To view an archived recording of this presentation please click the following link:

https://youtu.be/G8KmJv_tyaA

Please scroll down this file to view a copy of the slides from the session.

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AI and Public Health: The future is now

Public Health Ontario Rounds

November 16, 2023

Andrew Pinto MD CCFP FRCPC MSc

Sharon Birdi BMSc

Upstream Lab, MAP/Centre for Urban Health Solutions, Li Ka Shing Knowledge Institute, Unity Health Toronto
Department of Family and Community Medicine, Fac. of Medicine, University of Toronto
Department of Family and Community Medicine, St. Michael's Hospital
Dalla Lana School of Public, University of Toronto

Disclosures: Andrew Pinto

Relationships with commercial interests:

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Speakers Bureau/Honoraria: **None from for-profit/commercial entities.**

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Consulting Fees: **None.**

Other: I serve as an unpaid scientific advisor to a start-up company, Mutuo Health Solutions.

Disclosures: Sharon Birdi

Relationships with commercial interests:

Research Support: **None from for-profit/commercial entities**.

Canadian Institutes for Health Research

Speakers Bureau/Honoraria: **None from for-profit/commercial entities.**

Salary support: **None from for-profit/commercial entities.**

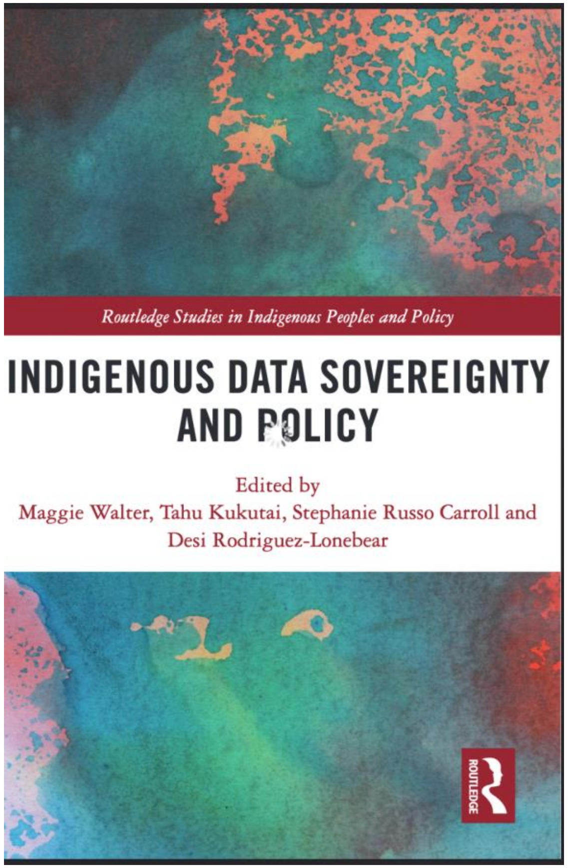
Consulting Fees: **None.**

Other: None

Land Acknowledgement

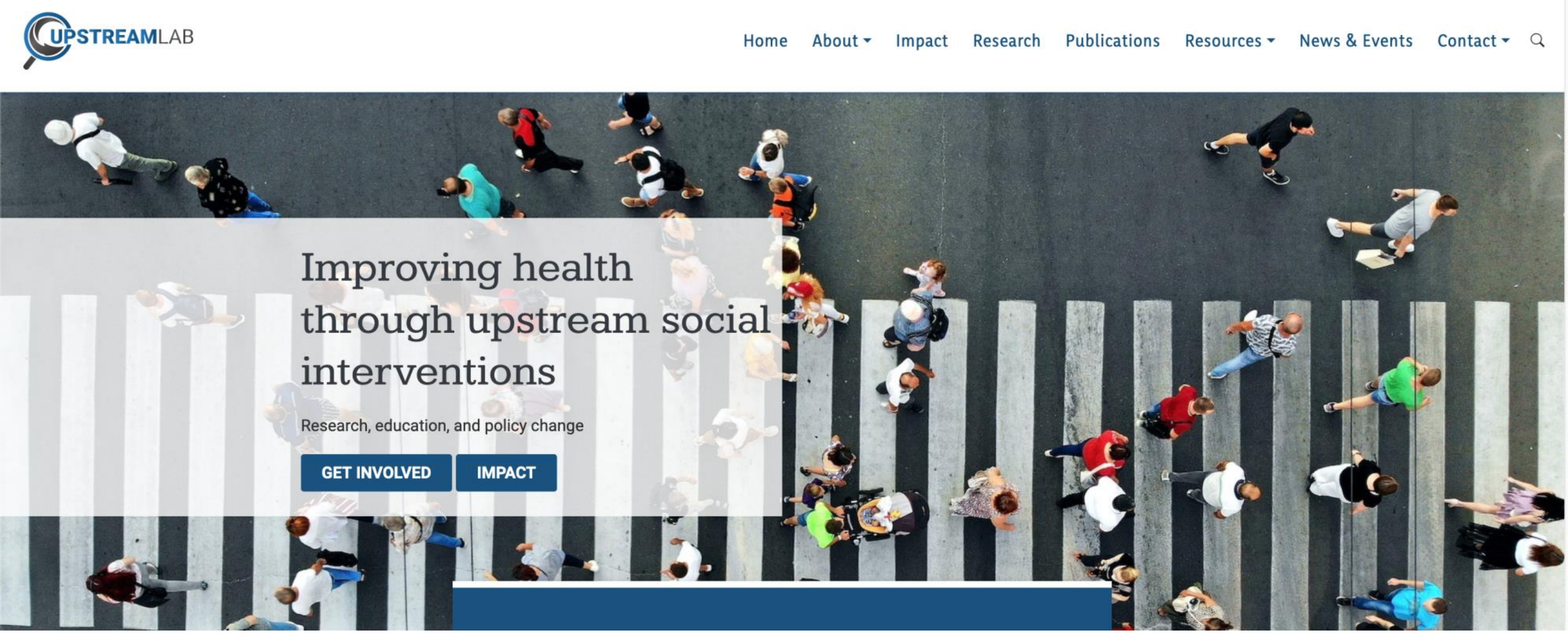
Truth and Reconciliation
Commission of Canada

https://nctr.ca/



https://doi.org/10.4324/9780429273957

UPSTREAMLAB



upstreamlab.org

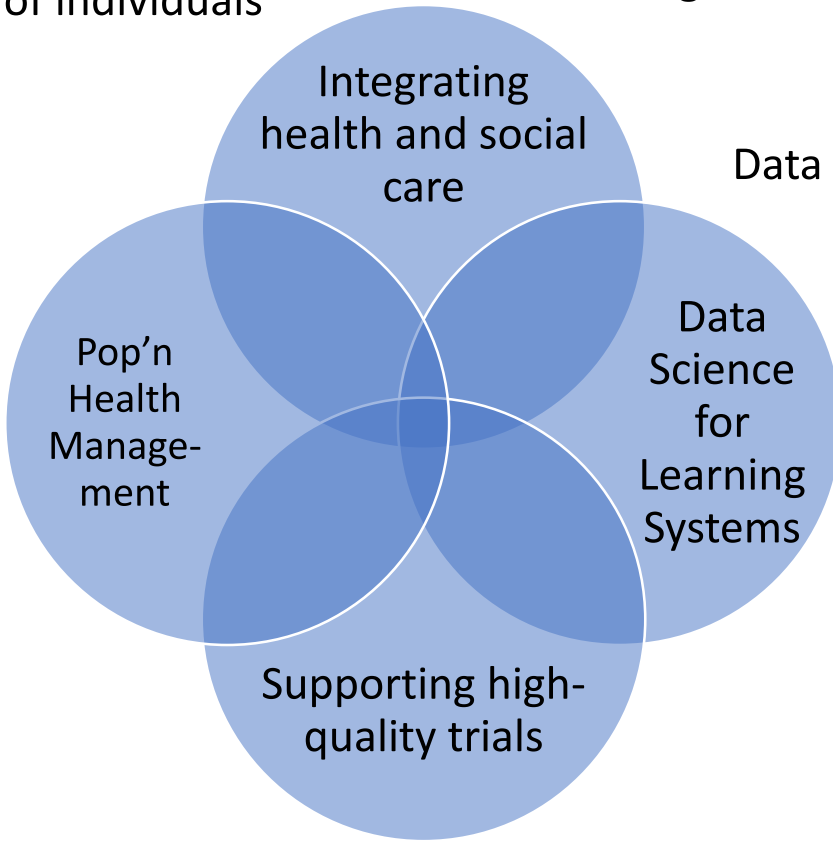
Anchor Institutions

Addressing social needs of individuals

Building local Upstream Action Networks

Data on sociodemo/social needs

Democratic engagement



Policy advocacy coalitions

AI integrated into care

AI for surveillance

AI for prediction

Randomized trials of population-level interventions

Primary care & out-patient trials

HAVE YOU TESTED POSITIVE FOR COVID?

Help us find therapies that reduce COVID symptoms & hospitalizations.

Who can participate?

- Canadian residents
- 50 years of age **OR** 18 - 49 years old with one or more chronic condition(s)
- who are within the first 5 days of experiencing COVID-19 symptoms

What will you do?

- Complete a daily diary for 14 days and fill out surveys
- THANK YOU! Receive an honorarium of $30 per follow up

CanTreatCOVID
Canadian Adaptive Platform Trial of Treatments for COVID in Community Settings

1-888-888-3308

Version 2.0; Date: November 8, 2022

CIHR IRSC
Canadian Institutes of Health Research | Instituts de recherche en santé du Canada

Health Canada | Santé Canada

Public Health Agency of Canada
Agence de la santé publique du Canada

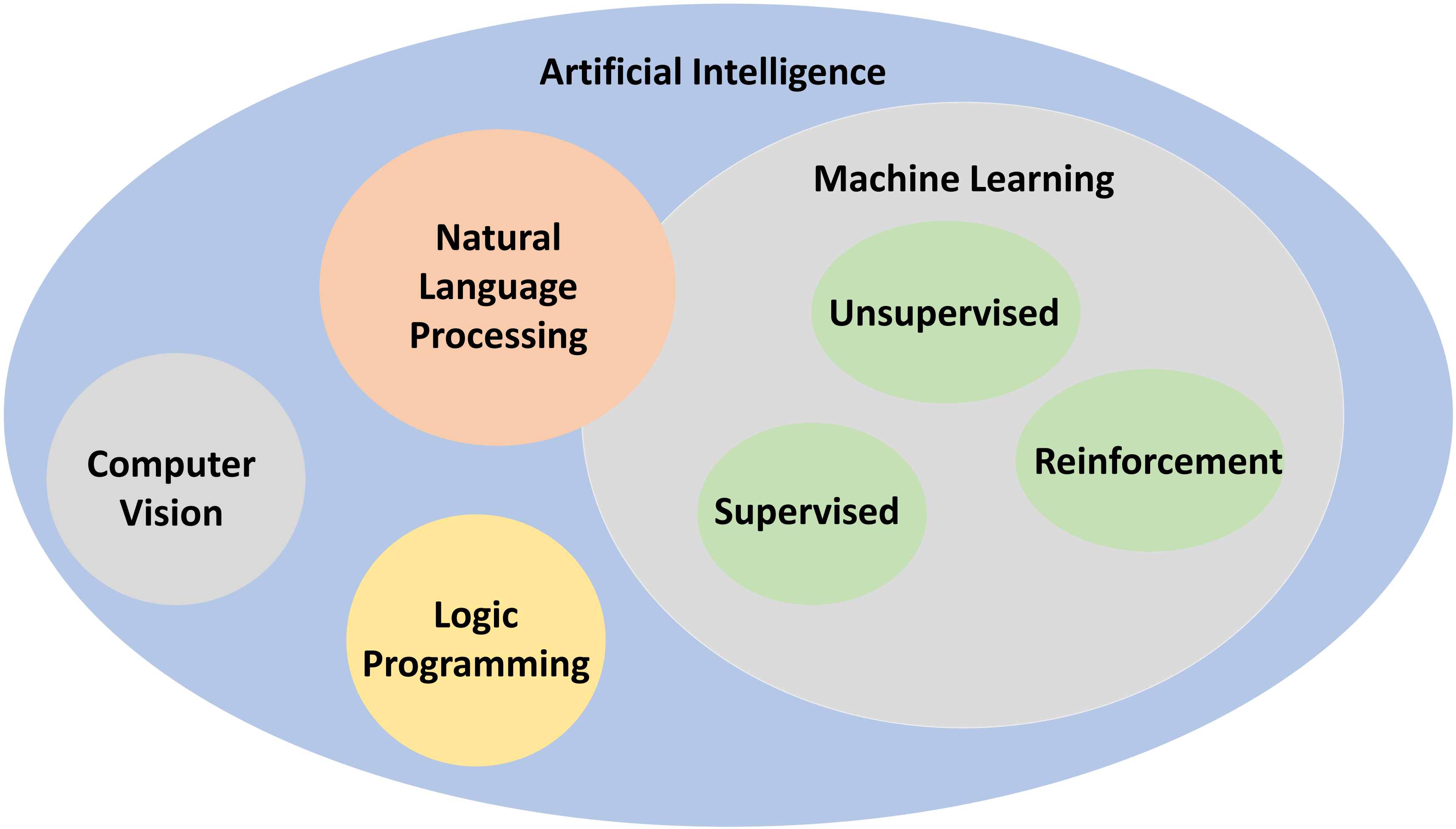
Learning objectives

- Recognize common terminology used in AI, and how AI can be applied within public health practice and research
- Identify and critique the strengths and limitations of machine learning
- Discuss how both data and new technologies can contribute to a Learning Public Health system and its future impact on public health practice

Outline

1. Discuss AI and different methodologies
2. Current applications of ML in public health
3. Guidelines for future work applying AI/ML in public health
4. Building a Learning Public Health System

Artificial Intelligence

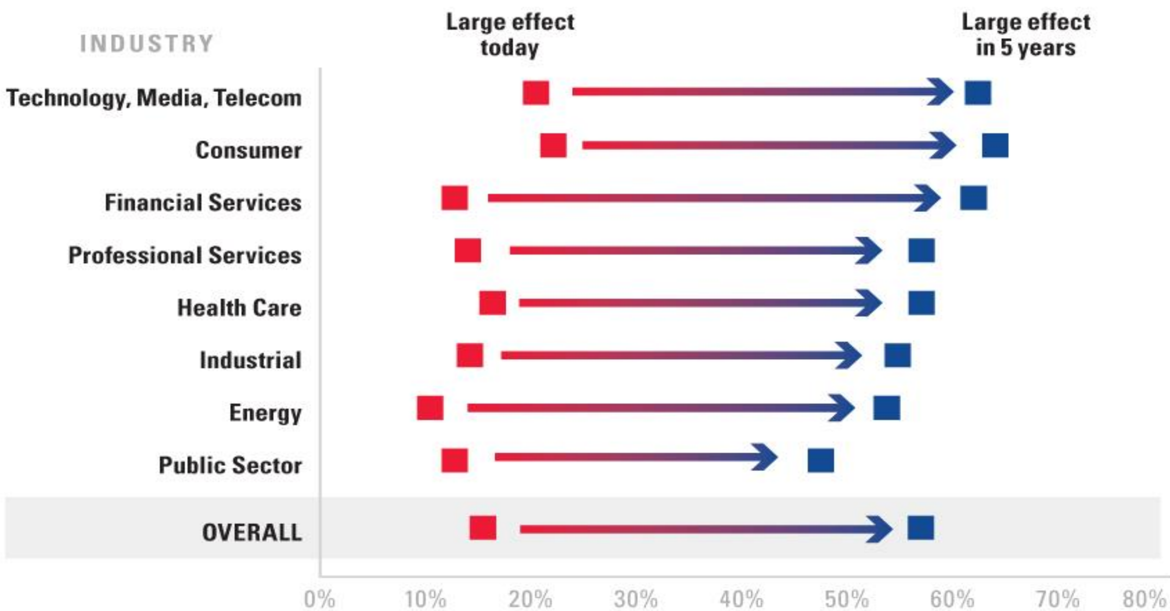


AI in daily life

- Education: AI-driven tools enhancing personalized learning and educational experiences
- Work: AI for task automation, improving efficiency and productivity
- Daily activities: AI-powered applications (e.g., personal assistants such as, Siri)

Expectations for AI adoption across industries: impact on processes

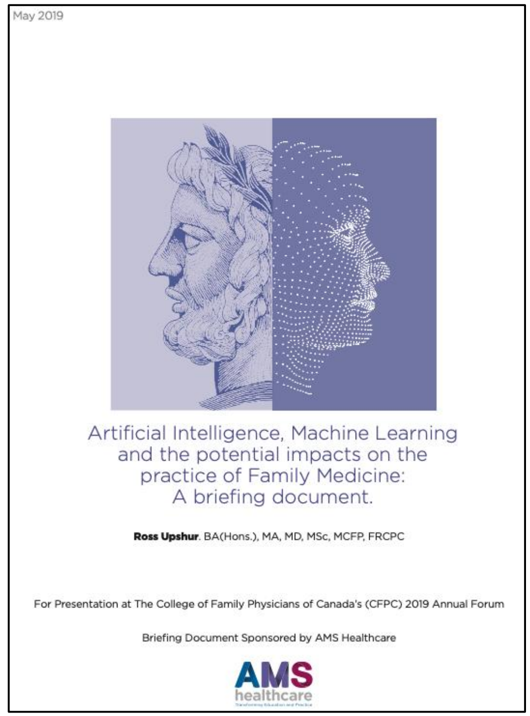
To what extent will the adoption of AI affect your organization's processes today and five years from today?

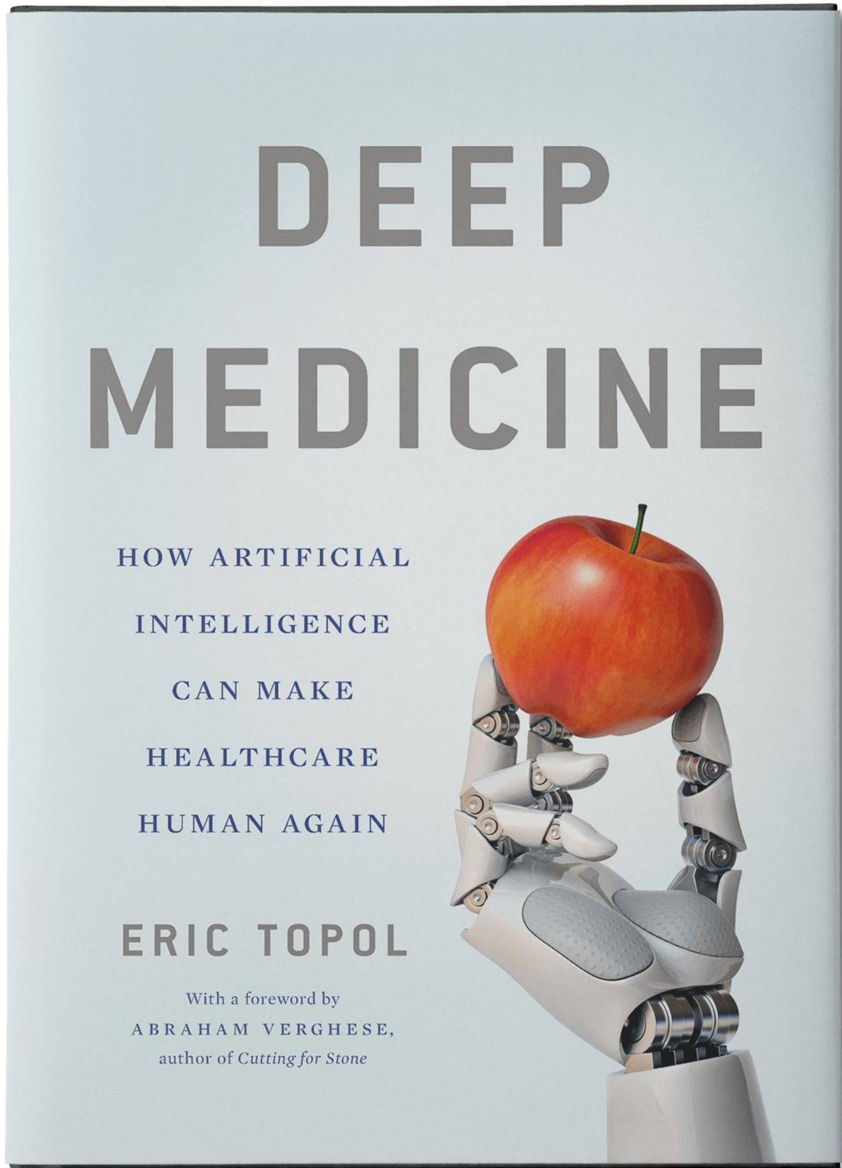


Percentage of respondents who expect a large ("a lot" or "great") effect on a five-point scale

https://sloanreview.mit.edu/projects/reshaping-business-with-artificial-intelligence/

AI and health



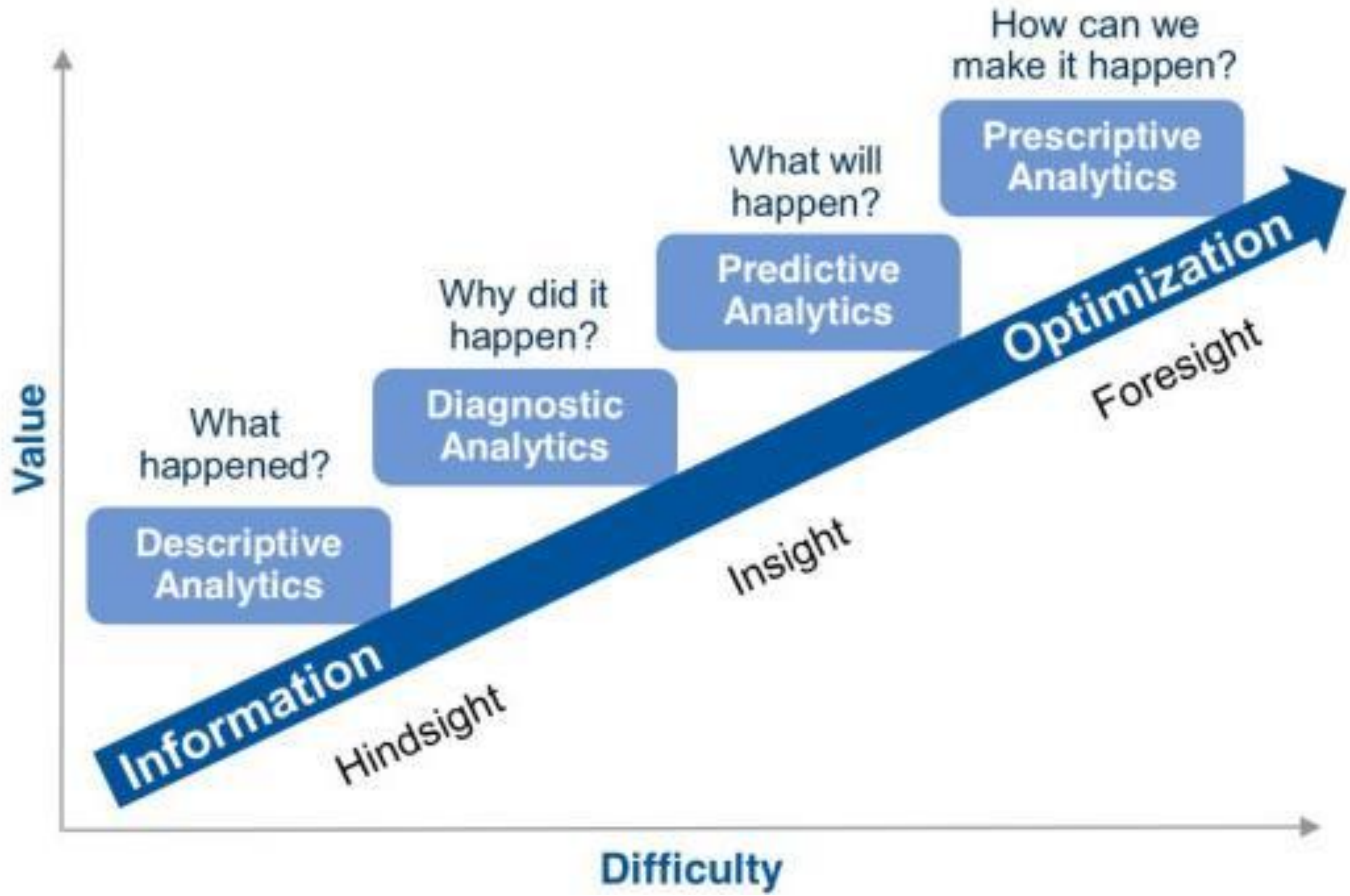


"The promise of artificial intelligence in medicine is to provide **composite, panoramic views** of individuals' medical data; to improve **decision making**; to **avoid errors** such as misdiagnosis and unnecessary procedures; to help in the ordering and interpretation of appropriate **tests**; and to recommend **treatment**."
p. 9

On the Prospects for a (Deep) Learning Health Care System

Naylor CD. JAMA 2018; 320: 1099-1100

- Highly adaptable for integrative analysis of heterogeneous data sets assembled from diverse sources
- Enormous capacity to inform the process of discovery in health research and to facilitate hypothesis generation by identifying novel associations
- Streamlining routine work by health care professionals and empowering patients



http://www.datascienceassn.org/content/descriptive-predictive-prescriptive-analytics

PLOS ONE

RESEARCH ARTICLE

Implementing artificial intelligence in Canadian primary care: Barriers and strategies identified through a national deliberative dialogue

Katrina Darcel[1,2], Tara Upshaw[1,3], Amy Craig-Neil[1], Jillian Macklin[1,2,4,5], Carolyn Steele Gray[6,7], Timothy C. Y. Chan[8], Jennifer Gibson[4,5], Andrew D. Pinto[1,5,9,10]*

1 Upstream Lab, MAP Centre for Urban Health Solutions, Unity Health Toronto, Toronto, Ontario, Canada, 2 Undergraduate Medical Education, Temerty Faculty of Medicine, University of Toronto, Toronto, Ontario, Canada, 3 Cumming School of Medicine, University of Calgary, Calgary, Alberta, Canada, 4 Joint Centre for Bioethics, University of Toronto, Toronto, Ontario, Canada, 5 Dalla Lana School of Public Heath, University of Toronto, Toronto, Ontario, Canada, 6 Bridgepoint Collaboratory for Research and Innovation, Lunenfeld-Tanenbaum Research Institute, Sinai Health System, Toronto, Ontario, Canada, 7 Institute of Health Policy, Management and Evaluation, Dalla Lana School of Public Health, University of Toronto, Toronto, Ontario, Canada, 8 Department of Mechanical and Industrial Engineering, Faculty of Applied Science and Engineering, University of Toronto, Toronto, Ontario, Canada, 9 Department of Family and Community Medicine, St. Michael's Hospital, Toronto, Ontario, Canada, 10 Department of Family and Community Medicine, Faculty of Medicine, University of Toronto, Toronto, Ontario, Canada

* andrew.pinto@utoronto.ca

Check for updates

OPEN ACCESS

Citation: Darcel K, Upshaw T, Craig-Neil A, Macklin J, Steele Gray C, Chan TCY, et al. (2023)

Priorities for Artificial Intelligence Applications in Primary Care: A Canadian Deliberative Dialogue with Patients, Providers, and Health System Leaders

Tara L. Upshaw, MHSc, Amy Craig-Neil, MSc, Jillian Macklin, MSc, Carolyn Steele Gray, MA, PhD, Timothy C. Y. Chan, PhD, Jennifer Gibson, PhD, and Andrew D. Pinto, MD, MSc

JABFM.ORG
JABFM
JOURNAL OF THE AMERICAN BOARD OF FAMILY MEDICINE

Priorities

1. Address tasks that do not usually need physician-patient contact (e.g. charting, prescriptions, scheduling, referral management)
2. Better allocate time for all members of the primary care team, including admin staff
3. Expert systems combining EMR data and evidence
4. Address infrastructure issues and variation across Canada
5. Training for clinicians on new tools (lessons from EMR adoption)

The Future is Now: AI in Family Medicine

A 6-part webinar series co-hosted by Upstream Lab and CFPC

1. **Introduction to AI & Applications in Primary Care**
   Dr. Jaky Kueper & Dr. Andrew Pinto
2. **Machine Learning to Solve Primary Care Challenges**
   Dr. Anders Lenskjold
3. **Machine Learning Applied to Primary Care EMR Data for Classification**
   Dr. Stephanie Garies, Dr. Matt Taylor and Dr. Tyler Williamson
4. **Natural Language Processing & its Role in Primary Care**
   Dr. Noah Crampton
5. **Machine Learning for Human Resource Management & to Predict Health Service Use**
   Dr. Muhammad Mamdani
6. **Social and Ethical Implications of AI and Primary Care**
   Dr. Melissa McCradden, Dr. Carolyn Steele-Gray, and Dr. Azza Eissa

Studies in-progress

- Prediction models using primary care EMR data: systematic review
- Patient engagement in guidelines for AI apps in health
- Machine learning in population and public health
- NLP and ML derive social data using primary care EMR data
- Health and social data visualization and integration into clinical workflows: co-design with clinicians and patients

Automating admin tasks to improve workflow

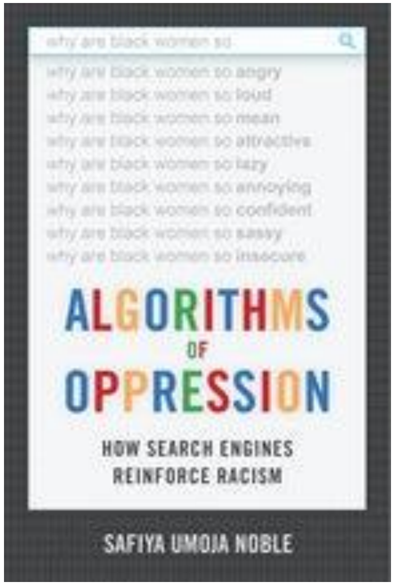
Supported by CFPC and Temerty Centre for AI Research and Education in Medicine (U of T)

- Data quality improvement
- Information extraction (esp. text/notes)
- Clinical decision support
- Personalized treatment
- Automated referrals

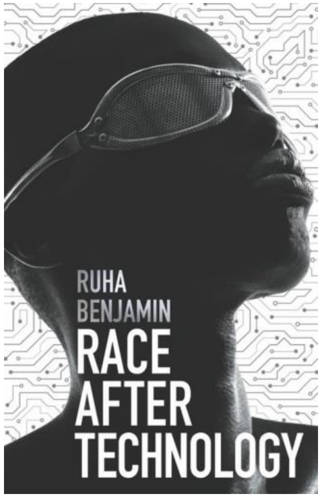
DEEP Network

Big Data to Enhance & Evolve Primary Care

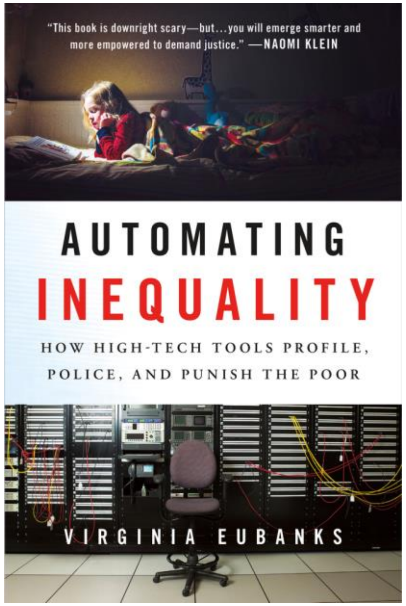
- National community of practice to support the development and evaluation of AI interventions in primary care in Canada
- Education
- Helping link computer scientists, providers and patients
- Coordinate policy advocacy



https://nyupress.org/9781479837243/algorithms-of-oppression/

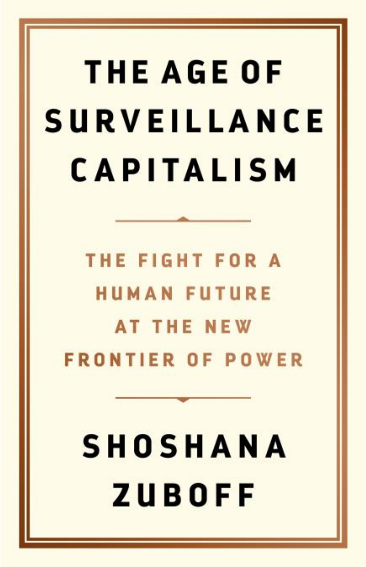


https://www.ruhabenjamin.com/race-after-technology

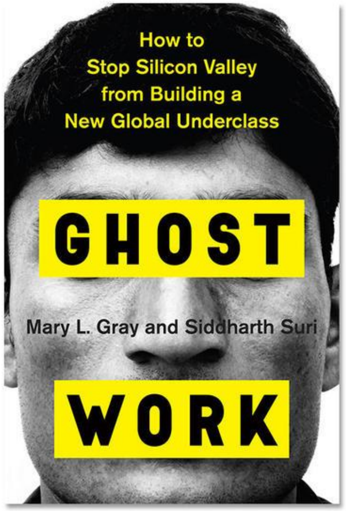


https://us.macmillan.com/books/9781250074317

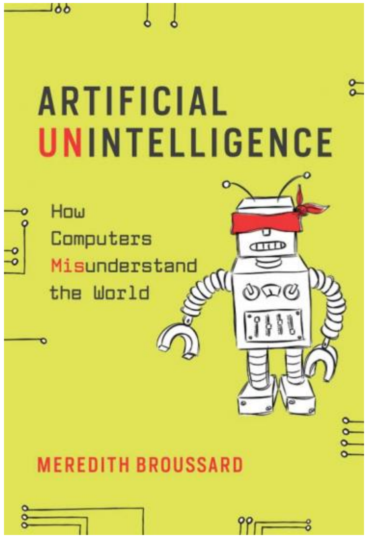
Concerns about AI



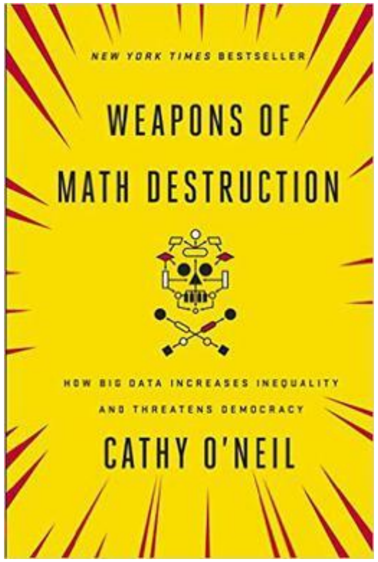
https://www.publicaffairsbooks.com/titles/shoshana-zuboff/the-age-of-surveillance-capitalism/9781610395694/



https://ghostwork.info/



https://mitpress.mit.edu/books/artificial-unintelligence



https://weaponsofmathdestructionbook.com/

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Algorithmic bias

Algorithmic bias in the context of AI and health systems is defined as: "the instances when the application of an algorithm compounds existing inequities in socioeconomic status, race, ethnic background, religion, gender, disability or sexual orientation to amplify them and adversely impact inequities in health systems." (Panch et al., 2019)

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Collect and annotate training data.

Human Biases in Data

- Reporting bias
- Selection bias
- Overgeneralization
- Out-group homogeneity bias

- Unconscious bias from "the world" that we might reflect in ML when using some of the world's data

Human Biases in Collection and Annotation

- Confirmation bias
- Automation bias

- Unconscious bias in our procedures that we might reflect in our ML

https://developers.google.com/machine-learning/crash-course/fairness/video-lecture

'The Godfather of A.I.' Leaves Google and Warns of Danger Ahead

For half a century, Geoffrey Hinton nurtured the technology at the heart of chatbots like ChatGPT. Now he worries it will cause serious harm.

https://www.nytimes.com/2023/05/01/technology/ai-google-chatbot-engineer-quits-hinton.html

Public Health and AI

New possibilities for population health and disease prevention:

- Modelling risk in populations
- Modelling disease incidence in populations
- Evaluating effectiveness of interventions
- Rapid processing of vast amounts of data, identifying new relationships

Machine Learning and Bias in Population Health Models

- Conducted three scoping reviews to identify ML models used in specific areas of population health and to examine whether and how biases were identified
  - Risk Factors
  - Non-Communicable Diseases
  - Communicable Diseases
- Developed guidelines for the use of ML in population health

CIHR IRSC
Canadian Institutes of Health Research
Instituts de recherche en santé du Canada

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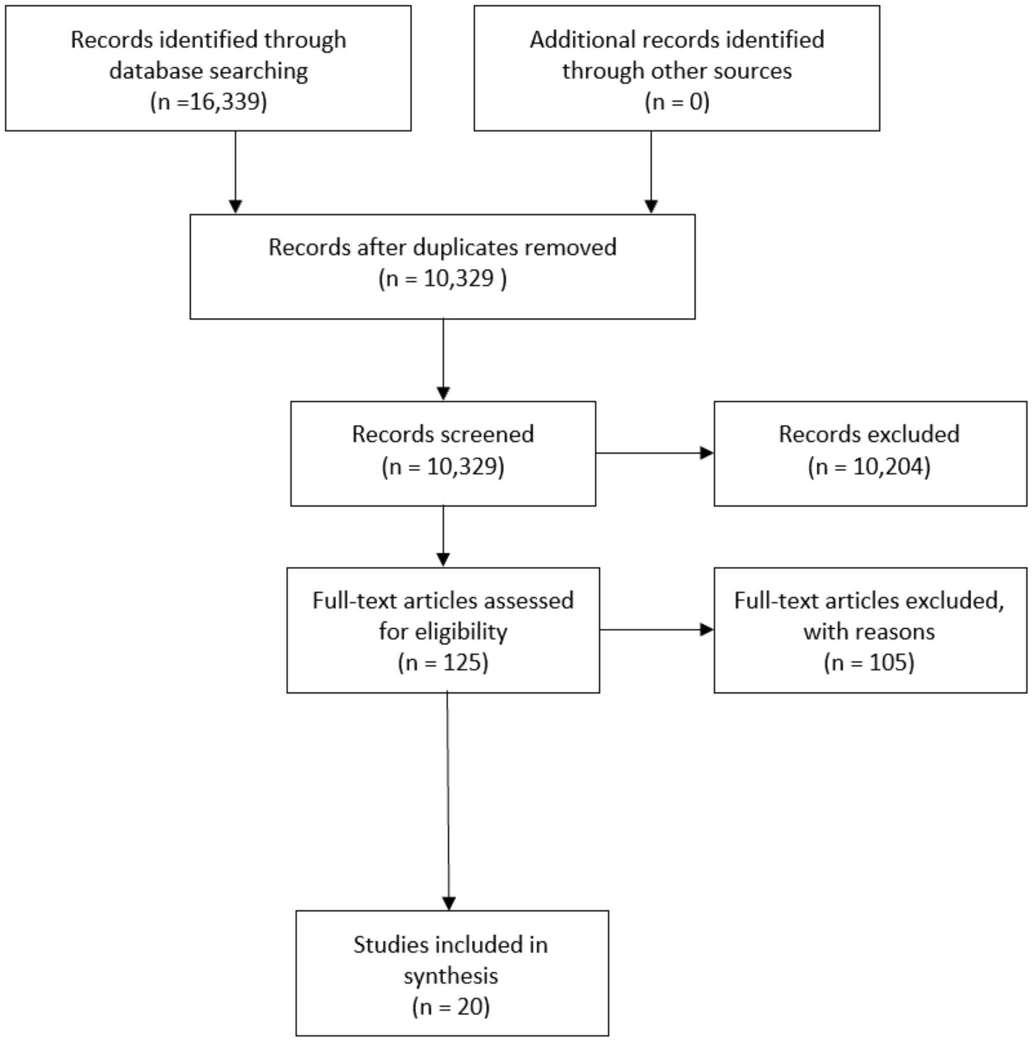
Methodology

Inclusion Criteria	Exclusion Criteria
Population-wide implications and/or a public health approach: e.g., subsets of the general population at a certain point in life-course (e.g., seniors, children)	Did not have a population-wide implication and/or public health approach: - population that was defined by one or multiple diseases - domains outside of public health systems or conventional population systems (e.g., occupational health) - high-risk groups (e.g., smokers) - specialised medical setting (e.g., hospitalized patients) - socio-demographic characteristics other than age (e.g., ethnicity, sex)
Pertained to at least one of the following conditions: varied for each scoping review	- Focus was not any of the conditions mentioned in the inclusion criteria, e.g., complications and conditions associated with the condition itself (e.g., diabetic retinopathy)
Described the use of at least one ML model (e.g., artificial neural networks, decision trees, support vector machines) to address a real-world population or public health challenge	No-real world data - general discussions of ML - studies that incorporated data from animal models or in-silico experiments, and proof-of-concept studies
There were no language restrictions for the studies reviewed	Commentaries, letters, editorials, conference proceedings, and dissertations

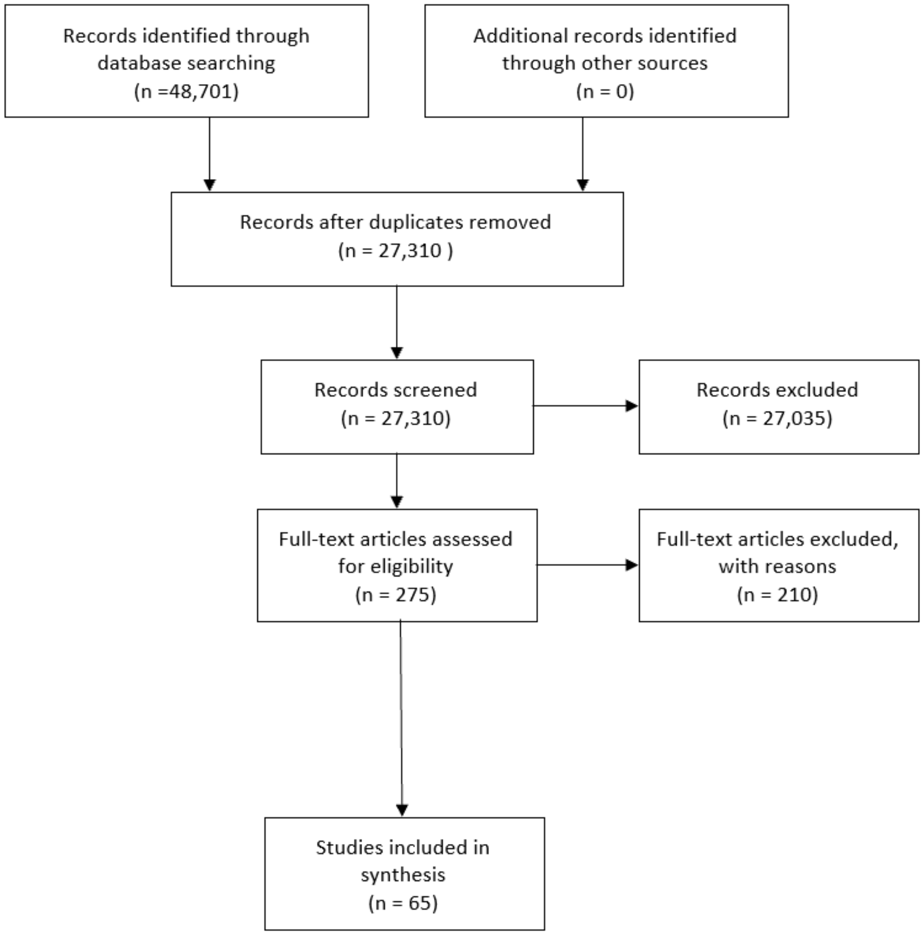
Review 1: Risk Factors



Review 1: Risk Factors

- 20 peer-reviewed studies (since 2017) using ML to study chronic disease risk factors in population health
- Lack of awareness of algorithmic biases and their impact on applications.
- COVID-19 accelerated ML development in risk prediction and population surveillance, underscoring the need to address biases.
- Studies unevenly focused on smoking, vaping, alcohol
  - Limited exploration of unhealthy eating/psychological stress
- ML's role in an emerging field with a global perspective, considering cultural and social influences on model development.

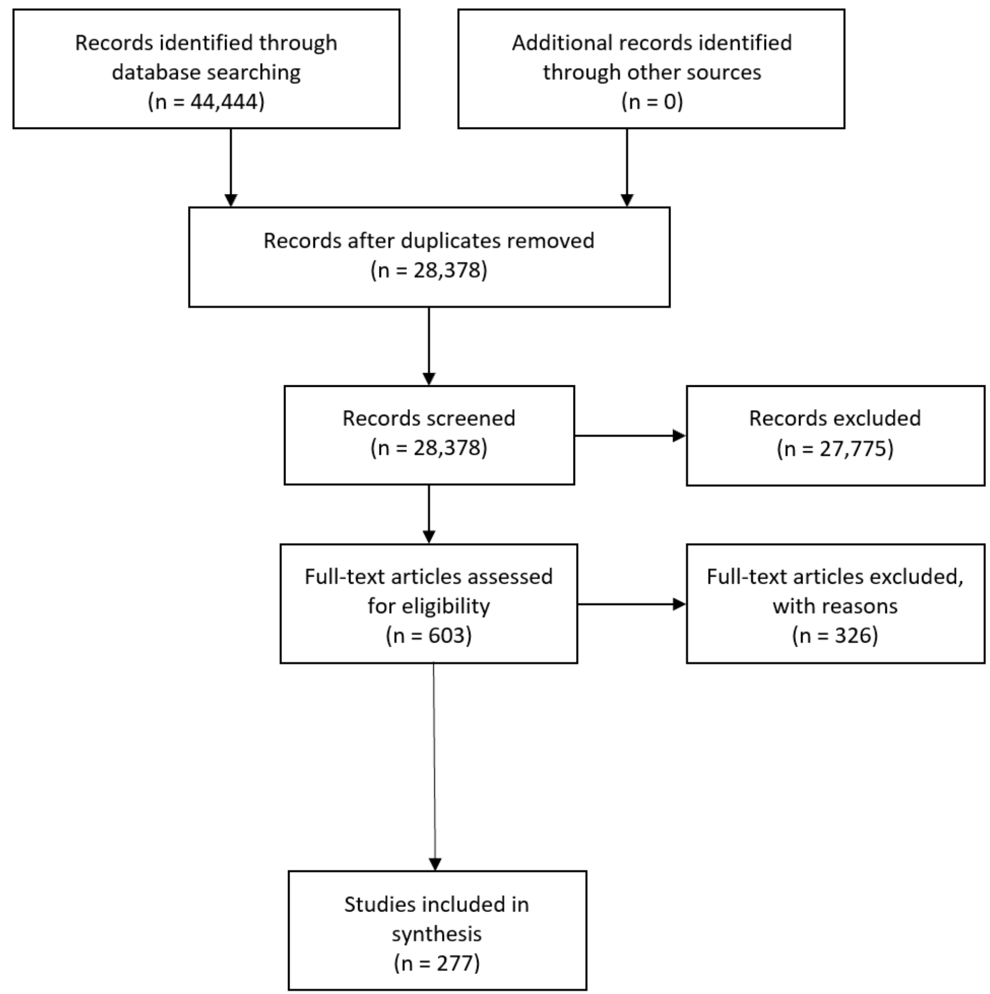
Review 2: Non-Communicable Diseases



Review 2: Non-Communicable Diseases

- 65 peer-reviewed studies (since 2017) using ML to study non-communicable diseases in population health
- Focused on diabetes, cardiovascular diseases, cancers, and chronic respiratory diseases
- Supervised learning as the most common algorithm, notable mention to NLP and text-mining
- Most popular ML application, modelling disease in the population
- Discrepancy in ML application frequency between high and low-income countries
- Lack of algorithmic bias discussion

Review 3: Communicable Diseases



Review 3: Communicable Diseases

- 277 peer-reviewed studies (since 2017) using ML to study non-communicable diseases in population health
- Focused on COVID-19, diarrheal diseases, hepatitis, HIV/AIDS, malaria, measles, tuberculosis
- Overwhelming majority of COVID-19 studies (n=177)
- Supervised learning as the most common ML algorithm
- Most popular ML application, modelling disease in the population
- ~5% of studies implemented bias mitigation strategies

Guidelines for the use of ML in population health

Recommendation 1

Prioritize work **to support communities historically disadvantaged by social and economic policies**

- Examples:
  - algorithmic-bias mitigation
  - capacity-building, or representation advancement
  - include diverse collaborators with expertise in ethical considerations concerning population and public health

Recommendation 2

Leveraging **ML in public health emergencies** involves the rapid collection, analysis, and use of **population-wide de-identified data**, even without explicit consent, assuming adherence to overarching **ethical principles**

Recommendation 3

Assess the harm risks associated with the ML model, particularly its impact on **policy**, ensuring alignment with the degree of **bias-mitigation**

Evaluate all aspects of the model's implementation, emphasizing **potential biases**, especially those involving **external or incompletely known entities**

- Such as
  - Model's oversight of vulnerable sub-populations due to social and economic policies
  - Biases in clinical scoring systems
  - Disadvantages in for-profit public data sharing

Recommendation 4

Encourage **higher-income countries** to assist l**ow- and middle-income nations** in adopting ML-based **data practices**

Recommendation 5

ML studies demand **transparency**, including **clear technical details**, **data/methodology sharing**, **alignment with existing datasets**, and bias mitigation through consideration of **socio-demographic variables** and **appropriate handling strategies**

Recommendation 6

Efforts to raise **public awareness** about ML benefits must include information on **potential harms**

- Examples
  - Consistent terminology
  - Established reporting guidelines
  - Plain language

Can AI support a Learning Public Health System?

Applying lessons from primary care practice-based research networks to a national network of local/regional public health organizations in Canada

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Rationale

- 2021 Chief Public Health Officer Report: calls for a stronger public health research agenda, accelerating knowledge translation, and **rapid and ongoing population health intervention research**.
- CIHR's Institute for Population and Public Health 2022 report on the top 10 opportunities for strengthening Canada's public health systems: calls to **generate context-specific research evidence and robust data, and to link research and practice**

What is a PBRN?

- "Laboratories for discovery"
- Networks of organizations (e.g. practices, local PH units)
- Working cooperatively to address pragmatic research questions.
- Bound by a shared commitment to improve health through systematic inquiry
- Central coordination: staff, REB applications, data sharing, analysis

Modified from Peterson K et al. AFM 2012; 10: 560-567

Example: POPLAR

Primary Care **O**ntario **P**ractice Based **L**earning & Rese**a**rch Netwo**r**k

- **7 Learning Networks**: 6 University DFMs and the Alliance (CHCs); 1.8M patients
- INSPIRE-PHC; Primary and Integrated Healthcare Innovation Networks

1. A provincial EMR database
2. Linked to ICES and other admin sources
3. Expansion to **2 million** patients across Ontario

Learning Health Systems

"a health system in which internal data and experience are systematically integrated with external evidence, and that knowledge is put into practice."

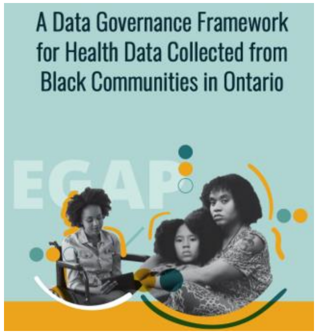
- Leaders committed to a culture of continuous learning and improvement
- Systematically gather and apply evidence in real-time, including to improve clinician decision-making
- Promote inclusion of patients
- Capture and analyze data and care experiences to improve care
- Continually assess outcomes to refine processes and training

https://www.ahrq.gov/learning-health-systems/about.html

A Canadian **Learning Public Health System**

1. Identify a research lead for each participating public health organization
2. Streamline research approaches (e.g. REB, data sharing and storage, contracts)
3. Establish a system to solicit and prioritize research questions
4. Support public health practitioners who conceive an intervention (emerging from work) to test it rigorously (e.g. cluster RCT)
5. To support public health practitioners to be thoughtful site investigators on intervention studies

How can this support communities?



A vision of community data governance from the Black Health Equity Working Group

https://blackhealthequity.ca/

- **Engagement:** genuine, ongoing, accessible, transparent consultation with community members, recognized leaders and organizations
- **Governance:** community decision-making about collection, analysis/interpretation, use, management
- **Access:** right to access data and determine who else can access community data trust
- **Protection:** safeguarding data, including the use of de-identified and anonymized data

RESEARCH ARTICLE

Social determinants of COVID-19 incidence and outcomes: A rapid review

Tara L. Upshaw[1,2☯], Chloe Brown[1,3☯], Robert Smith[1,4,5], Melissa Perri[1,6], Carolyn Ziegler[7], Andrew D. Pinto[1,4,5,6,8*]

1 Upstream Lab, MAP Centre for Urban Health Solutions, Li Ka Shing Knowledge Institute, St. Michael's Hospital, Toronto, Canada, **2** Translational Research Program, Faculty of Medicine, University of Toronto, Toronto, Canada, **3** Undergraduate Medical Education, Faculty of Medicine, University of Toronto, Toronto, Canada, **4** Institute of Health Policy, Management and Evaluation, Dalla Lana School of Public Health, Toronto, Canada, **5** Department of Family and Community Medicine, Faculty of Medicine, University of Toronto, Toronto, Canada, **6** Dalla Lana School of Public Health, University of Toronto, Toronto, Canada, **7** Health Sciences Library, Unity Health Toronto, Toronto, Canada, **8** Department of Family and Community Medicine, St. Michael's Hospital, Toronto, Canada

https://journals.plos.org/plosone/article/authors?id=10.1371/journal.pone.0248336

Collecting data on race during the COVID-19 pandemic to identify inequities

UPSTREAMLAB

April 14, 2020

Andrew D. Pinto MD MSc
Ayu Hapsari MSc

CIHI Update | **May 2020**

Race-Based Data Collection and Health Reporting

Summary

There is heightened awareness of and interest in collecting information to better understand the spread of COVID-19 and the impact of the pandemic, particularly within racialized communities.
The lack of data on race in Canada makes it difficult to monitor racial health inequalities. To help harmonize and facilitate collection of high-quality data, the Canadian Institute for Health Information (CIHI) is proposing an interim race data collection standard based on work that has been ongoing for a number of years, including engagement with researchers, clinicians, organizations representing racialized communities, and federal, provincial and territorial governments. It is intended for use by any jurisdiction or organization that decides to collect this type of data.

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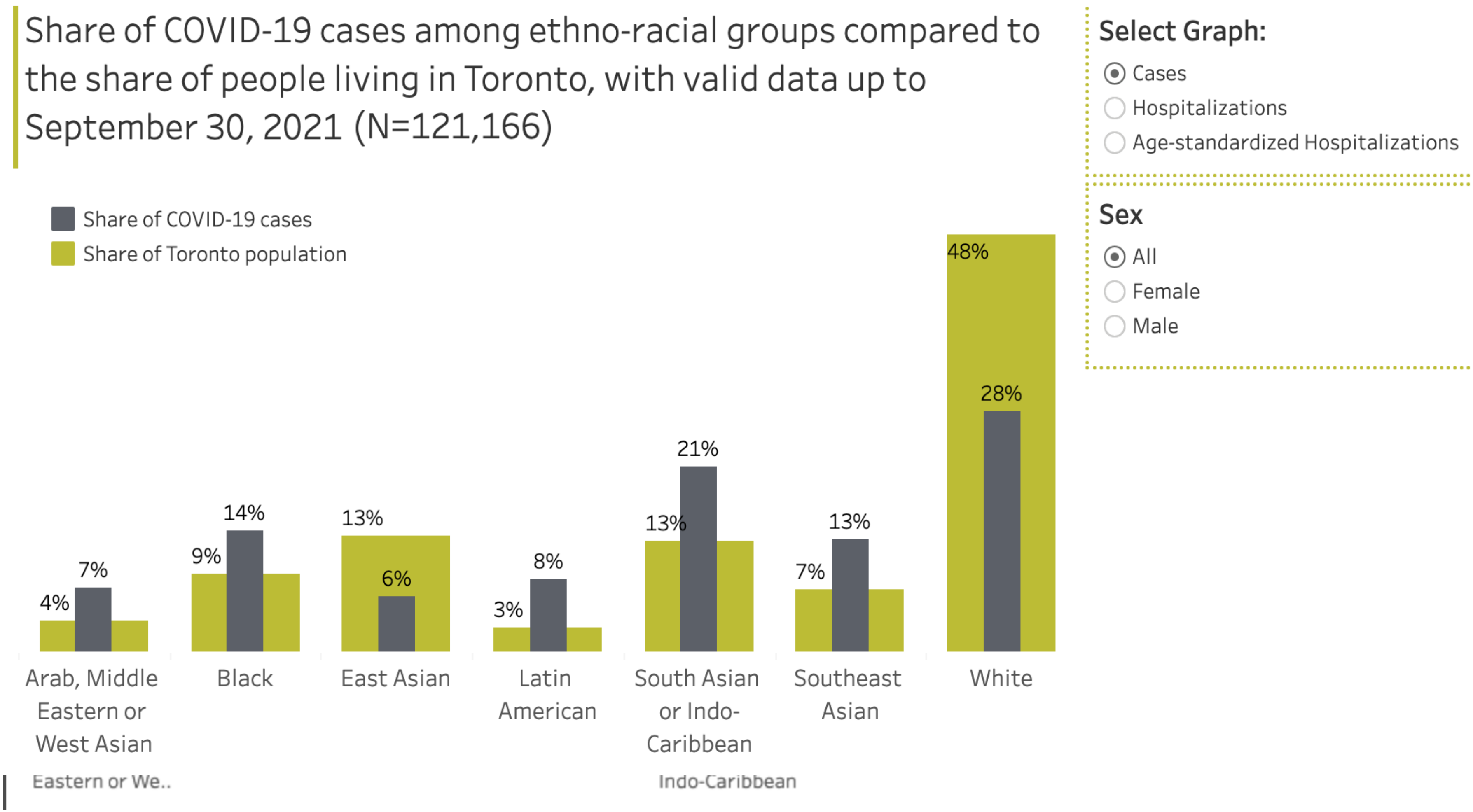
https://www.thestar.com/news/gta/2021/05/08/light-at-the-end-of-the-tunnel-toronto-set-to-reach-covid-19-vaccine-milestone-with-50-of-adults-having-had-first-jab.html

@upstreamlab

August 2020 → September 2021



https://www.toronto.ca/home/covid-19/covid-19-latest-city-of-toronto-news/covid-19-status-of-cases-in-toronto/

https://www.toronto.ca/home/covid-19/covid-19-pandemic-data/covid-19-ethno-racial-group-income-infection-data/

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Anticipated challenges

- “We don’t do research”
- Lack of research training
- Lack of experience, or negative experience
- Lack of dedicated time (health providers & other staff)
- “Helicopter research”
- Bureaucracy & not familiar with:
  - Ethics
  - Data sharing agreements
  - Contracts & finances

Engaging primary care centres: Solutions

- "We don't do research"
- Lack of research training
- Lack of experience, or negative experience (e.g. RAP)
- Lack of dedicated time (health providers & other staff)
- "Helicopter research"
- Bureaucracy & not familiar with:
  - Ethics
  - Data sharing agreements
  - Contracts & finances

Focus on public health as spaces for learning & innovation
PH research as most relevant

Increase support for research training

PGY3-5 screening for research interest
PHPM research project requirements

Grant funding to purchase time

Returning to sites ongoing (1 / yr)

PH Learning Sys staff support

Conclusion

- Machine learning offers an opportunity to address and mitigate existing inequities and biases in population health
- Careful consideration is essential in the design and application of machine learning to ensure equity
- Adherence to principles of equity, transparency, and engagement is crucial in the development and use of AI
- Continuous monitoring of outcomes is necessary to inform and refine guidelines, given the rapidly evolving nature of machine learning
- Proper use of machine learning can promote fairness and equity for all in population health.

Questions?

upstreamlab.org

upstreamlab@smh.ca

@AndrewDPinto

@UpstreamLab

@UpstreamLabToronto

Upstream Lab

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