Content Programming and Thought Leadership Committee

The HIMSS Ontario Chapter launched the Content Programming and Thought Leadership Committee in early 2023. Our goal is to share themes, success stories and resources each quarter to positively transform healthcare in Ontario. The committee selects themes based on industry trends and members' interest and feedback. Content will be shared via the HIMSS Ontario website, LinkedIn and other official marketing channels.

If you are interested in submitting content to the HIMSS Ontario Chapter, please contact us at: **ontario.info@himsschapter.org**.

April Feature: Multiple perspectives on the use of digital health data

Executive Summary

In April, we explored the importance of data in digital health from a variety of perspectives. We explore three different viewpoints: Equity and the Social Determinants of Health, Data Bias, and Natural Language Processing (NLP)/Clinical Artificial Intelligence (AI). Read these articles to learn how your peers in Canada and globally are addressing various aspects of data in digital health and what the future holds for these important building blocks, technologies, and initiatives.

Removing data bias in healthcare

There are several systemic barriers that need to be addressed to facilitate equitable provision of care and one key area is the bias within healthcare data. As we progressively move into a digital health system where data is used to support and drive patient care and health system decisions, it becomes more important to ensure that the data being used is of high quality and devoid of bias.

Tools such as artificial intelligence (AI) and machine learning are becoming more commonly used in healthcare in different areas from augmenting workflow and administrative tasks to actively aiding disease diagnosis. While these tools can have significant positive impact on the health system, there can be negative implications if the data being created and used is biased. It is important to note that outputs of AI systems are only as good as the data used to train the algorithms and where there is bias in the data, it can lead to algorithmic bias. In a 2019 paper in the Journal of Global Health, algorithmic bias was defined as the application of an algorithm that compounds existing inequities in socioeconomic status, race, ethnic background,

religion, gender, disability, or sexual orientation and amplifies inequities in health systems[1]. As called out in an article from the Harvard T.H. Chan School of Public health, it is important to note that algorithms in health care technology don't simply reflect social inequities but may ultimately exacerbate them[2]. An example of algorithmic bias[3] in action can be seen in the use of skin-cancer detection algorithms trained primarily with data from light-skinned individuals being worse at detecting skin cancer affecting darker skin[4].

Given Canada's history, particular attention needs to be paid to how algorithmic bias could impact health services received by Indigenous people. A recently published study by the University of Calgary found two-thirds of Alberta physicians surveyed have implicit anti-Indigenous bias - 67 per cent of participants showed implicit preferences for white people with only 13 per cent demonstrating a preference for Indigenous faces. While this does not provide evidence of AI systems used in Alberta or Canada being biased against Indigenous people, it can lead to a presumption that the implicit bias noted in the physicians could be reflected in the Indigenous health data captured by them, thereby rendering any solutions or systems (e.g. AI algorithms) that are based on such data biased.

Data bias is often invisible, and it is as much a reflection of the bias within society as it is about algorithms. Some of the ways in which we can start to address this include:

- Ensuring data sets represent a diverse range of sex, gender, education level, income level, race, and language.
- Examining how research questions are framed to ensure it is not framed only from the perspective of majority groups, as this can lead to implicit bias assumptions about the data.
- Updating hiring processes to ensure data science teams include professionals from diverse backgrounds and perspectives across executive leadership, senior and middle management, and individual contributors.
- Putting deliberate strategies and plans in place to engage with equity seeking and racialized groups as part of all digital health product development and management lifecycles.

Although this area is gaining momentum, we are still in the beginning phases of the journey towards uncovering and removing bias from healthcare data. We need to continually refine the process of algorithm development to not just optimize performance but also eliminate bias.

Addressing equity through better collection of SDOH data

Bias in our data is partly a result of not having a valid and consistent collection of social determinants of health (SDOH) data, which describes the conditions in which people are born and live and the wider set of forces and systems shaping the conditions of daily life[6]. Understanding these conditions better requires the collection of sociodemographic data, which refers to nonmedical factors that affect health outcomes like income, social status, race, gender, education, and physical

environment[7]. These factors have great influence on personal and population health, yet these data are seldom collected in healthcare, which means we are unable to leverage the information to provide more equitable care.

How can organizations improve capture of SDOH data? Ontario Health Data Council submitted a report on the vision for Ontario's Health Data Ecosystem with a series of recommendations that include integrating and using health data to improve health and equity outcomes; promoting appropriate collection, analysis, and use; establishing trustworthy governance and policies at the system level; respecting First Nations, Inuit, and Métis Peoples' Data Sovereignty; and building capacity for stewardship and sharing by default[8]. Organizations should establish data governance structures that include members of racialized and equity seeking groups, empower participation, gather data systematically and consistently to enable health information exchange.

To integrate SDOH data into our processes and systems, we need:
1. policies to make collection of these data a priority as well as implementation of sufficient resources to do so;
2. consistent terminology and taxonomy to ensure common definitions and to facilitate integration of data sources; and
3. to be mindful when gathering information from equity seeking groups and make sure we use the data to support their care needs.

Two Ontario initiatives offer useful guidance based on their research and experiences. First, the Alliance for Healthier Communities shares a socio demographic data toolkit[9] that was created using results from a study on how partner organizations were collecting socio demographic data to better understand the SDOH. Their campaign called "We ask because we care" led to the development of a sociodemographic questionnaire. The toolkit includes a script and plain language glossary, data collection guide, client brochure, sample workflow diagram, staff training materials, case studies, and EMR tools.

The "Screening for Poverty And Related Social Determinants and Intervening to Improve Knowledge of and Links to Resources (SPARK) Study"[11] funded by CIHR, is currently validating a tool that includes 18 standardized socioeconomic questions for use in primary care[12].

We encourage organizations and health system leaders to educate themselves on the importance of this matter and reflect on how they are collecting and using sociodemographic data to improve equitable care in Ontario.

There is data in those conversations

As much as 80% of data in healthcare in unstructured[13]. Excessive documentation requirements are a leading cause of clinician burnout and dissatisfaction[14]. Conversations between clinicians and their patients are the starting point for all care, but unrecorded details of those conversations can lead to data loss, which may create inefficiencies, patient safety risks and poor patient health outcomes. On the

other hand, documenting every detail of these conversations may lead to clinician burnout and possible errors affecting quality of care.

Enter NLP, Conversational AI and Clinical AI.

Natural language processing (NLP) refers to the branch of computer science—and more specifically, the branch of artificial intelligence or AI—concerned with giving computers the ability to understand text and spoken words in much the same way human beings can. NLP in healthcare has added challenges as there is a clinical context that needs to be applied for an accurate representation of the conversation between patients, physicians and the wider care team. For example, one of the challenges identified with NLP system implementation is linguistic complexity, which can include variation used over time and across care settings, complexity of textual targets, and ambiguity of clinical terms used. The effects of this challenge can be seen most clearly when applied across multiple care settings[15].

Clinical NLP (cNLP) is advancing, with Google, Watson and smaller organizations like Abridge breaking through these clinical complexities to provide an accurate representation of these conversations, and summarizing intents, clinical relevance and patient instructions.

More and more clinical conversations are happening virtually via phone calls, video calls, and chat. Leading edge cloud-based communications platforms are positioned to assist with automating the processes of generating clinical notes and patient facing content. If we apply cNLP, we can turn these conversations into meaningful information that can help reduce clinician burnout and potential errors that can affect quality of care rather than data.

We find cNLP solutions being applied to the following healthcare use cases:

- Nurse Triage
- Clinical onboarding / patient welcome
- Patient access
- In-person and virtual encounters
- Complex referrals and authorizations
- Member wellness interventions
- Medication Therapy Management
- Adherence counseling

Encounter Notes - Clinical documentation is one of the leading causes of burnout[16]. Incomplete notes can result in risks from communication breakdowns on the clinical team and inaccurate billing and coding. cNLP helps clinicians systematically capture details and quickly produce higher quality notes.

Patient Instructions - Patients may forget important information and missing details can cause confusion for caregivers, such as for care plans assigned to them by their care provider (such as a diet plan to reduce their sugar levels) . All of this adversely impacts outcomes and creates risks. cNLP and conversational AI helps clinicians systematically and quickly produce higher quality patient instructions that helps ensure these gaps are filled.

Wellness Program Notes - Insufficient documentation may lead to poor quality measures, gaps in care, and poor outcomes which can impact quality ratings and risk adjustments. NLP and Clinical AI helps clinicians systematically and quickly produce case notes and document next steps.

Check out the following from Abridge, an up and coming organization delivering these solutions, who integrate with cloud communications solutions like Genesys.
https://youtu.be/f7uOpmEXtTg

References

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Other Resources of Interest

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4. *Kelsey Berg, Chelsea Doktorchik, Hude Quan & Vineet Saini (2022) Automating data collection methods in electronic health record systems: a Social Determinant of Health (SDOH) viewpoint, Health Systems, DOI: 10.1080/20476965.2022.2075796*

5. *https://ehrintelligence.com/news/best-practices-for-integrating-sdoh-data-into-the-ehr The Gravity Project, provides a comprehensive set of resources on SDOH data implementation, recommendation, and terminology guide (terminology overview, educational materials, coding submissions, data element submissions) https://confluence.hl7.org/display/GRAV/Terminology+Workstream+Dashboard.*