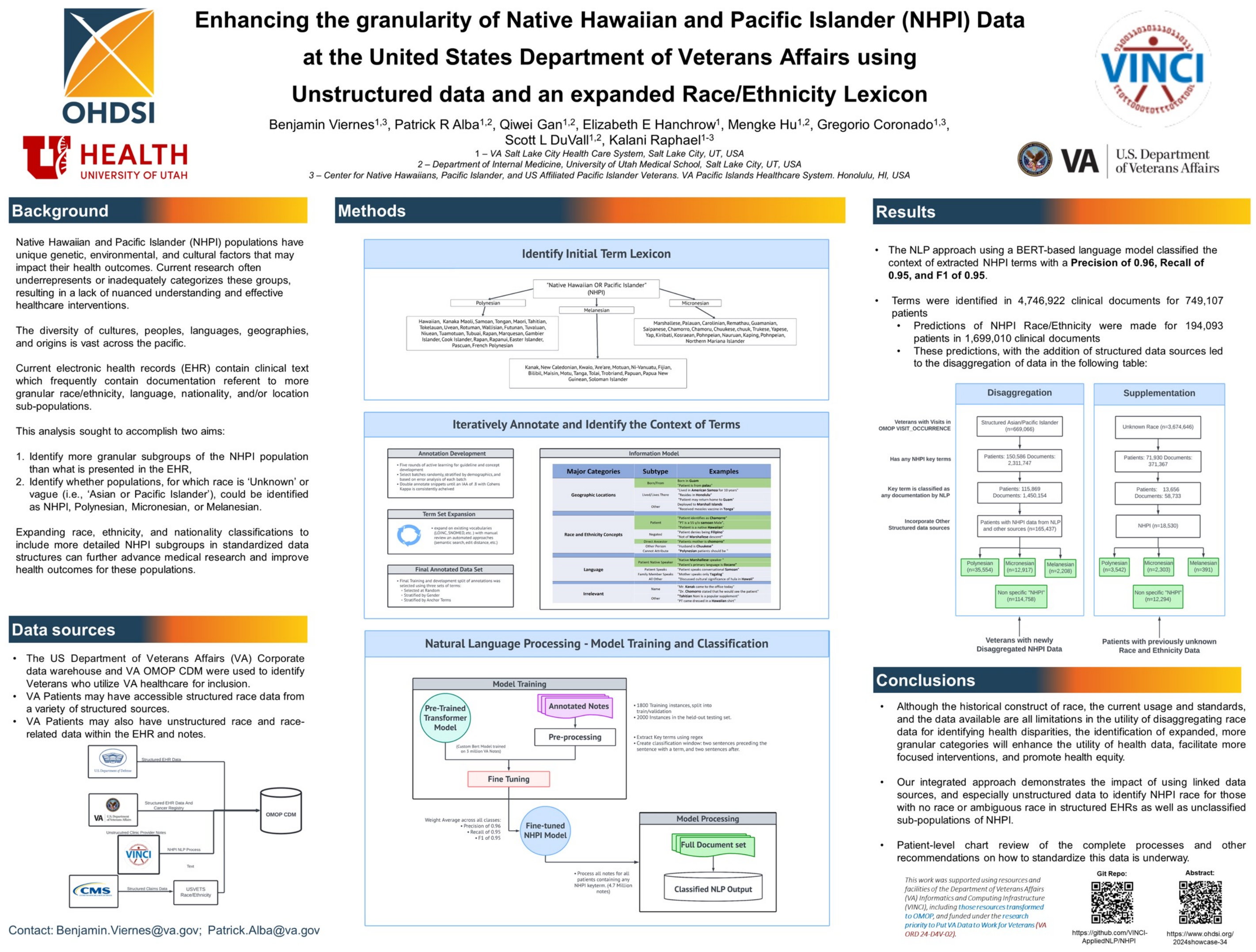
sciforce OHDSI

#OHDSISocialShowcase This Week

Tuesday

Moananuiakea: Enhancing the granularity of Native Hawaiian and Pacific Islander(NHPI) Data at the United States Department of Veterans Affairs using Unstructured data and an expanded Race/Ethnicity Lexicon

(Benjamin Viernes, Patrick Alba, Qiwei Gan, Elizabeth E Hanchrow, Mengke Hu, Gregorio Coronado, Scott L Duvall, Kalani Raphael)



Enhancing the granularity of Native Hawaiian and Pacific Islander (NHPI) Data at the United States Department of Veterans Affairs using Unstructured data and an expanded Race/Ethnicity Lexicon

Benjamin Viernes[1,3], Patrick R Alba[1,2], Qiwei Gan[1,2], Elizabeth E Hanchrow[1], Mengke Hu[1,2], Gregorio Coronado[1,3], Scott L DuVall[1,2], Kalani Raphael[1-3]

1 – VA Salt Lake City Health Care System, Salt Lake City, UT, USA
2 – Department of Internal Medicine, University of Utah Medical School, Salt Lake City, UT, USA
3 – Center for Native Hawaiians, Pacific Islander, and US Affiliated Pacific Islander Veterans. VA Pacific Islands Healthcare System. Honolulu, HI, USA

Background

Native Hawaiian and Pacific Islander (NHPI) populations have unique genetic, environmental, and cultural factors that may impact their health outcomes. Current research often underrepresents or inadequately categorizes these groups, resulting in a lack of nuanced understanding and effective healthcare interventions.

The diversity of cultures, peoples, languages, geographies, and origins is vast across the pacific.

Current electronic health records (EHR) contain clinical text which frequently contain documentation referent to more granular race/ethnicity, language, nationality, and/or location sub-populations.

This analysis sought to accomplish two aims:

1. Identify more granular subgroups of the NHPI population than what is presented in the EHR,
2. Identify whether populations, for which race is 'Unknown' or vague (i.e., 'Asian or Pacific Islander'), could be identified as NHPI, Polynesian, Micronesian, or Melanesian.

Expanding race, ethnicity, and nationality classifications to include more detailed NHPI subgroups in standardized data structures can further advance medical research and improve health outcomes for these populations.

Data sources

- The US Department of Veterans Affairs (VA) Corporate data warehouse and VA OMOP CDM were used to identify Veterans who utilize VA healthcare for inclusion.
- VA Patients may have accessible structured race data from a variety of structured sources.
- VA Patients may also have unstructured race and race-related data within the EHR and notes.

Contact: Benjamin.Viernes@va.gov; Patrick.Alba@va.gov

Methods

Identify Initial Term Lexicon

Iteratively Annotate and Identify the Context of Terms

Natural Language Processing - Model Training and Classification

Results

- The NLP approach using a BERT-based language model classified the context of extracted NHPI terms with a **Precision of 0.96, Recall of 0.95, and F1 of 0.95**.
- Terms were identified in 4,746,922 clinical documents for 749,107 patients
  - Predictions of NHPI Race/Ethnicity were made for 194,093 patients in 1,699,010 clinical documents
  - These predictions, with the addition of structured data sources led to the disaggregation of data in the following table:

Conclusions

- Although the historical construct of race, the current usage and standards, and the data available are all limitations in the utility of disaggregating race data for identifying health disparities, the identification of expanded, more granular categories will enhance the utility of health data, facilitate more focused interventions, and promote health equity.
- Our integrated approach demonstrates the impact of using linked data sources, and especially unstructured data to identify NHPI race for those with no race or ambiguous race in structured EHRs as well as unclassified sub-populations of NHPI.
- Patient-level chart review of the complete processes and other recommendations on how to standardize this data is underway.

This work was supported using resources and facilities of the Department of Veterans Affairs (VA) Informatics and Computing Infrastructure (VINCI), including those resources transformed to OMOP, and funded under the research priority to Put VA Data to Work for Veterans (VA ORD 24-D4V-02).

Git Repo: https://github.com/VINCI-AppliedNLP/NHPI

Abstract: https://www.ohdsi.org/2024showcase-34

#OHDSISocialShowcase This Week

Wednesday

Communication-Efficient Deep Learning Algorithms for Distributed Research Networks: A Model Merging Approach with Pareto Fronts

(**Lu Li**, Jenna Reps, Patrick Ryan, Yong Chen)

Communication-Efficient Deep Learning Algorithms for Distributed Research Networks: A Model Merging Approach with Pareto Fronts

Lu Li[a,b], Tianyu Zhang[h], Zhiqi Bu[i], Suyuchen Wang[h], Huan He[j], Jie Fu[k], Jiang Bian[l], Yonghui Wu[l], Yong Chen[a,b,c,d,e,f,g], Yoshua Bengio[h]

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c. Department of Biostatistics, Epidemiology, and Informatics, University of Pennsylvania Perelman School of Medicine, Philadelphia, PA
d. Leonard Davis Institute of Health Economics, Philadelphia, PA, USA
e. Penn Medicine Center for Evidence-based Practice (CEP), Philadelphia, PA, USA
f. Penn Institute for Biomedical Informatics (IBI), Philadelphia, PA, USA
g. Observational Health Data Sciences and Informatics, New York, New York
h. MILA & University of Montreal, Montreal, Quebec, CA
i. AWS AI
j. Auburn University, Auburn, AL
k. HKUST
l. University of Florida, Gainesville, FL

Background

- **Model Merging** aims to combines multiple fine-tuned models into a single generalized model to leverage their individual strengths.
- **Challenge**: Existing methods often overlook the conflicts between models, leading to trade-offs in performance.
- **Pareto Fronts** can provide optimal trade-off solutions, allowing practitioners to choose models based on specific preferences.
- In this work, we propose MAP algorithm, a computationally efficient method to identify Pareto fronts, minimizing trade-offs without requiring additional training.

Method

- **Motivation:**
  - Fine-tuned models tend to converge near the pre-trained model in parameter space.
  - Task vectors, representing the difference between fine-tuned and pre-trained models, exhibit small weight magnitudes compared to the pre-trained models (1% to 2%).

Metric	SUN397	Cars	DTD	SVHN	RESISC45	MNIST	GTSRB	EuroSAT
$\|\|\theta_{pre}\|\|_1$	1,270,487	1,270,487	1,270,487	1,270,487	1,270,487	1,270,487	1,270,487	1,270,487
$\|\|\mathbf{v}_n\|\|_1$	21,055	20,127	13,621	19,349	18,409	17,578	16,712	15,941
$\|\|\mathbf{v}_n\|\|_1/\|\|\theta_{pre}\|\|_1(\%)$	1.66%	1.58%	1.07%	1.52%	1.45%	1.38%	1.32%	1.25%

- **Main steps**:
  - Let θ_{pre} denote the pretrained model. Let θ_{ft}^n denote the finetuned model for task n, and $v_n = \theta_{ft}^n - \theta_{pre}$ denote the task vector for task n. The merged model can be written as $\theta_m = \theta_{pre} + \sum_{n=1}^{N} c_n \theta_{ft}^n$. Let $M_n(\theta_m)$ denote the evaluation metric of the merged model on task n. c_n are scaling coefficients and determine the preference for each task.
  - We approximate evaluation metrics using a **second-order Taylor expansion as** surrogate models for each task to approximate the original evaluation metrics efficiently.
  - Amortized Pareto Fronts: The algorithm estimates Pareto fronts by fitting surrogate models for each task, reducing computational complexity compared to direct optimization methods.
  - MAP Algorithm: The algorithm applies multi-objective optimization (e.g., NSGA-III) on the surrogate models to derive the Pareto front without gradient descent on the full model.

Contact: ychen123@pennmedicine.upenn.edu, luli1@sas.upenn.edu

Results

- The win rate is used to measure how often MAP outperforms other methods in terms of Pareto front solutions across tasks, especially for high-dimensional settings where brute-force becomes inefficient.
- MAP achieves a higher win rate and preference-weighted performance as the number of tasks increases, demonstrating better performance in discovering Pareto optimal solutions compared to direct search and baseline methods.
- MAP provides a well-distributed set of Pareto solutions, outperforming baseline methods in both low- and high-dimensional task setups.

N	# c (direct search)	# c per dim	# c (MAP)	Win rate (MAP)	R^2 (MAP)
2	200	14.14	30	49.81% (±0.30)	0.953 (±0.018)
3	300	6.69	50	46.90% (±0.71)	0.980 (±0.003)

N	# c (direct search)	# c per dim	# c (MAP)	Win rate (MAP)	R^2 (MAP)
4	300	4.16	60	50.67% (±2.44)	0.984 (±0.004)
5	500	3.47	85	53.00% (±1.88)	0.941 (±0.019)
6	500	2.82	100	60.71% (±1.34)	0.941 (±0.030)
7	1000	2.68	140	63.42% (±1.91)	0.891 (±0.024)
8	1000	2.37	250	65.58% (±0.94)	0.868 (±0.028)

Preference weighted sum of accuracies (↑)

# tasks	2	3	4	5	6	7	8
Single task models	75.84±1.76	77.03±1.84	82.43±4.40	87.69±4.50	88.52±4.02	89.26±3.58	90.62±2.52
MTL	73.63±0.30	75.13±1.00	80.10±2.79	84.93±3.58	86.78±2.94	87.40±2.56	89.11±2.36
Model soups (Wortsman et al. (2022a))	67.79±1.46	64.25±2.15	66.04±3.22	67.01±3.42	63.11±1.99	63.35±2.17	64.36±2.77
TIES-merging (Yadav et al. (2024))	69.30±0.33	67.60±0.58	71.79±2.93	76.49±3.10	73.74±2.96	72.54±2.87	72.24±1.91
DARE-TIES	67.62±1.65	66.49±2.34	71.39±4.45	74.55±4.55	73.34±4.10	71.43±3.84	71.89±2.86
Task Arithmetic (Ilharco et al. (2022))	**70.73±1.84**	61.15±2.33	52.69±4.23	61.58±4.62	51.37±3.84	39.79±3.97	60.77±2.84
TA with preference as weights	69.22±1.4	66.88±2.37	68.73±5.48	71.92±5.5	68.13±4.69	68.14±4.2	68.17±2.89
DARE-TA	70.61±0.22	64.18±1.24	58.04±8.19	65.39±7.03	56.76±7.01	46.75±5.73	64.51±3.81
MAP	70.70±0.21	**69.05±1.41**	**72.84±1.05**	**77.31±0.83**	**74.26±0.52**	**73.40±-0.14**	**72.96±0.73**

Conclusions

- We introduced a novel, low-compute method, MAP, for model merging that identifies Pareto fronts, allowing for efficient balancing of trade-offs across tasks without gradient descent.
- This work introduces an innovative approach for deep learning-based models. Our research aligns with the mission of OHDSI by advancing the frontier of methodology in clinical evidence generation and evidence synthesis.
- Our next step is to apply MAP to electronic health records data using the 17 benchmark tasks established in OHDSI PatientLevelPrediction package.

Reference

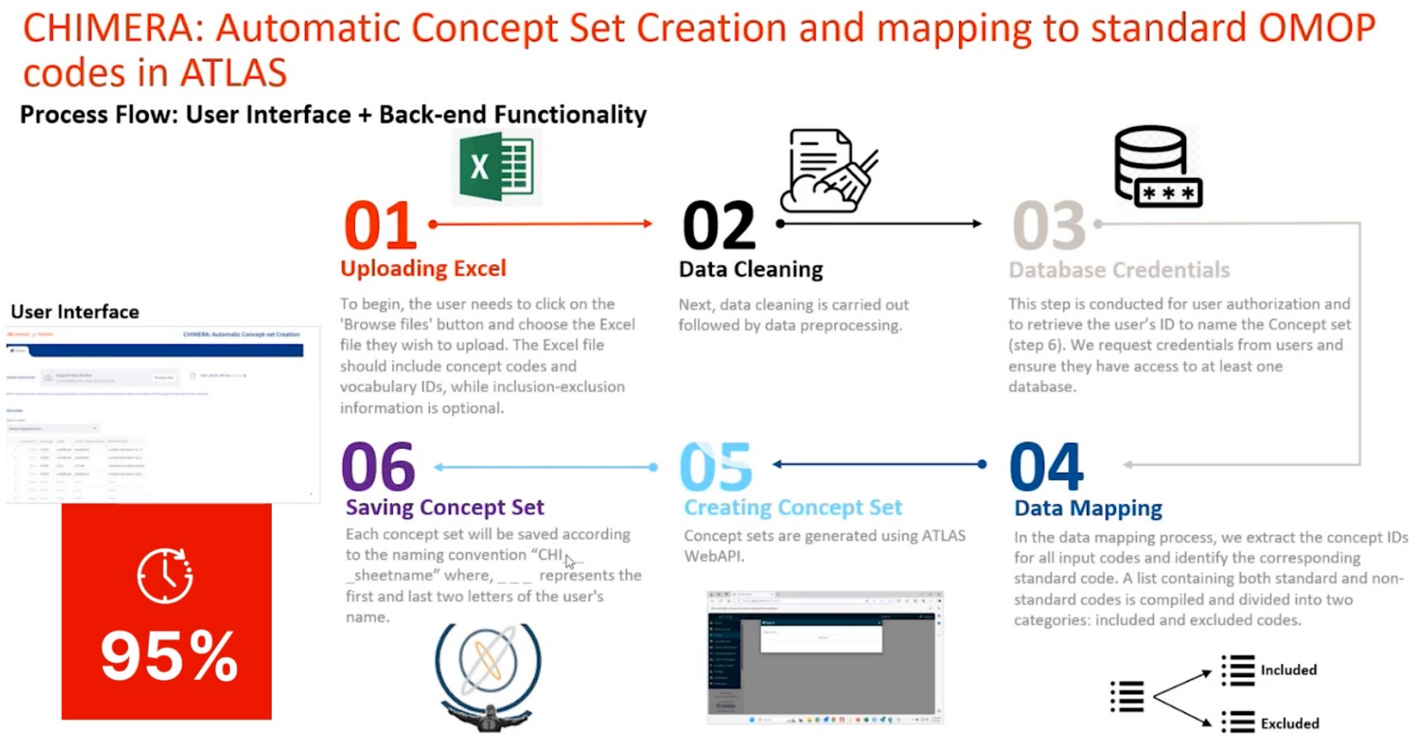
- Lin, X., Zhen, H.L., Li, Z., Zhang, Q.F. and Kwong, S., 2019. Pareto multi-task learning. Advances in neural information processing systems, 32.
- Ilharco, G., Ribeiro, M.T., Wortsman, M., Gururangan, S., Schmidt, L., Hajishirzi, H. and Farhadi, A., 2022. Editing models with task arithmetic. arXiv preprint arXiv:2212.04089.
- Li, L., Zhang, T., Bu, Z., Wang, S., He, H., Fu, J., Wu, Y., Bian, J., Chen, Y. and Bengio, Y., 2024. MAP: Low-compute Model Merging with Amortized Pareto Fronts via Quadratic Approximation. arXiv preprint arXiv:2406.07529.

#OHDSISocialShowcase This Week

Thursday

CHIMERA: Automatic Concept Set Creation and Mapping to Standard OMOP Codes in ATLAS

(Marcela Rivera, Shahithya Lalitha Prabakaran, Satyajit Pande, Anna Ostropolets)



#OHDSISocialShowcase This Week

Friday

Obesity and Long-term Gastrointestinal Outcomes after COVID-19 Infection: Finding from the RECOVER

(Ting Zhou, Bingyu Zhang, Dazheng Zhang, Qiong Wu, Jiayi Tong, Jiajie Chen, Yuqing Lei, Yiwen Lu, Christopher B. Forrest, Yong Chen)

Obesity and Long-term Gastrointestinal Outcomes after COVID-19 Infection: Findings from the RECOVER

Ting Zhou[a,b], Bingyu Zhang[a,c], Dazheng Zhang[a,b], Qiong Wu[a,b,d], Jiayi Tong[a,b,e], Jiajie Chen[a,b], Yuqing Lei[a,b], Yiwen Lu[a,c], Christopher B. Forrest[f], and Yong Chen[a,b,c,g,h,i]*

a The Center for Health Analytics and Synthesis of Evidence (CHASE), University of Pennsylvania, Philadelphia, PA, USA
b Department of Biostatistics, Epidemiology, and Informatics, University of Pennsylvania Perelman School of Medicine, Philadelphia, PA, USA
c Applied Mathematics and Computational Science, School of Arts and Sciences, University of Pennsylvania, Philadelphia, PA, USA
d Department of Biostatistics and Health Data Science, University of Pittsburgh, Pittsburgh, PA, USA
e Department of Biostatistics, Johns Hopkins University, Baltimore, MD, USA
f Applied Clinical Research Center, Children's Hospital of Philadelphia, Philadelphia, PA, USA
g Leonard Davis Institute of Health Economics, University of Pennsylvania, Philadelphia, PA, USA
h Penn Medicine Center for Evidence based Practice (CEP), University of Pennsylvania, Philadelphia, PA, USA
i Penn Institute for Biomedical Informatics (IBI), University of Pennsylvania, Philadelphia, PA, USA

Background

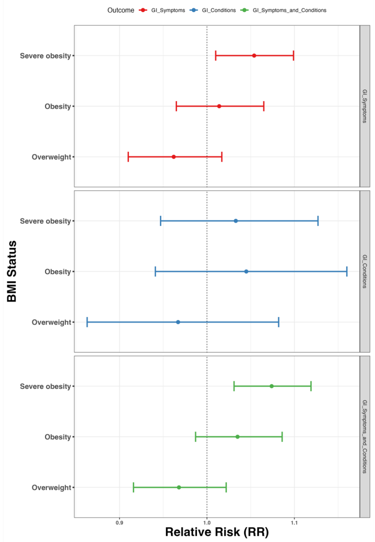
- **PASC** is defined by the World Health Organization (WHO) as the persistence of at least one physical symptom for 12 weeks following initial testing without an alternative diagnosis and expanded by the National Institutes of Health (NIH) to include ongoing, relapsing, or new symptoms four or more weeks post-acute infection
- PASC may involve multiple organ systems, especially, **gastrointestinal (GI)**, thus influences daily life.
- Children may face greater long-term GI complications due to chronic inflammation and altered gut microbiota after SARS-CoV-2 infection.

- **Our goals** are to:
  - Focus on pediatric population
  - Examine the **incidence** of long-term GI outcomes among COVID-19-positive patients with different body mass index (BMI) status, i.e., healthy weight, overweight, obesity, severe obesity
  - Investigate the **relationship** of BMI status prior to SARS-CoV-2 infection with long-term GI outcomes accounting for demographic and clinical risk factors
  - Further assess if the possible associations affected by other factors, e.g., race/ethnicity, vaccination status, etc.

Methods

- Outcome: (1) GI symptoms, (2) GI conditions, and (3) GI symptoms and conditions
- Covariates:
  - Demographic characteristics (age, sex, race and ethnicity)
  - Virus-variant-predominant periods
  - Healthcare utilization metrics
  - Severity of acute phase COVID-19
  - Pediatric Medical Complexity Algorithm (PMCA) index
  - Other clinical factors (chronic diseases, vaccination status, type of insurance, etc.)
- A cutoff incidence value of 0.1% to avoid overfitting for rare GI outcomes was used before fitting the model
- Association analysis:
  - Estimate **relative risks (RRs)** and 95% CIs
  - Fit **modified Poisson regression model** for binary outcome
- Additional analysis:
  - Conduct a series of comprehensive sensitivity analyses
  - Use **negative control outcomes (NCOs)** to help to identify the presence of residual bias
  - Calculate the **population attributable risk percentage (PAR)**

Results



- **Data source:** This retrospective cohort study is part of the NIH Researching COVID to Enhance Recovery (RECOVER) Initiative (https://recovercovid.org/), which aims to learn about the long-term effects of COVID-19

- **Cohort:** A total of 242,034 patients with SARS-CoV-2 infection in the RECOVER program between March 2020 and September 2023 with at least 6 months of follow-up time

- **Results::**
  - Nine GI symptoms and disorders were identified by using the 0.1% incidence cutoff during the post-acute phase (28 to 179 days after the index date): abdominal pain, bloating, constipation, diarrhea, nausea, vomiting, gastroesophageal reflux disease, irritable bowel syndrome, and functional dyspepsia.
  - Compared to participants with a healthy weight, the risk for any GI symptoms or disorders increased in those with severe obesity (RR, 1.074; 95% CI, 1.031-1.119).

Conclusions

- Elevated BMI status contributed to the development of long-term GI outcomes among the pediatric population.
- A disadvantageous dose-response relationship may exist between BMI status and risk of long-term GI outcomes.

Contact: ting.zhou@pennmedicine.upenn.edu and ychen123@pennmedicine.upenn.edu

Job Opening

Senior Program Officer, Clinical AI Innovation, Gates Foundation

Senior Program Officer, Public Health Surveillance, Data Integration, and Artificial Intelligence

Apply

What You'll Do

Are you passionate about using the power of information technology to support better surveillance and public health decision making and thereby improve health and reduce inequality in low- and middle-income countries? Do you have experience working in low- and middle-income countries on AI or digital public health initiatives? If so, we want you to join our team at the largest nonprofit fighting poverty, disease, and inequity around the world.

The Senior Program Officer, Public Health Surveillance, Data Integration, and Artificial Intelligence is a key member of the foundation's Surveillance unit in the Pneumonia and Pandemic Preparedness Team. This role will focus on public health informatics and AI for the Foundation's cross-cutting public health surveillance initiative and will also support other groups in PPP that are considering investments in public health informatics and AI. Beyond the PPP portfolio, this role requires cross-foundation collaboration with surveillance activities with other teams, including Africa Regional Office; Genomics, Epidemiology, & Modeling; Global Policy & Advocacy; and Global Health Agencies & Funds. This role also collaborates with the AI Core Team and Program Strategy Teams on other infectious disease surveillance programs to ensure coordination and integration of surveillance activities. Taking advantage of the promise of AI and preventing an AI digital divide in Africa and other areas of the global south is a high priority area for the Foundation. As such, this role will be responsible for developing our overarching strategy for public health surveillance applications in AI, as well as other applications of information technology to public health surveillance and epidemic readiness. This person will also provide technical assistance to other PSTs and advocate for the safe, responsible use of AI as a force multiplier to improve public health surveillance in LMICs.

- Create and implement a strategy for digital innovation, including AI, to improve actionable, integrated, and timely information for public health decision-makers in the global south
  - Develop a strategy for the Foundation's work on public health informatics and AI for public health surveillance, consistent with our theory of change, with quantifiable impact goals
  - Develop a clear understanding of specific ecosystem constraints and opportunities related to AI for public health surveillance
  - Map the pathways by which promising public health surveillance technologies transition from small, defined proof-of concepts to minimal viable products and ultimately scaled products/applications that are sustainable across multiple countries
  - Identify a key set of partners and stakeholders for success in this focus area across the technical, advocacy, government, academic and funding spheres

- Use your scientific and technical expertise to identify, develop, and manage a portfolio of strategic investments related to our strategy
  - Review submitted concept notes and grant proposals to support projects and programs on public health informatics for surveillance, including global and national data architecture, norms, and standards; unique health ID and privacy-preserving record linkage; early warning systems for outbreak detection and notification
  - Shape and manage investments on AI tool effectiveness, safety, and regulatory strategies for AI-informed public health surveillance in LMICs
  - Develop an overarching evaluation plan to understand the viability of tools deployed in LMIC settings and why they succeed or fail
  - Ensure that funding is appropriately managed and where appropriate, done in collaboration with other foundation teams and external funders

Where Are We Going?

Any other announcements of upcoming work, events, deadlines, etc?

Three Stages of The Journey

Where Have We Been?

Where Are We Now?

Where Are We Going?

Health Equity / OMOP + FHIR WG Collaboration: HL7 Gender Harmony IG

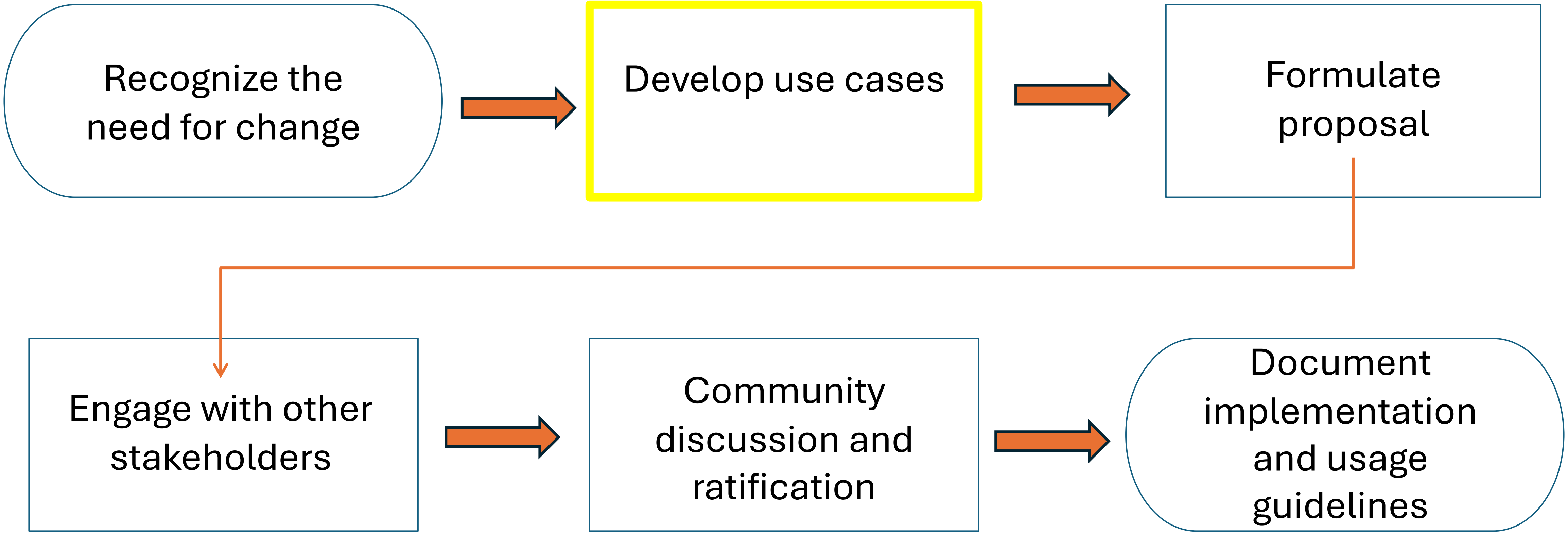
Community Call to Action:

Use Cases supporting Gender Harmony conventions on OMOP

HL7 Cross Paradigm Implementation Guide: Gender Harmony - Sex and Gender Representation, Edition 1 Elements

1. Gender Identity
   - Self-reported, an individual's personal experience of being male, female, nonbinary, or another identity
2. Name to Use
   - A patients' chosen name, which may differ from their legal name
3. Pronouns
   - An individual's chosen set of pronouns reflecting preference or gender identity
4. Sex Parameter for Clinical Use
   - Context-specific categorization of sex used in diagnostics, analytic and treatments
5. Recorded Sex and Gender
   - Sex or gender data derived from documents like IDs or medical records

Best practice for creating a Themis proposal



How can you help?

- Attend Health Equity OOC / Bi-weekly Calls
  - Fridays 9am EASTERN US
  - Next call: 15Nov24

- Contact
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The weekly OHDSI community call is held every Tuesday at 11 am ET.

Everybody is invited!

Links are sent out weekly and available at:
ohdsi.org/community-calls