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Horizon Scan

2025 Watch List: Artificial Intelligence in Health Care

Key Messages

What Is the 2025 Watch List?

- The Watch List is an annual Horizon Scan report from Canada's Drug Agency that presents emerging technologies and issues that have the potential to shape the future of health care in Canada.
- The 2025 Watch List focuses on the use of artificial intelligence (AI) technologies in health care and the issues that may arise with the implementation of these technologies.
- AI technologies have the potential to significantly transform health care systems. These technologies could increase efficiency by reducing administrative burden, improve patient outcomes, and enhance patient experience by creating more access points to the health care system. However, there are also legal, ethical, environmental, and social implications with the rollout of these technologies.

Why Is This an Issue?

- Substantial public and private investments are being made in AI technologies for health care. AI technologies are already being implemented in some parts of the Canadian health care system. Commercial options, such as ChatGPT, allow AI technologies to be used by patients to assist with their health care journeys. Because they are readily available and easy to use, these same tools are sometimes used by clinicians and, in some cases, without sanction or training from employers or regulators.
- AI health care technologies also present an opportunity to fundamentally change health care by their ability to replace, displace, or augment tasks that have traditionally required human cognition. The potential health human resources impact of machines taking on some this load is significant given the increasing demand for health care services and the finite capacity of health care systems in Canada.

What Is the Potential Impact?

- The Watch List signals which technologies are poised to make an impact and the policies, regulatory or organizational enablers, and/or guardrails that are needed to optimize the proliferation of these technologies in the health care system.
- The 2025 Watch List also focuses on considerations for optimizing and accelerating implementation, such as the massive potential impact on operations, clinical outcomes, and staff and patient experience, while minimizing risks.

Key Messages

What Else Do We Need to Know?

- The 2025 Watch List of AI technologies and issues in health care was developed through consensus-based decision-making at a workshop in November 2024 including individuals from across Canada with experience and expertise in AI.
- The 2025 Watch List identifies and describes the top 5 new and emerging AI technologies in health care. Examples include AI for notetaking and AI for disease detection and diagnosis. We also explore some considerations for health care decision-makers about the impact these technologies may have on health human resources, health care infrastructure, and health equity.
- The 2025 Watch List also identifies the top 5 issues related to AI technologies in health care. Examples include the importance of establishing guidelines around what data are used to train AI algorithms and how that might contribute to bias as well as considerations about the liability and accountability of health care providers and systems that use these technologies. These are key issues that warrant more attention and will influence the wider adoption, diffusion, and implementation of new and emerging AI technologies.
- Monitoring ongoing developments and evidence related to the top technologies and issues highlighted in the 2025 Watch List can help guide health system planning in Canada and improve access to high-quality care.

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Abbreviations

AI	artificial intelligence
CDA-AMC	Canada’s Drug Agency
HCP	health care professional
JLA	James Lind Alliance
LLM	large language model

Definitions

Table 1: Key Definitions

Term	Definition used by project
AI agent	A system or program that can independently plan its workflow and utilize resources to carry out tasks on behalf of a user or another system. AI agents can perform various functions, including decision-making, problem-solving, interacting with external environments, and executing actions.[1]
AI technology in health care	Technologies that include interventions that incorporate AI-based computational methods within a product, process, or service that supports health care delivery directly to the patient, health care provider, and/or to institutions. This may include AI-driven medical devices, algorithms, software applications, and other systems; technologies without direct patient- or health system–related outcomes (e.g., AI to facilitate clinical research, data extraction processes in reviews) are not included.
Artificial intelligence (AI)	An umbrella term used to describe a variety of approaches (e.g., machine learning, natural language processing) that allow computer programs to perform tasks that have been traditionally done by humans.[2]
Bias	“A conscious (explicit) or unconscious (implicit) opinion, preference, prejudice, or inclination, formed without reasonable justification, that prevents a balanced or even-handed judgement.”[3]
Clinical decision-making	The process by which health care professionals evaluate and choose interventions based on evidence, patient preferences, and other contextual factors. This includes gathering information, ordering tests, interpreting results, and suggesting treatments.[4]
Deep learning	A type of machine learning that uses multilayered neural networks (deep neural networks) to replicate the intricate decision-making capabilities of the human brain. These networks are composed of numerous interconnected layers of nodes, with each layer refining and enhancing predictions or classifications based on the previous layer.[5]
Environmental costs	Negative environmental impacts associated with the development, deployment, and operation of AI technologies, such as energy consumption, resource usage, and e-waste generation.[6]
Generative AI (gen AI)	A subset of AI capable of generating new text, images, videos, or audio. It accomplishes this by extracting patterns and structures from large databases to create fresh data with similar properties. Generative AI is usually based on deep learning methods, including large language models and other technologies to generate new context.[7]
Human-in-the-loop	A collaborative approach that integrates human input and expertise into the life cycle of machine learning and artificial intelligence systems. Humans participate in the training, evaluation, and operation of machine learning models and provide valuable feedback. This collaborative approach aims to enhance the accuracy, reliability, and adaptability of ML systems by harnessing the unique capabilities of both humans and machines.[8]
Issues relating to AI in health care	Broader considerations (e.g., clinical, health systems planning, social, ethical, legal, or regulatory) that crosscut the implementation and use of AI in health systems and may affect how these technologies are developed or adopted in Canada.
Large language models (LLMs)	Advanced computational models designed to understand, generate human language, and perform a wide range of tasks. LLMs use deep learning techniques to learn statistical relationships between words and phrases, enabling them to perform tasks like language translation, text summarization, and question answering. Examples of LLMs include OpenAI’s GPT-4, Google’s BERT and PaLM, and Meta’s LLaMA.[9]
Machine learning	AI and machine learning are frequently used synonymously, but machine learning is technically a specific branch within the broader field of AI. Machine learning involves implementing automatic processes that move away from traditional procedural software programs toward problem-solving approaches based on learning models. These models are related to computational statistics and data mining techniques.[2]

Term	Definition used by project
Natural language processing	A branch of computer science and AI that uses machine learning to enable computers to understand and communicate in human language. It combines computational linguistics with statistical modelling, machine learning, and deep learning to recognize, understand, and generate text and speech. Natural language processing research has advanced generative AI, including large language models and image generation models.[10]
New or emerging technologies	Technologies that are not yet available in Canada or have been available for clinical use for 1 to 2 years with limited use and are in the launch or early postmarketing stage. It also refers to technologies available in Canada but with diffusion or availability limited to a few health care facilities or centres.
Opportunity costs	The allocation of resources to a specific use, resulting in the loss of potential benefits that the resources could have generated if they had been used for their next-best alternative. This represents the missed opportunity to invest in that alternative.[11]
Public health surveillance	The continuous and organized gathering, analysis, understanding, and sharing of health information to guide the planning, execution, and assessment of public health measures. It is widely recognized as a crucial public health activity and a key tool in preventing epidemics.[12]
Quality improvement in health care	Systematic efforts aimed at enhancing the delivery of health care services, improving patient outcomes, lowering the cost, and optimizing the overall quality of health care.[13]
Shared decision-making	A collaborative process in which health care professionals and patients collaborate to make decisions about patient care. This approach ensures that medical decisions align with the patients' preferences, values, and individual circumstances.[14]

Introduction

Through horizon scanning, Canada's Drug Agency (CDA-AMC) routinely identifies new and emerging technologies that are likely to have a significant and meaningful impact on Canada's health care systems. This work supports decision-makers by informing them about emerging health technologies and their related issues to prepare for the introduction and wider adoption of these new technologies. CDA-AMC (formerly CADTH) releases an annual Watch List[15,16] to identify technologies that have the most potential to transform health systems and shape the future of health care in Canada. The annual list signals how technology innovations may affect future health system needs and provides early assessments to help guide health system planning. In recent years, the Watch List has focused on a particular theme or area of medicine. In keeping with this trend, the 2025 Watch List focuses on the use of artificial intelligence (AI) technologies in health care.

What Is AI?

AI is an umbrella term used to describe a variety of approaches (e.g., machine learning, natural language processing) that allow computer programs to perform tasks that have been traditionally done by humans, such as large language models (LLMs) (e.g., ChatGPT) that generate answers to specific text prompts.[18] AI is a fast-growing economic sector, particularly AI technologies related to health care.[17] AI technologies in health care include interventions that incorporate AI-based computational methods within a product that supports health care delivery directly to the patient, health care provider, and/or health care institution. This may include AI-driven medical devices, algorithms, software applications, and other systems. Technologies without direct patient-, health system–, or health human resources–related outcomes (e.g., AI in evidence generation) were excluded from consideration in this report.

The Promise of AI in Health Care

Canada's health care systems are in need of improvement: wait times for some services are too long,[19] many health care workers experience administrative burdens and related burnout in the profession,[20] and there is a mismatch in supply and demand for some health care professionals (HCPs). AI technologies have been proposed as a solution to address some of these issues. For example, AI technologies that undertake administrative tasks such as notetaking[21] and scheduling[22] have already been launched in Canada and show promise in increasing efficiency so that health care provider time can be redeployed to other parts of the system, such as direct patient care. AI is also being used in patient care to improve diagnostic accuracy in the area of medical imaging.[23] For improving timely access to health care, there are app-based AI mental health supports[24] available 24 hours a day 7 days a week used as part of a patient's overall treatment plan.

These are only a small sample of the exciting developments in the uses of AI for health care. Advancements in the development and training of LLMs (such as GPT-4o which ChatGPT is based on) along with significant financial investment are accelerating the pace of innovation in Canada and abroad. According to a 2023 report by the Commonwealth Fund, Canada's annual health care spending has steadily increased as a percentage of the gross domestic product since 1980; health care spending now makes up 11.3% of the gross domestic product.[25] However, according to the same report, Canada's performance is considered "modest to poor," with Canada ranking very low on 4 indicators related to the timeliness of care.[25] Integrating AI solutions that replace, displace, or augment tasks that have traditionally required human cognition will result in major changes to the health care systems. In particular, the introduction could allow systems to reap the benefits of AI, such as cost reduction, and optimize system management by redirecting workers to other parts of the system.[26]

The increased use of AI technologies in health care raises an appealing proposition for delivering more efficient, accurate, and accessible care to people living in Canada; however, the use of AI in health care has also raised some unique questions around the readiness of the system to adopt these potentially disruptive technologies. The introduction of such quickly evolving technologies brings significant complexity to health systems. If AI technologies are adopted into routine use, they are likely to change multiple aspects of care, including resource utilization, health human resources, health care delivery and organization, patient and caregivers' outcomes and experiences, as well as raising equity and ethical considerations. AI technology comes with some challenges associated with other digital health care technologies, such as concerns around the safety of private patient health data,[27] and more unique considerations, such as the liability for health care providers[28] relying on the judgment of an AI technology.

CDA-AMC has recently published 2 reports that discuss considerations for digital health and AI. One provides recommendations for data privacy and digital equity in the context of remote monitoring for cardiac conditions.[29] The other is about the implementation of AI-enabled medical devices that identified 8 Canadian and 5 international guidance documents on how to implement AI in health care, including considerations for inclusivity, data quality testing, transparency, data governance, privacy, and security.[30] Implementation considerations in this report included clinical safety; data protection; technical security; interoperability; usability and accessibility; transparency, explainability, and intelligibility; inclusiveness, equity, and minimizing bias; responsibility and accountability; user buy-in and organizational readiness; and monitoring, maintenance, and sustainability. Further recommendations on implementing AI ethically can be found in work by WHO,[31] the United Nations Educational, Scientific and Cultural Organization (UNESCO),[32] and the European Commission,[33] and on using AI responsibly in systematic review research from Europe.[34,35]

To alert decision-makers to innovations within AI technologies used in health care as well as the possible implications for health systems, the 2025 Watch List identifies new and emerging AI technologies and the issues related to the implementation of these technologies that are likely to have a significant impact on health care systems in Canada over the next 5 years.

Developing the 2025 Watch List

A short list of emerging technologies and issues was identified through a literature search of published medical literature, news articles, and industry reports with input from an expert advisory group (refer to Appendix 1 for detailed information about Advisory Group members and workshop participants). Early on, the Advisory Group recommended that, due to the fast-moving nature of this field, we should work with categories of technologies rather than individual technologies. However, even in the time frame of this project, a category of AI technology emerged that was not considered by our workshop participants: AI agents (sometimes known as autonomous AI). AI agents are significant advancements in AI because they work independently to carry out tasks on behalf of a user. AI agents are beginning to appear in several categories on the 2025 Watch List, from notetaking to clinical training and education to disease detection and diagnosis. We acknowledge that the research and development of AI agents are progressing rapidly, and the implementation of AI agents must consider the issues outlined in the 2025 Watch List.

The final items on the 2025 Watch List were selected at a workshop through a consensus-based decision-making process. CDA-AMC has a partnership with the James Lind Alliance (JLA) and the 2025 Watch List was developed using a modified JLA priority-setting approach. The workshop brought together diverse views and experiences, and included patient partners, caregivers, policy experts, researchers, members of industry, and HCPs from across Canada. Further details about the selection and identification process of the items are described in Appendix 2.

The outcome of this process is a final Watch List that reflects the values and experiences of the diverse group of workshop participants. The goal of the 2025 Watch List is to contribute to a larger conversation about what uses AI technologies should be put toward in our health care systems and what that may mean for people who work in or seek care from these systems. To paraphrase one of the workshop participants: the [Canadian health care] system needs whatever efficiencies it can get, and [decision-makers] need guidance about how and where to make those efficiency gains.

Watch List Objectives

The 2025 Watch List aims to highlight the AI technologies that are poised to have the most significant and meaningful impact on health care systems and that are likely to shape the future of health care in Canada over the next 5 years. It also serves as a guide to separate the hope, or promise, from the hype and extensive publicity about AI technologies. It describes considerations for their implementation. Contextualizing the technologies alongside the broader issues can provide insight about the future of AI technologies used for health care and support health systems planning. Collectively, the top 5 technologies and top 5 issues constitute the 2025 Watch List.

The 2025 Watch List

The workshop to arrive at the final Watch List took place in November 2024. Although the Watch List is enumerated, **the list is not ranked**; the fifth item is not more or less important than the first. The workshop group was clear that all items on the draft list were important. Items that did not make the final list are listed in Appendix 3.

The top 5 AI technologies in health care are:

1. AI for notetaking
2. AI tools to accelerate and optimize clinical training and education
3. AI for disease detection and diagnosis
4. AI for disease treatment
5. AI for remote monitoring

The top 5 issues related to AI technologies in health care are:

1. Privacy and data security
2. Liability and accountability
3. Data availability, quality, and bias
4. Data sovereignty and governance
5. Environmental costs

Top Technologies Related to AI in Health Care to Watch

1. AI for Notetaking

Context

Health care providers spend a significant amount of time managing health records and taking notes to document patient history, physical examinations, test results, referral reports, and other administrative tasks.[36] Because these data are often unstructured, health care providers have to spend excessive time on notetaking. This increased time negatively impacts their workflows and workloads, potentially resulting in burnout.[37] Furthermore, when health care providers are documenting patient information on paper or computers during consultations, they tend to have decreased eye contact with their patients.[38] This can create communication barriers and reduce overall patient satisfaction. The considerable time additionally spent on documentation outside of direct patient interactions can feel tedious or as an increased workload, leading to feelings of burnout and professional dissatisfaction for health care providers.[38]

Definition

AI-powered notetaking applications use advanced technologies, such as automatic speech recognition and natural language processing (which enables machines to understand, interpret, and generate human language) to transcribe conversations between patients and health care providers and to generate clinical notes.[39] These technologies work by automatically creating notes from conversations, which simplifies the notetaking process, and by converting patient data into structured information from unstructured sources. Health care providers can then edit, review, and sign the generated note.[38]

Examples

- AI scribes use machine learning technologies to create written summaries of conversations between patients and health care providers.[21] These are capable of producing conversation transcripts, medical notes, and referral letters.
    - Using AI scribes significantly reduced the time spent on administrative tasks: a reported 69.5% reduction in laboratory settings and an average of 3 hours less per week in routine practice settings in Ontario.[21] Primary care providers using AI scribes have reported reduced administrative burden, lower cognitive load, and less after-hours work. They also noted improved efficiency, increased job satisfaction, and enhanced quality of care.[21]
    - A 10-week pilot study also demonstrated that AI scribes could decrease the time physicians spend on documentation during appointments. The authors of the study noted that this technology is capable of generating high-quality clinical notes, facilitating more meaningful interactions with patients, and reducing the workload that often extends beyond office hours.[40] Patients reported feeling comfortable with AI scribes and observed that health care providers spent less time on their computers.[40]
    - Current studies and reports indicate that AI scribes are imperfect and can have errors or omissions that require a review of notes by HCPs.[41]
- Other AI tools are used for notetaking.
    - PhenoPad is an open-source interface for clinical notetaking that captures both free-form notes and standardized phenotypic data (e.g., information captured on a tablet by clinicians) through various methods, such as speech recognition, natural language processing, and handwriting recognition.[38]
    - Tali AI technologies integrate AI scribes, medical dictation, and medical information retrieval to enhance clinical documentation and streamline clinical workflows.

Potential Positive Impacts

- AI for notetaking could reduce the administrative burden by streamlining notetaking, minimizing errors, and enhancing overall efficiency in health care systems.[42]

- Implementing AI for notetaking could potentially decrease the time spent on documentation, thereby enhancing patient-provider interactions.[43,44]
- Accurate notetaking could enhance health outcomes and improve patient experiences.[44]
- By consolidating patient data into high-quality medical notes, health care providers could gain a comprehensive view of the patient's medical history, which may lead to better access to critical information for care teams.[45]
- It can also improve health care provider satisfaction, potentially reducing burnout rates.[45]

Additional Insights

The workshop participants mentioned that AI for notetaking is essential for successfully implementing other AI technologies. High-quality clinical notes and structured data are critical for facilitating discussions between patients and health care providers about their concerns, laying the groundwork for disease detection and diagnosis, treatment optimization, and other AI technology categories discussed in the 2025 Watch List.

The workshop participants also emphasized efficiency gains associated with AI for notetaking because clinical notetaking consumes a significant amount of health care providers' time. Most health care providers, whether in primary care, specialized fields, or other areas, need to complete clinical notes based on conversations with patients, physical examinations, and other information. As a result, there was considerable enthusiasm and demand among health care providers about adopting AI technologies for notetaking. Furthermore, some participants pointed out that various AI technologies for notetaking are already being used in health care in Canada, which could help alleviate health care provider burnout. A crucial insight shared at the workshop was that using AI for notetaking may be a safer early adoption of AI in health care than other applications (e.g., diagnosis and treatment).

AI can enhance notetaking efficiency, but accuracy is critical in health care because errors may lead to significant risks in diagnosis and treatment. However, using AI for notetaking can lead to errors, such as AI hallucinations (instances when AI generates distorted or inaccurate information).[46] In the context of notetaking, AI tools may record events that did not happen or leave out important information. AI may have difficulties with various languages and may not accurately document physical examinations.[41] To prevent errors and AI hallucinations, and to ensure inclusivity in various languages, AI tools should incorporate strong error-checking measures and support multilingual capabilities. This includes providing comprehensive user training, ensuring that clinicians review AI-generated documents, and having developers focus on producing accurate AI outputs. Further research is needed to explore the trade-offs between administrative gains (i.e., efficiency) and the risks of bias or errors.[47]

Additionally, there is a need to integrate AI for notetaking into electronic health records to assist health care providers in eliminating the need to copy and paste clinical notes from various applications.[48] The integration of AI and electronic health records is a challenging endeavour, potentially requiring coordinated efforts from multiple teams. If AI-generated notes can be securely integrated into electronic health records, it will further enhance workflow efficiency and reduce manual entry errors.

2. AI Tools to Accelerate and Optimize Clinical Training and Education

Context

Clinical training and education enable HCPs to gain the knowledge and skills necessary for diagnosing and effectively treating patients. A common approach in medical education for health care providers emphasizes knowledge retention and relies heavily on memorizing evidence, procedures, and guidelines.[31,49] Using AI tools to accelerate and optimize clinical training and education may significantly enhance personalized learning, real-time feedback, skill development, and objective, automated assessment.[50] This could potentially transform the current medical education system, including both medical school and continuing medical education.[51]

Integrating AI into clinical training and education offers the potential to reduce health care costs, enhance the quality of care, and broaden access to care by empowering health care providers with advanced technological AI tools.[52,53] This includes incorporating AI-powered learning resources within the medical curriculum and continuing medical education as well as training health care providers to understand and effectively apply AI tools in diagnosis, treatment, and care delivery. These 2 areas are interconnected because it is necessary to understand the particulars of AI technology to make the best use of AI in clinical education.

In addition to AI tools supporting education, HCPs require training and education that equips them with the necessary skills to effectively implement AI into clinical practice. This could include understanding the language of AI and developing the technical skills to operate AI-driven tools by gaining knowledge of how these tools work and familiarity with basic concepts and principles behind AI technologies.[49] Additionally, training may need to address other considerations related to AI, such as maintaining critical thinking abilities when using AI tools.[49]

Both the Royal College of Physicians and Surgeons of Canada and the College of Family Physicians of Canada acknowledge the importance of AI in health care. For example, the Royal College of Physicians and Surgeons of Canada has made recommendations regarding implementing AI and digital technologies in residency training and health care delivery.[54] The recommendations emphasize the potential impacts of AI on both clinical practice and medical education, not just AI-specific skills. For example, the recommendations propose introducing a new discipline focusing on clinical informatics to equip physicians with AI tools for practice, encouraging collaboration with medical schools in Canada to promote AI through MD and PhD programs, and fostering “clinical innovators” as emerging careers in AI-driven health care.[54] The College of Family Physicians of Canada has also published a statement supporting AI research and development in family medicine and primary care.[55]

Definition

AI tools to accelerate and optimize clinical training and education could summarize available evidence for physicians, medical students, and patients, providing general background knowledge and the latest evidence regarding interventions.[56] AI technologies should support upskilling and reskilling for both health care providers and patients.[57]

Examples

- OpenEvidence is a language model specifically designed for medicine to aggregate and synthesize clinically relevant evidence in formats that are understandable and accessible, enabling more evidence-based decision-making and improving patient outcomes.[58] The tool has demonstrated significant accuracy in answering the US medical licensing examination questions. Health care providers and learners can set up an account for unlimited, free access to the tool. This tool offers a distinct advantage over other models by providing citations for its responses, allowing users to validate the information quickly. However, it was designed for targeted point-of-care clinical use, so its short responses may make it less useful as a comprehensive information resource.[58]
- ChatGPT, a generative LLM, presents numerous opportunities for enhancing clinical training and education. Although some AI tools do not explicitly mention ChatGPT, they may use ChatGPT to generate their response. ChatGPT can be used to create virtual patient simulations and quizzes for medical students.[59] It can also critique simulated doctor-patient communications, summarize research articles, and generate a curriculum for health professionals. However, when using ChatGPT for medical education, it is important to use proper prompting and to be aware of the issue of AI hallucinations, particularly when ChatGPT fabricates references or contents.[59]
- AI-VSP (Artificial Intelligence Virtual Simulated Patients) can be used in clinical teaching as a complementary learning tool. This technology represents an advancement in health care education, providing a powerful tool for training future HCPs.[60] By combining AI and virtual reality, the technology can create immersive, interactive, and personalized learning experiences that improve clinical skills and enhance decision-making abilities.[60]

Potential Positive Impacts

- AI could enhance the learning experience and improve training efficiency by summarizing large amounts of information and reducing the training burden on health care systems and easing the research burden on individual HCPs.[53]
- AI technologies may help address health care resource crises by promoting innovative solutions and encouraging curiosity among HCPs by providing opportunities for personalized educational materials, novel solutions, and data-driven insights. AI could facilitate the exploration and adoption of other technologies and support more efficient resource allocation and problem-solving strategies.[61]
- Training health care providers to effectively use AI in their practice and incorporating these technologies into clinical training and medical education could ultimately improve the quality and efficiency of patient care and contribute to positive health outcomes.[53]

Additional Insights

During the workshop, participants highlighted how AI can serve as a tool to enhance clinical training and medical education overall. For example, one workshop participant mentioned that trainees have already begun using ChatGPT to support their clinical education, help them prepare presentations, and facilitate their learning processes.

The discussion also touched on the need for health care providers to receive education on how to effectively use AI technologies in their clinical practice within the health care system (training in AI or AI as a training subject). This education is essential for successfully implementing other technologies, including AI Technology 1: Notetaking, AI Technology 3: Disease Detection and Diagnosis, AI Technology 4: Disease Treatment, and AI Technology 5: Remote Monitoring. For instance, health care providers need to understand what AI is, how to interact with AI systems, how to use them to solve problems, and how to critically appraise AI models. The dual role of AI as both a training subject and as a tool to accelerate clinical training highlights the importance of integrating these 2 aspects.

Participants emphasized the importance of involving patients in this educational process, recognizing that AI has the potential to enhance patient engagement. AI technologies could offer more accessible and personalized materials for patients as well. Educating patients about AI tools in health care could encourage them to take more responsibility for their health and improve proactive self-management skills. Health care providers should actively support patients and caregivers to help facilitate the process.

3. AI for Disease Detection and Diagnosis

Context

Disease detection and diagnosis are essential for timely treatment. Early detection and effective treatment are the most important solutions to reduce the death rates caused by chronic diseases.[62] Health care providers typically need to consider and interpret various pieces of information, including clinical manifestations, physical examinations, and other relevant data, making the diagnosis process quite complex. Given the dynamic and changing environment of the health care system and the limited time that HCPs are in clinical practice, making accurate disease detection and diagnosis can become a cognitively challenging task.[63] AI technologies offer potential advantages in supporting this process. As of August 2024, the US FDA had authorized approximately 950 medical devices that use AI or machine learning.[64] Most of these devices are designed to assist in the detection and diagnosis of treatable diseases.[64] The top 5 medical specialties using AI technologies are radiology (e.g., Overjet Image Enhancement Assist), cardiology (e.g., EchoGo Heart Failure 2.0), neurology (e.g., BrainSee), hematology (e.g., AI-4510 Urine Particle Analysis System), and gastroenterology and urology (e.g., EndoScreener).[64]

Definition

AI for disease detection and diagnosis refers to using AI technologies, such as machine learning models, to assist health care providers in improving disease detection and diagnosis based on various data, such as medical images, physical examinations, family history, environmental factors, and dietary habits.[65] Radiology has been leading the way in AI for disease detection and diagnosis.[66] In recent years, there has been an explosion of AI technologies for analyzing medical images (e.g., radiology, pathology) to make faster and more accurate diagnoses.

Examples

- ASIST-TBI was developed to quickly identify traumatic brain injuries by screening the CT scans of patients with head injuries in the emergency department. If the model indicates the need for surgery, the physician can consult a neurosurgeon directly, bypassing the wait for a radiologist review. The model showed accurate prediction for neurosurgical intervention with an area under the receiver operating characteristic curve of approximately 0.90, with accuracy, sensitivity, and specificity all exceeding 80%.[67]

- LumeNeuro uses machine learning techniques to detect neurodegenerative brain diseases at an early stage by screening for retinal protein biomarkers. This technology is low cost and noninvasive, using polarimetric imaging to identify retinal amyloid deposits without dyes. The machine learning models developed by the researcher from the University of Waterloo can predict thioflavin positivity with high accuracy, sensitivity, and specificity, which is an indicator of amyloid presence and potentially Alzheimer disease.[68]

Potential Positive Impacts

- AI for disease detection and diagnostics may improve health systems by enhancing diagnostic accuracy and making advanced diagnostic tools accessible (e.g., AI tools could detect patterns that human health care providers might miss).[69] However, one workshop participant highlighted that AI technologies might increase the demand for diagnostic tests (e.g., lab workload), which could increase the burden on our health care system. The Advisory Group experts recognized that leaving conditions undiagnosed over several years can negatively impact health care resources, which often leads to a need for more invasive tests, specialized care, and greater costs. It is important to find a balance between early disease diagnosis and the risk of overdiagnosis and misdiagnosis (e.g., false positives and false negatives), with the primary goal of minimizing potential harm.
- AI could enhance care pathways by identifying diseases or conditions earlier, which may reduce the waiting time for interventions or enable health care providers to assess and manage patients more efficiently.[69]
- A recent randomized controlled trial conducted in the US found that the LLM ChatGPT Plus alone demonstrated higher performance in diagnostic reasoning compared with physicians, even when the LLM was available to them. However, when physicians used the LLM as a diagnostic aid, it did not statistically significantly enhance their clinical reasoning or reduce time spent per case compared with using traditional resources, such as UpToDate or Google.[70] The study only focused on diagnostic reasoning, but did not focus on other critical clinical skills (e.g., patient interaction or data collection) and the authors noted that LLMs should not be used for autonomous diagnosis without physician oversight. Although LLM shows promise in diagnostic reasoning, further research and development are needed to determine their real-world impacts on patient care.

Additional Insights

During the workshop, participants agreed that there is a high demand for AI in disease detection and diagnosis. Progress in machine learning models, particularly deep learning models, has made these AI tools for disease detection and diagnosis more accurate. Early disease detection and diagnosis support disease prevention, which keeps people healthy and out of the queue for intensive medical care. In addition, a vast amount of data are available for training these models in disease detection and diagnosis. However, participants noted that this category includes a broad range of AI technologies, related to both radiology and other medical areas. These technologies may have different timelines for significantly impacting the health care system. Concerns about the readiness of the health care system to implement AI technologies for disease detection and diagnosis were raised during the discussions.

Using AI technologies to enhance disease detection and diagnosis could negatively impact health care system capacity due to increased demand for follow-up testing and interventions, potentially exceeding the current health care system capacity in Canada. There is a need to apply appropriate methods to identify the right populations for further diagnostic testing to mitigate these negative impacts. For example, colorectal cancer screening was suggested for high-risk populations (i.e., 15-year risk of colorectal cancer greater than 3%) while it was suggested against for low-risk populations (i.e., 15-year risk of colorectal cancer less than 3%) based on absolute risk reductions at population level.[71] In addition to traditional methods for identifying high-risk populations, AI technologies using advanced machine learning models may help detect the right populations more accurately and efficiently for further screening, reducing the screening burden on our health care system. Another method to reduce the burden of screening or testing is to systematically use incidental data, often referred to as "opportunistic screening."[72] For instance, researchers have developed an AI-powered approach for detecting pancreatic cancer, which can accurately identify and classify pancreatic lesions using noncontrast CT scans that are routinely performed for other clinical purposes (i.e., not for screening purposes).[73]

4. AI for Disease Treatment

Context

Clinical treatments, including pharmacological and nonpharmacological interventions, are a critical component of health care and are central to the clinical decision-making process. Disease treatment is the process of selecting the most appropriate and effective treatment based on available evidence, individual patient clinical needs, patient values, and other factors (e.g., costs).[74] This approach aims to achieve the best clinical outcomes while minimizing unnecessary interventions and side effects. Treatment is closely related to health care resource allocation and clinical results. Health care providers require various data and information to make informed decisions about treatment options.

Definition

AI technologies for disease treatment offer a new way for patients to access the most appropriate and effective treatment, complementing traditional in-person health care and digital options such as telemedicine. The potential roles of AI in treatment optimization include:

- Identifying optimal treatment plans: AI can assist health care providers in determining the best medication, dosage, and treatment plan for each patient.[75] This involves considering potential drug interactions and customizing the treatment plan according to the patient's unique genetic profile and medical history.[76] Additionally, AI has the potential to continuously update treatment plans based on new evidence and patient responses, which could enhance the overall patient experience.[77]

- Assisting the triage process (especially in the emergency department): AI has the potential to enable earlier intervention. It may enhance health care decision-making by improving discrimination capabilities and predictive accuracy, leading to better risk assessments. This could help assess the need for hospitalization and optimize resource allocation.[78]

Examples

- Kaia Health is a digital therapeutics company offering accessible, evidence-based treatments for disorders such as musculoskeletal pain, chronic obstructive pulmonary disease, and osteoarthritis. Using machine learning, it delivers interventions to help patients self-manage their conditions. Kaia Health is a member of the Digital Therapeutics Alliance, a nonprofit organization focused on advancing digital therapeutics.
- Wysa is an AI mental health chatbot for stress, anxiety, depression, self-care, and sleep disorders.[79] It offers a conversational AI tool that provides mental health support, guiding users through both cognitive behavioural therapy programs and on-demand assistance with a therapist.[79] The platform supports individuals experiencing subclinical symptom levels and helps them establish proactive prevention routines. The technology is especially beneficial because an AI chatbot can be available 24 hours a day.
- Valence Labs offers AI tools and software for drug discovery, such as LOWE — an LLM-orchestrated workflow engine designed to execute complex drug discovery workflows using natural language. It aims to provide an easy-to-use tool for drug discovery. LOWE may serve as a foundation model that accurately represents or simulates the biological and chemical aspects of drug discovery. It could assist people in formulating hypotheses, learning from results, and designing and executing experiments for hypothesis testing.[80]

Potential Positive Impacts

- AI for disease treatment could support a more efficient and sustainable health care system, enhance health care provider and patient satisfaction, and improve overall population health by focusing on the most appropriate and effective treatment.[81]
- Using AI technologies to optimize treatment plans, health care providers could improve clinical outcomes, minimize adverse effects, reduce unnecessary interventions, and promote cost-effective care.[82]

Additional Insights

During the workshop, participants engaged in a similar discussion about using AI for disease detection and diagnosis. Patients need the most effective treatment for their condition. Using AI for treatment allows for assessing personalized treatment plans rather than using one-size-fits-all strategies. It also helps mitigate the health care human resource crisis, particularly for primary care providers in the community,[83] by providing physician decision support and improving operational efficiencies and patient self-management. However, the health care system may require significant resources to incorporate AI for treatment and other technology categories included in this Watch List, such as financial investment, training for HCPs, and ongoing technical support and updates.[51] Concerns about the readiness of the health care system to implement AI technologies for treatment optimization were raised during the workshop discussions. These concerns included insufficient funding, disparities in technology adoption across geographic regions in Canada, and other issues discussed in the 2025 Watch List (e.g., privacy and data security and data availability, quality, and bias).

5. AI for Remote Monitoring

Context

Remote monitoring uses various biomedical sensors to collect health-related data outside of hospitals, typically in patients' homes.[84] Health care providers can access these data wirelessly to make informed decisions about patient care, such as heart rate, respiration rate, temperature, blood pressure, and oxygen saturation. AI-powered analytics or machine learning algorithms can then process the collected data to identify risk factors and patterns, predict potential health issues, and provide clinicians with actionable insights beyond data. This system enables patients to maintain their usual activities while being monitored, potentially reducing health care costs, the inconvenience of in-person visits, and traffic congestion associated with hospital or clinic visits.[84]

Definition

AI for remote monitoring refers to using AI technologies to collect, analyze, and interpret patient health data remotely and provide real-time data to health care providers in other locations to ensure appropriate and timely interventions without frequent in-person visits.[84] AI could use different types of data for remote monitoring, including information from wearable devices, smart home sensors, and smartphones. For instance, AI can track heart rate, blood pressure, respiratory rate, temperature, and physical activity.[84] These data can be collected in real time to identify any deviations from typical patterns or specific thresholds. AI for remote monitoring combines remote monitoring data and health care providers' clinical judgment with machine learning algorithms. Potential roles of AI for remote monitoring include:

- generating alerts and notifications for health care providers, allowing for timely interventions and reducing the risk of adverse events[84,85]
- predicting potential health issues or adverse events based on the analysis of both historical and real-time data, enabling proactive interventions[84,85] and, because AI algorithms can learn over time, their predictive ability may improve.[84]

Examples

- AlayaCare offers software solutions that include remote patient monitoring, clinical documentation, and patient and family portals. These solutions empower care providers, particularly for home care providers, to achieve better health outcomes through AI technologies and data insights. According to research conducted by AlayaCare, its technology with machine learning could improve event predictions by 11% while reducing overdiagnoses by 54%. A clinical study in Canada reported that implementation of the AlayaCare program reduced both the number and cost of emergency department visits and hospitalizations for patients with chronic obstructive pulmonary disease or chronic heart failure.[86] Specifically, when the technology was implemented for 3 months, the number of emergency department visits was reduced by 68% and hospitalizations decreased by 35%

compared to baseline before using the technology.[86] The average cost of emergency department visits fell from $243 at baseline to $67, and the average cost of hospitalizations dropped from $3,842 to $1,399 during the 3-month period.[86]

- Coughy uses AI-based sound analysis technology to analyze digital audio biomarkers to assist patients and health care providers in making smarter, faster, and more informed decisions. It offers an AI-powered real-time remote cough monitoring solution that provides objective measurements for tracking chronic coughs. Patients can record their cough sounds using smartphones or smartwatches. Health care providers can monitor these recordings remotely and in real time.

Potential Positive Impacts

- AI-powered remote monitoring could increase monitoring capabilities to expand access to health care by facilitating continuous, real-time monitoring of patient health and minimizing the need for frequent in-person visits, especially for those living in remote and rural areas.[87]
- AI-powered remote monitoring could enable patients to receive medical and health care in their homes, reducing the need for hospitalization, allowing more efficient allocation of medical resources, and saving costs for both patients and health systems.[88] However, this is closely related to the accuracy of the AI tools.[88] If AI tools produce false positives or false negatives or overdiagnoses, it could increase costs or impose a greater burden on patients and the health care system. AI for remote monitoring is closely linked to AI Technology 3: Disease Detection and Diagnosis discussed in this Watch List.
- AI for remote monitoring could impact health care human resources by improving efficiency and allowing medical staff to concentrate on their core medical tasks.[88] By analyzing monitoring data, AI algorithms can evaluate patient flow, resource utilization, and staffing patterns, enabling better resource allocation.[88]
- AI-powered remote monitoring could use algorithms that analyze large, real-time datasets to identify patterns and trends that allow for adjustments to treatment plans as necessary, resulting in more dynamic and responsive care.[88] Implementing AI for remote monitoring can enhance the quality of life for patients and help prevent potential adverse outcomes.[88]

Additional Insights

The workshop participants highlighted the importance of including AI for remote monitoring in the 2025 Watch List for several reasons. There are abundant data available from various wearable devices, and increasingly advanced machine learning models are being developed for data analysis. The shift in demographics toward an aging population and the growing prevalence of chronic diseases and comorbidities are generating increasingly large health care datasets. This increases the need for AI technologies in remote monitoring, especially for patients in rural and/or remote areas and underrepresented populations, such as Indigenous communities. Additionally, AI for remote monitoring can improve community-based and home-based care by prioritizing the needs of patients, caregivers, and health care providers, thus enhancing clinical outcomes and quality of life. However, implementing AI technologies for remote monitoring must consider challenges such as limited internet access in rural and/or remote areas, the populations' technical literacy, and technical issues, particularly for older adults who may experience issues if technologies are not intuitive or do not accommodate their needs.

The accuracy and quality of these measurements are crucial, and it is important to be aware of any AI limitations in measurement. For example, studies have shown that the accuracy of pulse oximetry can be decreased in patients with darker skin tones.[89] Future research is needed to comprehensively assess the accuracy of these measures that contribute to AI technologies.

Top Issues Related to AI in Health Care to Watch

The following are the top 5 issues selected by the 2025 Watch List workshop participants through the priority-setting process of the JLA[90] detailed in Appendix 2. The issues selected by the participants in this project may differ from those selected by experts of other AI guidance documents being used globally.[31-33]

1. Privacy and Data Security

AI in the health care system can learn patterns from large dynamic multidimensional datasets that include patient, provider, and health system data.[66] Because these databases contain personal health information that is used to make recommendations or predictions for patient care, there is concern about how this information can remain private and secure (i.e., safeguarding sensitive medical information to ensure it remains confidential and in secure locations) and how exactly it will be used (i.e., will its use be beneficial or harmful to patients).[27,66]

Examples of recent AI privacy and data security concerns in Canada:

- A 2024 survey of physicians in Canada showed that 21% were confident about AI and patient confidentiality, whereas 79% were either not confident or unsure.[91]
- Canada ranks 10th in number of security breaches worldwide. From 2015 to 2023, there were at least 14 reported major cyberattacks on Canadian hospitals, labs, and health networks, including blocking services, using ransomware to lock access to personal health information, and compromising personal health information by removing it from health systems and sharing it illegally.[92,93]

In the global market, not all AI technologies are designed to be applied in Canada. As described in the CDA-AMC report on the implementation of AI-enabled medical devices and other digital health technologies,[30] Canadian legislation for the private sector's collection, disclosure, and use of personal information for commercial and for-profit endeavours falls under the *Personal Information Protection and Electronic Documents Act* (PIPEDA);[94] for the public health care sector (e.g., hospitals, long-term care facilities), it is under local provincial and territorial laws.[94,95] This includes jurisdictional-specific legislation, such as the *Personal Health Information Privacy and Access Act* in New Brunswick; the *Personal Health Information Acts* in British Columbia, Newfoundland and Labrador, Nova Scotia, and Manitoba; and the *Freedom of Information and Protection of Privacy Act* and the *Personal Health Information Protection Act* in Ontario.[94-96]

It may be unclear to what extent AI technologies, such as scribes, comply with these legislative protections; therefore, it may be difficult for HCPs, patients, and decision-makers to know what is legally and ethically required to safeguard patient, provider, and health system information. For example, some publicly available AI scribe technologies that HCPs currently use to summarize conversations with patients may store data securely within Canada but their use by HCPs is still not regulated in Canada. Some local provincial colleges of physicians and surgeons (e.g., College of Physicians and Surgeons of British Columbia) have advised physicians to be cautious and risk-aware when using these tools.[41,96,97] There are other technologies (e.g., ChatGPT) that patients may use to understand their personal health information that are also not regulated in Canada and do not comply with security or privacy laws in the US (i.e., *The Health Insurance Portability and Accountability Act* [*HIPAA*]) where the data are stored.[96,98]

Some patients may have concerns about privacy and consent when using AI. A 2024 scoping review[99] of 37 studies on patient perspectives on the use of AI in health care found that patients were concerned about the use of AI, such as informed consent, regulation, and trustworthiness. Patients were interested in knowing how AI tools were being applied, how they were developed, and whether their data would be used anonymously. There were also questions about who they could approach if errors were made.[99] As the use of AI becomes more integrated into the health care system in Canada, it will be important to consider privacy concerns, whether patients have fully consented to include their data in AI databases and understand the potential uses of their data in AI algorithms, and what different care pathways could look like for patients who opt in or out of AI processes.

Workshop participants stated that there is a strong need for privacy guardrails related to the use of AI in health care. They highlighted how this issue is related to AI Issue 4: Data Sovereignty and Governance because how data are managed can set the stage for its security. They mentioned how establishing clear privacy and security measures can create trust and help build support for the adoption of new AI technologies. An example of trust in action is Quebec's *Bill 64, An Act to modernize legislative provisions as regards the protection of personal information* which received royal assent in 2021. This legislation requires that patients know how medical decisions using their personal information were made (i.e., if they were made exclusively using automated processes such as AI or in conjunction with physicians) and gives them the right to request to have these decisions reviewed, including review by a human if the decision was fully automated.[100,101]

Solutions can include:

- proactive adoption of data privacy and security protocols for encryption, secure storage, access control, data anonymization and de-identification, and data transmission[51]
- frameworks and guidance to train HCPs and patients on using AI securely with a focus on patient care[51]
- compliance with local privacy laws[51]
- policies to allow patients to withdraw or grant informed consent about AI tools being used for their health, have access to their data, and have information about how AI uses their data.[51]

2. Liability and Accountability

Issues of liability (legal responsibility) and accountability (moral, legal, procedural, or organizational responsibility) arise from the use of AI in health care.[28,102] The use of AI in health care can take many forms and may include interpretation of data by AI and/or a human (i.e., the HCP) at various stages of the AI feedback loop, which is known as "human-in-the-loop."

HCPs do not control how a particular AI system's functionality was developed, the decisions it makes, or the recommendations it provides. As a result, it can be difficult for HCPs to understand how an AI system came to certain conclusions based on their input.[102] This challenge relates to both explainability and transparency in AI. *Explainability* refers to how well an AI system's reasoning, validation, and reliability can be communicated to users.[31]

However, AI systems can be so complex that they are not easily explainable or understandable for nontechnical users. They are sometimes referred to as "black boxes" because their processes are opaque. Therefore, HCPs may be using AI in their practice but not have the expertise to comprehend how the AI works or makes decisions.[31,103]

There are different ways that humans can work with AI systems. There are some approaches that employ human-in-the-loop AI in which humans actively provide feedback on AI outputs that the AI learns from and incorporates into future predictions; this is an example of collaborative decision-making between AI and humans.[104] Other approaches may use predefined algorithms designed by AI developers and engineers and the static AI outputs are then checked by humans. In the case of health care, an HCP may check an AI application's output to determine whether it will be useful and safe for patients.[104] In either approach, the design of AI systems that include human involvement is complex given the variations of human understanding of AI functions.

Where does the responsibility for the actions of AI lie, especially in the event AI makes errors or causes patient harm in ways that are potentially unknown or hidden to HCPs?[102] If HCPs use an AI system's suggestions and a patient is harmed, who would be held legally liable — AI developers, the health care system, or HCPs?[103] The Canadian legal system does not have clear-cut answers to these questions because broad legislation for AI regulation is still being discussed in parliament (i.e., *Bill C-27, Digital Charter Implementation Act, 2022*).[101,105] Therefore, there will be challenges in dealing with these issues in the coming years.[28]

Examples of recent AI liability and accountability concerns in Canada include the following:

- Outside of health care, AI chatbots have come under scrutiny. In 2022, Air Canada was liable for damages relating to an AI chatbot promising a discount that did not exist to a customer.[106]
- Several organizations have joined Canada's Voluntary Code of Conduct on the Responsible Development and Management of Advanced Generative AI Systems.[107]
- On November 12, 2024, Canada launched the Canadian Artificial Intelligence Safety Institute to invest $50 million over 5 years to support AI research, including cybersecurity. This is linked to AI

Issue 1: Privacy and Data Security and with managing risks to the development of AI that can be a danger to human insight.[108,109]

Workshop participants expressed that both developers and users of AI need to be clear about accountability. Also, when HCPs use AI, it is currently still viewed as something that the HCP is ultimately responsible for. They expressed that it may not be appropriate to place this burden on HCPs and patients who are the end-users of AI and not experts on AI development and regulation. These concerns overlap with concerns raised about overreliance on AI by clinicians and health systems (Appendix 3).

Ways that developers can work in collaboration with health care providers, patients, and HCPs in a shared decision-making process to manage issues such as explainability, intelligibility, transparency, accountability, responsibility, and liability include:

- minimizing liability risks through agreements or predefining who is liable in certain scenarios[28]
- establishing disclosure requirements[28]
- improving hospital policies that help HCPs use AI tools safely[28]
- providing guidance and support for HCPs on using AI to make decisions within health care system and legislative policies[51]
- providing guidelines on how HCPs can communicate with patients about AI use and how to incorporate recommendations from AI (i.e., informed consent)[28]
- ensuring algorithm transparency so that AI systems are explainable to end-users such as HCPs and patients.[51]

3. Data Availability, Quality, and Bias

To be useful, AI in health care will require a high volume of data to train algorithms or generate new information. Data availability, quality, and bias are closely related and are factors that must be considered for its use.

- **Data availability**: The reliable access to and use of data without interruptions to performance and functionality, including considerations for data validation and integrity, storage and retrieval of information, network responsiveness, and system performance.[110-112]
- **Data quality**: The accuracy, reliability, completeness, and relevance of data that can lead to effective learning and decision-making by AI systems.[113]
- **Data bias**: The perpetuation of existing social biases by inaccurate and unreliable AI systems that can cause inequities, discrimination, and inaccurate decisions.[114] AI bias can occur along the different stages of AI development — from data collection to model deployment and evaluation. This can include data bias (unrepresentative, skewed, and inaccurate data being put into AI systems), algorithmic bias (errors in machine learning algorithms because of how the data were coded and trained), or user bias (who gets to use AI and how they interpret AI outputs to make decisions).[114-116]

There are already concerns about the quality and bias of AI. One study found that AI chatbots that use LLMs propagated inaccurate and harmful race-based medical content furthering existing biases, had different responses for the same clinical questions, and provided incorrect responses about already debunked or outdated information depending on when and how the information databases were updated.[117,118] AI can easily perpetuate incorrect notions about underserved communities that experience inequities because it may learn incorrect ideas about how health conditions are currently understood and treated by the health care system and HCPs. Examples of this can include making assumptions about 1 group of people having higher rates of a disease, forming recommendations based on datasets that are misrepresentative of those affected by the health condition (e.g., missing data from equity-deserving groups), providing predictions with a one-size-fits-all approach when some groups may have different outcomes and needs, and using proxy variables based on correlations in models that are inaccurate (e.g., conflating an individual's neighbourhood with their race, their health care spending with their need for complex care, their income with their knowledge, or their spending patterns with their medical conditions).[116,119,120]

Examples of the concerns about data availability, quality, and bias include:

- **Availability**: Canadian health data are currently fragmented across jurisdictions and health systems. Although 93% of physicians in Canada use an electronic medical record in their local context, there have been challenges with coordination of care, including scheduling referrals, sharing information, and receiving reports from other HCPs.[121,122] This lack of harmonization within local systems and across the country can make it difficult to establish large central datasets with information from a variety of sources. This results in challenges when clinically and technically validating AI models that require seamless inputs of large volumes of data. Leaders across Canada have been addressing this issue in the following ways:
    - Canada Health Infoway and jurisdictional leaders have developed the *Shared Pan-Canadian Interoperability Roadmap*, which is a framework that promotes interoperability (i.e., communication, collaboration, and connection between HCPs, facilities, and health systems across geographies). The application of this framework can guide the seamless flow of information between different parts of the health care system.[123] This sharing of information can be used for patient care, health system planning, and research.[123]
    - In June 2024, the Parliament of Canada established *Bill C-72*, the *Connected Care for Canadians Act.* In practice, patients and providers would be able to easily access patient data and health information, and technology vendors would be prevented from "data blocking" (interfering with the access or exchange of electronic health information) or incur financial penalties if its software does not meet policy requirements, which allows for patient health to remain a priority over AI vendor interests.[124] In this way, health data can be safely shared and accessed across systems and HCPs to promote timely and coordinated patient care, facilitate easier access and exchange of data, and drive health system innovation.[125,126]
- **Quality**: Poor quality data (i.e., have errors or are imprecise, unvalidated, incomplete, or unreliable) can occur when the training data used to teach AI and build algorithms does not structurally match the new inputs it receives for processing.[127-129] This can cause direct harm to patients when AI systems use this incorrect data to make decisions about patient health and treatment. The decisions

can be harmful, discriminatory, and ultimately may infringe on human rights or right to receive health care (e.g., being denied care based on AI outputs).[127-129]

- **Bias**: The data that AI uses should be representative of the population it will serve. Systemic biases in health care have historically omitted or misrepresented various equity-deserving groups based on factors such as sex, gender, race, and disability.[130] Existing health care data, ways that medical technologies are used, and current human health care practices can lead to AI systems perpetuating biases and exacerbating disparities, which can cause misdiagnoses, fatal outcomes, and issues with generalizability.[131] Algorithmic bias has already been observed in current uses of AI that show racial bias against Black communities and perpetuate debunked assumptions about races being biologically different from one another. Some clinical algorithms have been harmful by falsely assuming that individuals who are Black have different muscle mass than those from other racial groups. Other algorithms have used health care spending as a proxy for care, leading to the flawed assumption that patients who are Black do not need as much care as those who are white because they have historically spent less on health care and they need to be sicker to be recommended for care.[132-135] There is evidence that medical devices such as pulse oximeters, scalp electrodes, and thermal thermometers are biased against groups with higher melanin concentrations in the skin which can compound potential harm to patients when combined with biased AI algorithms.[132-135]

  AI algorithms become biased if they do not include data from diverse populations, their data are influenced by human subjectivity, their design is not regulated from inception, or they repeat inequities from historically discriminatory human practices.[131] If equity-deserving groups are not included in datasets and models are not trained appropriately, algorithms will not be able to recognize patterns for these groups or be able to diagnose or treat these patients. Biases need to be actively prevented during the early stages of AI development because they can be difficult to recognize later on.[131] For example, some studies have shown that there are differences in how chest pain is reported by women and how women are diagnosed with heart attacks.[136,137] Because symptoms were historically documented based on men, coronary symptoms in women are often labelled as “atypical” and can be missed or misdiagnosed by HCPs. If AI models use historical electronic medical record data based on the “typical” symptoms in men, they may not catch cardiac symptoms in women that require further testing.[136,137] This can harm women who need life-saving treatment but may have to wait longer because their symptoms were not recognized.[136,137]

  The methods for preventing algorithm and other biases for new technologies are extremely complex and may require different equity-based approaches. For data and algorithm biases used to train AI, the first step is to ensure the appropriate collection of diverse data in a comprehensive data collection before deciding the appropriate approach for using — or not using — these data in AI models.[130]

Workshop participants noted that this issue is related to AI Issue 1: Privacy and Data Security and AI Issue 4: Data Sovereignty and Governance. They expressed that data are a foundational part of how AI technologies work and that this needs to be set right from the beginning. High-quality data are essential, otherwise there can be harmful, irrelevant, and biased data going into and out of AI systems on a widespread scale (referred to by participants as “garbage in, garbage out”).

- Participants highlighted there are gaps in our current health care system and the existing data are of poor quality; there is a lack of information on social demographics, patient-reported experiences, and economic factors. It is difficult to measure how algorithms can be biased across race, language, and many other factors. Participants suggested that people know these factors are important; however, they are not well measured and thus de-emphasized. It is also unclear whether the health care system should wait for validated thresholds for patient data that are not well measured or continue to use AI in its current state with the information that is available to take advantage of this emerging technology. For example, data from patients with rare diseases or those living with disabilities are very limited. Workshop participants highlighted that AI technology is highly developed and progressing faster than the health care system’s capacity to produce high-quality datasets.
- Participants discussed how there is already a combination of biases in existing data (e.g., from medical research) that can give rise to potentially toxic feedback loops that perpetuate the status quo. Biased information is being put into an AI “black box,” and it is hard to identify how the data are being used to make decisions or where the flaws are. This black box issue is referred to as *opacity* and is discussed as part of AI Issue 2: Liability and Accountability. Workshop participants also noted that electronic medical records are optimized for health care transactions (lab and medication information) and billing documentation but not to understand data at the level that research studies would use (e.g., including longitudinal data; documenting risk factors, socioeconomic status, education levels).[138]
- Participants indicated that there may be a delay between clinical practice and AI development. As an example, the Ontario Renal Network and the Ontario Association of Medical Laboratories recommended the removal of a race-based variable in the equation for estimated glomerular filtration rate.[139] This change was disseminated through a memo to HCPs in Ontario and not through more widely available evidence sources, such as clinical practice guidelines or randomized controlled trials, which are developed by clinicians and researchers; this makes it unclear if the developers of the original AI algorithm were aware of the practice modifications at the same time that the HCPs stopped adjusting the rate for patients. This example speaks to the need for strong partnerships between the health care system and AI developers to ensure that when practice standards are made by frontline workers who use AI tools, AI developers are also aware.
- Furthermore, race-based data are not routinely collected in Canada; therefore, it is unclear how our health care system would be able to implement this so that patients would be able to give appropriate consent for the use of this information in AI models in scenarios that require knowledge about demographic information and whether the data could be collected without measurement bias.

Solutions can include:

- Increasing data availability by
  - collaborating and sharing health information across Canada under the *Shared Pan-Canadian Interoperability Roadmap*

- Improving data quality with
  - legislation to correct AI source data such as patient records[140]
  - automated error correction methods[140]
  - allowing patients to access or correct errors in data[140]
- Mitigating algorithmic bias by
  - framing the problem for AI prediction models correctly (diversity in the development team and design of the AI model including assumptions)[120]
  - combining multiple datasets to capture diversity and representation[120]
  - identifying sources of bias based on populations, settings, and demographics and managing bias in the preprocessing of data, such as standardized data collection (e.g., how it is measured and labelled) and the processes for how missing data are handled[51]
  - reducing bias when models are developed and validated (e.g., assessing training data, applying real-world testing, assessing generalizability and reproducibility when using models in different settings, investigating whether bias adjustments are appropriate)[120]
  - postimplementation monitoring and managing of AI models to assess bias and user feedback (e.g., review and correct data, manage historical biases)[119,120]
  - establishing bias and fairness guidelines[51]

4. Data Sovereignty and Governance

The use of large datasets in AI systems has led to discussions about ownership and management of data. *Data sovereignty* refers to the rights a group of people have to control their own data, including how it is collected, stored, and interpreted.[141] *Data governance* defines who has the authority and control to manage the data.[142] Designing AI systems and their datasets requires working together with equity-deserving groups so they have control over their data and consent over how AI-enabled technologies interpret their data and generate new information from it. The goal is not just to collect data from these groups but to actively work to represent the data correctly, allow equity-deserving groups to have autonomy in how the data are used, and work toward a reduction of health inequities to dismantle structural racism.

Some communities have created frameworks to address the ownership of and the rights to their health data; examples include:

- As a result of colonialism, the government in Canada has historically collected, held, and destroyed data from Indigenous Peoples about their health care, demographics, and Residential School records.[143] The *Access to Information Act*, which has mechanisms to allow individuals and corporations to request access to information held by the federal government,[144] continues to have barriers for Indigenous Peoples in how their data are stored, preserved, and archived.[143] *Indigenous data sovereignty* is the fundamental right of Indigenous Peoples to control data about their lands, communities, and cultures, which are principles described in
  - the *United Nations Declaration on the Rights of Indigenous Peoples*[145]

    - CARE Principles for Indigenous Data Governance (collective benefit, authority to control, responsibility, ethics) from the Global Indigenous Data Alliance[146]
    - Canada's Tri-Agency Research Data Management Policy[147]
    - OCAP principles for First Nations communities (ownership, control, access, possession) from the First Nations Information Governance Centre[148]
    - Inuit Qaujimajatuqangit and the National Inuit Strategy on Research from the Inuit Tapiriit Kanatami and Inuit Qaujisarvingat National Committee[149-151]
    - OCAS principles for Métis governance practices (ownership, control, access, stewardship) from the Manitoba Métis Federation.[152,153]
- The COVID-19 pandemic revealed existing disparities due to structural and institutional anti-Black racism: Black communities were disproportionately exposed to COVID-19, experienced more infections, had lower rates of screening, and had lower uptake of COVID-19 vaccines.[154,155] In Ontario, these inequities have resulted in calls for the responsible collection of race-based data; however, this must be done appropriately.[156,157]
    - One group working on this is the Black Health Equity Working Group in Ontario that developed the EGAP (engagement, governance, access, and protection) framework for the sovereignty of data for Black communities so they have control over and can make decisions related to their data collection, use, management, and analysis.[154]

In the context of AI, these frameworks can allow equity-deserving groups the opportunity to ensure that AI correctly understands information about them and generates outputs that can help improve the health of their communities, rather than perpetuating known historical biases. Ways of referring to equity-deserving groups, as well as the language they use to understand and communicate their health needs, are also evolving. AI technologies must stay up-to-date with these ways of knowing.

At our workshop, participants expressed the need for trust and governance of data especially for pan-Canadian clinical decision-making including a structure on how to use AI data in the health care system, clarity on who owns the data, and guidance for users of these systems. They also noted that this issue along with alignment with societal values, sets the stage for other issues such as AI Issue 1: Privacy and Data Security and AI Issue 3: Data Availability, Quality, and Bias.

Solutions can include:

- policies to empower patients to be involved in the use of their data, including control, access, and interpretation[51]
- participatory approaches to AI development between equity-deserving groups and AI developers to establish control of data at the beginning of the AI loop.[158]

5. Environmental Costs

Climate change is causing floods, droughts, and heat waves that affect the Earth's biodiversity as well as human health — and often the most vulnerable people are the most affected.[159] Although AI can provide potential benefits in the health care sector, it can also affect the environment negatively in several ways:

- AI systems use high amounts of energy because the data centres they require run on electricity. These centres also need water for cooling, a process that is increasingly difficult to maintain given rising worldwide temperatures.[6] This infrastructure contributes to carbon emissions as algorithms train and become more advanced.[6,160] As of October 2024, there were 239 data centres in Canada and the number was increasing.[161] In Ontario, electricity demand is projected to increase 75% by 2050 because of electric vehicle manufacturing and AI data centres; by 2035, 16 large data centres are projected to be in service.[162]
- Rare earth-derived metals are being used to develop the hardware for AI (e.g., fuel cells, insulation, capacitors), its energy sources (i.e., batteries, devices), and its miniaturization for portability.[6] Extraction of these metals harms the environment and humans; the process is dangerous, results in toxic waste, and is not sustainable because most of the materials are not recycled.[6]
- The physical devices that run AI do not last forever and the eventual electronic waste is often discarded in resource-poor settings and landfills or is incinerated in pits. These sources of pollution expose animals and humans to toxic waste.[6]

Workshop participants expressed that the environment should be top of mind so that the health care system does not contribute further harm to the planet, noting that this issue was related to AI Issue 2: Liability and Accountability. They highlighted there were not enough discussions about the environmental costs of AI, which can sometimes be an afterthought, and noted the need for environmental advocacy. Other participants acknowledged that AI could potentially reduce environmental costs in some cases (e.g., helping to optimize energy use). Participants were worried about devastating forest fires in Canada in 2023 and flooding in Europe in 2024 due to climate change. They were also concerned about the private sector's role in purchasing nuclear reactors to fund AI; for example, Microsoft, Google, and Amazon have recently made nuclear energy deals to meet the high demands of AI use (e.g., data centres with routers, severs, cooling devices).[163] If AI in health care is here to stay, developers and the health care system need to work together to balance the expected benefits to patients with the potential harms to the environment to ensure AI technologies are sustainable.

Solutions can include:[160]

- building energy-efficient models
- establishing green computing systems
- integrating routine life cycle assessments for appropriate ecodesign
- optimizing how data are managed and stored
- implementing workflows that reduce waste and energy consumption
- using low-carbon energy solutions

- practising sustainability with regards to AI hardware and the disposal of electronic waste
- increasing awareness among the health care sector, HCPs, AI developers, policy-makers, patients, researchers, and sustainability experts.

Final Thoughts

The items on the 2025 Watch List were selected by people with lived experience using AI in a health care context as patients, caregivers, health care providers, members of industry, and health care decision-makers. The strength of this work is our ability to bring together multiple perspectives to discuss AI both where it might bring major benefits to the Canadian health care systems and where there is a need for caution.

The 2025 Watch List encompasses categories of technologies and associated issues that are interconnected and require systems-level thinking to enhance health care and avoid unintended effects. Adding AI technologies into the health care system without first establishing robust liability and accountability structures, for example, could lead to delayed uptake by some health care providers. However, delaying rollout of these powerful tools until conditions are perfect could also potentially cause harm to people who would not be able to reap the benefits of these technologies in a timely fashion.

There was a feeling shared in the workshop that the widespread use of some AI technologies in the health care system is inevitable — particularly the consumer-led technologies. These technologies will be added to the system whether the system is ready for them or not. As a result, the issues that made the 2025 Watch List emphasize investing in system readiness: ensure that foundational elements related to governance, privacy, and liability are in place to build trust, support the introduction and uptake of these powerful technologies, and lay the necessary groundwork for future developments in this rapidly evolving space.

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Appendix 1: List of Advisory Group Members and Workshop Participants

Advisory Group

Canada's Drug Agency is grateful to the Advisory Group for the 2025 Watch List. They provided project oversight and considerations about items to include, helped refine the short list, and reviewed earlier versions of the draft report.

Sandra Holdsworth Patient partner

Zayna Khayat University of Toronto, Deloitte Canada, Teladoc Health Canada

Muhammad Mamdani Unity Health Toronto

Daniel Raff Fraser Health Authority

Duncan Steele Alberta Health Services

Workshop Participants

Canada's Drug Agency is grateful to the workshop participants for their time, sharing their expertise and experiences, and selecting the final items included in the 2025 Watch List. Their participation, insights, and willingness to collaborate were integral to developing the list. Participants were generous with their ideas and their time — we thank you for your collaboration and expertise.

Arun Bala Patient partner

David Beyer Health care provider, Alberta Precision Labs

Jaron Chong Health care provider, London Health Sciences Centre

Marcia Clark President Elect, Royal College of Physicians of Canada

Anne Dabrowski Director of Information Services, Centre for Effective Practice

Moushir M. El-Bishouty Senior Innovation Technology Consultant, Alberta Health Services

Monica Field Executive Director Health Informatics Branch, Saskatchewan Ministry of Health

Simon Hagens Vice President Performance, Canada Health Infoway

Ron Johnson Vice President and Chief Operating Officer – Eastern Urban, Newfoundland Health Services

Amy Ma Patient caregiver

Glenda O'Hara Patient partner

Donna Rubenstein Patient partner

Bryan Santone Vice President, Centre for Effective Practice

Eleftherios Soleas Director, Lifelong Learning, Queen's Health Sciences

Lisa Tang Computer Scientist, British Columbia Centre for Disease Control

Carla Velastegui Parent caregiver

Amol Verma Health care provider, St. Michael's Hospital

Conflicts of Interest

Advisory group members declared the following conflicts:

Sandra Holdsworth indicated she has worked with various research institutions to evaluate AI technologies, such as Centre for Digital Health Evaluation to evaluate AI scribe and using AI in equalizing the MELD score in end-stage liver disease for research at the University Health Network.

Dr. Zayna Khayat indicated financial interests from Teladoc Health Canada Inc. and Deloitte Canada.

Dr. Muhammad Mamdani indicated financial interests from Eli Lily, and is in an advisory role with 2 artificial intelligence start ups: Signal 1 and Mutuo Health.

Dr. Daniel Raff indicated financial interests from UBC Digital Emergency Medical Group, Tenzr Group, Doctors of BC.

Workshop participants declared the following conflicts:

Dr. Jaron Chong declared the following financial interests: Deputy Editor of JMRI, Board of Directors for AMS Healthcare, and Radiologist and Assistant Professor at London Health Sciences Centre and Western University. He declared financial and nonfinancial interests as the Chair of the Canadian Association of Radiologists AI working group as well as nonfinancial interests relating to his work as an ad hoc member of Health Canada's Scientific Advisory Committee, Digital Health.

Dr. Marcia Clark declared nonfinancial interests relating to her work as an advisor for a medical device start up, Prova, and declared financial interests relating to grants received from the department of surgery for studies on gender as well as imposter syndrome in surgeons.

Anne Dabrowski disclosed financial interests from the Ontario College of Family Physicians for presenting on AI.

Donna Rubenstein declared she was a patient advisor on many digital and virtual health initiatives, including an Ontario Ministry of Health project on AI scribe.

Eleftherios Soleas reported financial interests from Queen's University in the capacity of his role as Director, Lifelong Learning, relating to the use of AI in teaching and education.

Carla Velastegui declared her participation from 2022 to present as a caregiver advisor for The Ontario Caregiver Organization.

Dr. Amol Verma indicated financial interests in an AI early warning system, Signal1.

Appendix 2: Approach Used to Create the 2025 Watch List

Project Overview

Advisory Group

In July 2024, we invited 5 experts (external to CDA-AMC) to participate as members of the Advisory Group to guide the project. The Advisory Group brought diverse perspectives and expertise on the applications of AI in health care as patients, caregivers, health care providers, researchers, innovators, and health care decision-makers. We sought experts with experience in developing and applying clinical AI tools, health system transformation, policy and ethics, as well as those who could provide input from the patient and/or caregiver point of view. Roles of this group included:

- providing guidance and input on the project scope, including validating the definitions and selection criteria
- helping to identify and refine items for the draft Watch List
- suggesting potential workshop participants
- reviewing the content of the draft report.

Key Steps

The key steps in developing the 2025 Watch List are briefly described in Figure 1.

Figure 1: Key Steps Used to Develop the 2025 Watch List

Step 1. Identifying Items for the Long List

The goal was to identify and describe new and emerging AI technologies and related issues in the health care setting with the potential to substantially impact health care delivery and planning in Canada in the next 5 years. The project team considered impact to be significant and meaningful changes in health and human resources, patients’ and caregivers’ experiences and health care outcomes, pathways of health care delivery, and health care equity and access. These areas of change were selected because they are relevant to health care policy and planning and support system readiness for integrating new technologies.

A 5-year time frame was chosen to identify technologies that were further along in the research phase or that have the potential for greater adoption in Canada or similar health care contexts. This time period was intended to limit the technologies that were still in the early development phase in which their potential value proposition remained largely uncertain or those that were unlikely to achieve substantial adoption outside of limited research settings. Early on, the Advisory Group recommended that, due to the rapid advancements in this field, the list should focus on categories of technologies rather than individual technologies. However, even within the time frame of this project, a new technology category emerged that was not considered by our workshop participants: AI agents.

For clarity, *significant and meaningful change* was defined as that which would require the addition of new, or modification of existing, resources, policies, or procedures to successfully adopt and implement technologies.

Domains for criteria for selecting items for the Watch List were identified using the International Network of Agencies for Health Technology Assessment (INHATA) position statement on disruptive technologies,[164] the CDA-AMC Strategic Plan,[165] health system priorities as determined by CDA-AMC intelligence gathering, as well as past Watch Lists. We identified relevant and common criteria across these documents to build domains with prompts and key items that included health system–, health care facility–, and patient- and/or caregiver–level issues. The criteria were circulated to the Advisory Group for their input to ensure its accuracy and relevance.

Table 2: Criteria for Selecting Items for the Long List

Domains	Area of significant and meaningful change
Resource utilization (technical, environmental, and health human resources)	• The need for more or less staffing • Administrative efficiency and workload distribution (e.g., reallocation of time toward patient care instead of administrative tasks, addressing health care provider burnout) • The need for ancillary equipment (e.g., smart devices), additional facilities, data storage, and information technology infrastructure • Environmental impacts (e.g., electronic waste, energy usage, carbon emissions)
Patients' and caregivers' experiences and outcomes	• Patients' and caregivers' experiences of delivery of care, such as changes in the location of care (need to travel) and changes in the accessibility or pathway of care • Patient outcomes, such as clinical benefits (e.g., earlier diagnoses), safety, quality of life, and quality of care (e.g., personalized care plans)
Health care delivery and organization	• Changes in care setting (e.g., hospital, community care, at-home care), and/or care modality (e.g., virtual care or asynchronous messaging, videos, telecommunication, chatbots) • Changes in the legal, regulatory, and governance frameworks (e.g., data protection legislation or standards) • Cost-effectiveness for the health care system

Domains	Area of significant and meaningful change
Health equity and access	• Patient access to care (access includes accessibility, availability, and acceptability) • Whether the technology addresses or exacerbates inequalities in geographic access to care • Whether the technology addresses or exacerbates health inequities • Respect for persons and communities (e.g., implications for informed consent) • Confidentiality and patient privacy (e.g., considerations related to data ownership, retention, and transfer, including biological specimens or legal or regulatory aspects)

Step 2. Preparing the Draft Watch List

Once approximately 30 items were identified, the project team reviewed the draft list and reflected on the project scope, definitions, and selection criteria. Through discussion the items and their labels and definitions were revised, including collapsing, separating, and removing some items. The draft list was then shared with the Advisory Group for validation and to assess the credibility of items. Based on the written and oral input of the Advisory Group, items were once again added, removed, and modified. The final draft list was used in Step 3.

Step 3. Workshop to Select the Top 5 Technologies and Top 5 Issues for the 2025 Watch List

We adapted the transparent and inclusive priority-setting process of the JLA[90] to guide the online workshop and the selection of the top 10 items for the 2025 Watch List. The JLA principles align with CDA-AMC priorities of equal involvement and inclusivity (e.g., balanced representation from patients, health care providers, and other impacted parties), transparency (e.g., visible audit trail of submitted technologies and trends), and a commitment to using and contributing to the evidence base (e.g., using technologies and trends to inform future products produced by CDA-AMC.

Identifying and Recruiting Workshop Participants

We identified potential participants through project scoping, a literature review, CDA-AMC networks, and the Advisory Group's recommendation. There was also an open call for participation on the CDA-AMC website from August to November 2024. Interested individuals completed a web form describing their connection to the topic and how their experiences could add to the diversity of ideas being shared. Members of the project team selected and invited 19 individuals to participate (2 participants were unable to attend on the day). The goal was to select a group of participants with a wide range of experience and backgrounds. Selection of participants emphasized the need for a range of geographical settings (i.e., jurisdictions in Canada), diversity of professional and personal experiences, and expertise as patient partners, caregivers, policy experts, researchers, members of industry, and HCPs.

Engagement With Indigenous Peoples and Organizations

CDA-AMC recognizes the sovereignty and jurisdiction of First Nations, Métis, and Inuit Peoples over community well-being. We understand that Indigenous Peoples' experiences, values, needs, and priorities are important for understanding and improving the use of AI in health care in Canada. In particular, organizations representing Indigenous Peoples, such as the First Nations Information Governance Centre,[166] are leading the way in the development of principles and guidance around data sovereignty. The OCAP principles[148] establish how First Nations' data and information will be collected, protected, used, or shared, and the First Nations Data governance strategy[167] highlights what steps should be taken to best serve the data and statistical needs of First Nations in an increasingly complex digital environment, including digital health care. In conjunction with our Strategic Partner, Indigenous Engagement and Partnerships, CDA-AMC is currently fostering relationships with Indigenous Peoples and organizations. Over the course of this project, our Strategic Partner, Indigenous Engagement and Partnerships, reached out to organizations such as the Association of Fist Nations (AFN), the Canadian Institute of Health Information (CIHI), First Nations Information and Governance Centre (FNIGC), and Inuit Tapiriit Kanatami (ITK) to participate in the workshop. However, we were unable to partner with these groups on this project. CDA-AMC acknowledges the lack of engagement and inclusion of Indigenous Peoples' perspectives and voices as a major limitation and gap of this work.

The Half-Day Workshop to Select the Top 10 Technologies and Issues

Before the workshop, we provided participants with a hardcopy or electronic workshop guide, the draft list with summaries about each technology and issue, and a participant worksheet. Before attending the workshop, participants were asked to individually review and rank the technologies and issues in the short list using the participant worksheet.

The half-day virtual workshop occurred November 5, 2024. The workshop was led by a CDA-AMC staff member who is a JLA Advisor. Two additional team members facilitated the small group workshop sessions. The facilitators used a facilitation guide to ensure that all participants were actively included in the discussion, so the JLA principles of equal involvement were upheld. Additional CDA-AMC team members participated in the workshop as observers and to provide technical support and/or take notes.

The workshop had 2 parts. In the first part, participants were split into 3 smaller groups for a listening exercise in which each participant was asked to share their top-ranked and lowest-ranked items and their rationale. Responses were recorded by the facilitator to form a draft list that reflected the individual choices shared in each group. In the second part of the workshop, the draft rankings of the groups were combined and used as a starting point in a facilitated discussion toward consensus. The group selected the top 5 technologies and top 5 issues that reflected the diverse perspectives and discussion of the group.

Step 4. Preparing the Final Report

We prepared a final report that described the top 10 technologies and issues and their impact on patients, caregivers, and health systems. Descriptions and examples were based on the published literature (identified during the list generation stage and/or by supplemental searching as needed), additional targeted internet searches, and discussions from the workshop. A draft version of the report was shared with the Advisory Group, and the report was revised based on their input.

Appendix 3: Technologies and Issues Not Included in the Watch List

Table 3: List of Technologies Not Included in the Watch List

Technology (category or intervention)	Description	Insights from the workshop
AI for human resource scheduling	• A group of AI applications have been used in various settings, such as emergency departments, operating rooms, and private practice, to predict the duration of patient-provider interactions, optimize resource allocation, and predict patient length of stay.[168] • These technologies could assist with staff scheduling and enable proactive decisions for calling in additional staff.	During the workshop, participants mentioned that using AI for human resource scheduling could improve response rates, especially in high-demand situations, such as in emergency departments. However, some participants expressed concerns about the trustworthiness of the technology and its efficiency, which may be limited due to existing technological constraints. They expressed that our health care system is not currently prepared to implement this technology. Additionally, some pointed out that human resource scheduling may not be a significant challenge for the health care system.
AI for optimization of other administrative tasks	• This category includes other AI administrative tools. For example, some AI tools have been developed to manage patient messages to the electronic inbox system of the emergency department.[169] The tool can automatically fill out forms based on previous clinical decisions and patient responses.	During the workshop, participants noted that using AI to assist with administrative tasks is safe because most data can be controlled. Additionally, these tools can help alleviate the triage and administrative burden in health care. However, participants also noted that addressing these tasks may not be the top priority.
AI for prognosis and risk stratification	• AI technologies used to predict patients' risks for clinical outcomes based on multiple data inputs.[170] AI technology has the potential to forecast the progression of different medical conditions by examining a range of datasets, such as patient history, genetic information, and real-time health metrics. • It can also assess baseline risk levels and determine absolute risk reduction, aiding clinical decision-making. These advancements allow for smart risk stratifications, enabling health care providers to pinpoint patient subgroups that would benefit most from clinical interventions.	During the workshop, participants highlighted that the accuracy of AI for prognosis and risk stratification has improved through deep learning models, and the necessary data are available. AI has the potential to be beneficial for the health care system by identifying high-risk patient groups for intervention and proactive strategies. It is important to note that the prediction models are not always stable. Additionally, the discrimination and calibration of clinical prediction models may sometimes be inadequate.
AI for error reduction and quality improvement	• These technologies enhance the precision and efficiency of various operations by leveraging data analytics and advanced machine learning techniques in clinical decision-making, including but not limited to diagnosis, risk stratifications, and treatment optimization. The technologies may identify errors or quality issues and improve patient outcomes.[171]	During the workshop, participants expressed several concerns about using AI for error reduction and quality improvement: • AI has the potential to introduce new errors, which largely depends on how people use it. • The feasibility of using AI technologies to reduce errors and improve quality may be low. • High-quality data are lacking. • The current health care system is not ready for implementation.

Technology (category or intervention)	Description	Insights from the workshop
		• This category of technologies is not a driver for decision-making; instead, its implementation incurs costs.
AI for enhancing shared decision-making process between clinicians and patients	• This category captures technologies that provide interfaces for both health care providers and patients. • AI technologies could consolidate all relevant information, such as patient charts and the most reliable evidence, by improving the accessibility of information in an easily understandable manner and providing personalized data.[172] • These technologies free up health care providers to engage in more meaningful conversations with patients. They enhance the shared decision-making process between health care providers and patients.	During the workshop, participants discussed the importance of enhancing the shared decision-making process between health care providers and patients. This generalized technology is related to a wide range of topics and aims to make medical information more accessible and focus on enabling and empowering patients in their health care. However, considering the current state of a development, this technology category may have a significant impact, but the implementation seems far off, and our health care system is not currently prepared to adopt it.
AI for public health surveillance and response	• Public health involves mass amounts of data; AI can augment our ability to collect and analyze data to help with public health surveillance and response.[173] • AI can use additional data modalities, such as imaging, genomics, and environmental and geographic data in models. • AI technologies can also be used to support precision public health, such as tailoring public health messages (i.e., the importance of cancer screening) to individuals in a way that is most likely to be effective (i.e., specific to an individual's first language or degree of literacy).[174]	During the workshop, participants discussed the potential of using AI for public health surveillance and response. They mentioned that it could assist in redeploying health care resources and managing situations similar to the COVID-19 pandemic in the future, and there are already some relevant large datasets and improved models. However, they noted that our health care system currently lacks interagency coordination, which is essential for effective responses. There are many missing components needed to support this initiative, and the quality of the data also needs to be improved.
AI for personalized medicine	• Focuses on integrating genomics and AI to tailor treatment plans based on individual genetic, environmental, and lifestyle factors for various conditions.[175]	During the workshop, participants expressed several concerns about using AI for personalized medicine. They noted that: • This is a narrow focus and would primarily benefit a small group of people. • Challenges exist in data collection, validating outcome measures, collecting high-quality data, and conducting N-of-1 trials. • Combining AI tools with genomics could introduce risks in many situations, particularly concerning privacy. • From the patient's perspective, the use of AI in personalized medicine may not offer advantages over the current model. • There may be potential resistance from the current health care system.

Technology (category or intervention)	Description	Insights from the workshop
		• More basic science is needed to support advancements in personalized medicine.

Table 4: List of Issues Not Included in the Watch List

Issue	Description	Insights from the workshop
Redeployment of health care resources	AI can affect workflows and the allocation of resources in the health care system[176] through the following potential changes in workforce roles and responsibilities: • training and education for existing health care staff to develop their knowledge and skills about AI[177] • AI administrative support (e.g., data entry, managing medical records digitally, reducing errors, clinical documentation, and summaries)[43,178] • AI labour support (e.g., robotics-assisted surgery, automated medication dispensing)[43] • AI decision-making support for HCPs managing a patient's clinical pathway (e.g., AI-supported diagnostics and treatment) • AI assistance for HCP monitoring and communication activities (e.g., remote monitoring, patient education, patient emergency support, patient manual, and social assistance).[43,178]	Participants in the workshop noted the distinction between resources in terms of human resources (i.e., the health care workforce) and nonhuman resources (e.g., physical supplies the workforce needs) Participants had different views on the relative importance of this issue: • Some felt that supply chain resources were more of a concern than human resources. • Some felt that redeployment of resources was a top issue because it could help correct existing health care issues, such as human resource management, and could make the health care system more efficient. • Some felt that redeployment was not a top issue because they did not feel AI would be the driving force behind how health care resources are managed or that human resources could be easily addressed without AI.
Overreliance on AI by clinicians or health systems	Because AI can be used at any point in the clinical pathway, there is a need to balance its functions with the value of human presence and expertise. • There is a concern that HCPs can consciously or unconsciously overrely on AI (i.e., have automation bias[179]), which can lead to overdiagnosis, overtreatment, and defensive medicine (i.e., being overly cautious of potential malpractice litigation).[180,181] • There is a risk that integrating AI in the health care system can affect how new HCPs are trained and whether "traditional" skills are developed and maintained.[182] There are concerns about situations in which AI fails to work, and HCPs are required to rely on more conventional decision-making processes without the help of AI.[182] Training HCPs to work together with AI, rather than AI working autonomously, can ensure humans are part of decision-making for patients.[182] This training involves continuously learning about both	Participants in the workshop spent a long time discussing this issue. They expressed how this issue related to 1 of the top issues, AI Issue 2: Liability and Accountability. For example, with 1 of the top technologies included in the 2025 Watch List, AI Technology 1: Notetaking, HCPs are still responsible for notes and need to review and confirm that they are accurate. However, if they use AI to free up time in their schedule for other activities while relying solely on its interpretation, there is a risk of harm. Using AI could also become a burden on HCPs to be accountable for the technology. Participants had different views on the relative importance of this issue: • Some felt that it was a top issue because of their experience implementing AI. For example, HCPs in a rural setting with transient physicians who were given a medical technology found the AI was incorrect and subsequently stopped using it. Overreliance on AI was impacting how HCPs

Issue	Description	Insights from the workshop
	the technical aspects and ethical limitations of an AI system so that the powerful and efficient capabilities of AI can be combined with the valuable judgment and critical thinking skills of HCPs.[182]	worked and their ability to formulate proper diagnoses. • This was not a top issue for participants who used AI for educational purposes or who viewed it as a supportive tool rather than as a primary clinical decision-maker. • Some participants felt it was difficult to measure and perhaps too early to be concerned about. • A health care provider mentioned that this was not a top issue because, historically, new technologies have emerged (e.g., ECG readers, CT scans) and HCPs have had to learn new technical skills along the way. They felt that HCPs would eventually adapt as they have in the past.
Alignment with societal values	AI value alignment is when AI systems perform in ways that match the ethical principles and human values in society.[183] These values can differ across jurisdictions and cultures, meaning alignment depends on the context in which AI is used and can make it more challenging to implement.[183] Patients, HCPs, and society at large may not trust AI or be willing to adopt it in light of questions about its usefulness, biases, or potential for errors and misinformation.[184] The implementation of AI should include explicit alignment with ethical principles and societal values with a process for auditing.[185] Patient values, such as privacy, fairness, and autonomy, should be taken into account and can affect their trust and willingness to adopt AI.[185]	Participants in the workshop spent a long time discussing this issue and felt that it related to 1 of the top technologies, AI Technology 2: Tools to Accelerate and Optimize Clinical Training and Education, and is a bounding principle that underpins most of the other top issues (e.g., privacy and data security; data availability, quality, bias; data sovereignty and governance, and environmental costs). Participants had different views on the relative importance of this issue: • Some expressed they were not worried about how societal values aligned with AI for medicine but that it could be a worry for other industries. They felt that for health care, AI could have good alignment with societal values in Canada. • Some participants said that this was a top issue for them because complex AI models need to consider societal values for transparency, education, awareness, and trustworthiness. They discussed how societal values related to several other connected concepts, such as change management, the competing requirements between communities wanting data and the government's provision of guardrails, as well as the balance between opting in to AI and potentially giving up data ownership with the potential loss of access to services for patients who do not want to provide their data and who may miss out on the benefits from AI. Societal values were also seen as a potential way to get trust, buy-in, and engagement from HCPs.

Issue	Description	Insights from the workshop
Copyright	Copyrights are the legal rights to produce, publish, or prepare derivative works of all or part of an original work.[186] Generative AI systems use data inputs from multiple sources to create new outputs; therefore, there are questions about who owns the copyright to its outputs. The data inputs themselves, which come from large databases, may or may not have their own copyrights and are not originally sourced from the AI system that is using them.[187] The legal status of generative AI in Canada is currently unclear,[188] and there remain questions about: • intellectual property and potential copyright infringement of the source material that is used to train AI, which is often unknown[188] • whether it is worth adopting AI in health care before laws and regulatory frameworks are established[188] • whether the use of AI in its current state will result in changes in patient care in the future once laws become established.	Most participants in the workshop agreed that copyright was not a top issue to watch for relative to the others. They expressed that copyright in fields such as art and journalism may be a concern, but not in medicine. One participant noted that when working with developers using a value-based procurement approach, both sides were working together to achieve gains. Other participants mentioned that there are currently mechanisms and laws in place to deal with copyright issues that can happen quickly and that the concern or risk is not as high as it was 2 years ago.

AI = artificial intelligence; ECG = electrocardiogram; HCP = health care professional.

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