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Identifying key characteristics of developed artificial intelligence algorithms to achieve meaningful impact on Canadian healthcare: a scoping review protocol

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ABSTRACT

Introduction Empirical data on the barriers limiting artificial intelligence (AI)'s impact on healthcare are scarce, particularly within the Canadian context. This study aims to address this gap by conducting a scoping review to identify and evaluate AI algorithms developed by researchers affiliated with Canadian institutions for patient triage, diagnosis and care management. The goal is to identify characteristics in the developed AI algorithms that can be leveraged for a better impact.

Methods and analysis A scoping review will be conducted following the JBI Methodology for Scoping Reviews and reported following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews guidelines. Relevant literature will be identified through comprehensive searches of MEDLINE (PubMed), CINAHL (EBSCO) and Web of Science (Clarivate) databases, combining keywords related to AI, clinical management and the Canadian context. Studies published after 2014, in English or French, that discuss AI algorithms developed for patient triage, diagnosis or care management by researchers affiliated with Canadian institutions will be included. Data from the selected articles will be extracted and analysed descriptively, and findings will be presented in tabular form accompanied by a narrative summary.

Ethics and dissemination Ethical approval is not required for this study as it involves the review of publicly available literature. The scoping review is expected to be completed by November 2025. The findings will be disseminated through publications in peer-reviewed journals and presentations at conferences focused on AI and healthcare practice.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ The use of established methods for the review with the inclusion of multiple databases enhances the likelihood of capturing a wide range of relevant studies.
⇒ While the method focuses on Canada allowing for in-depth analysis within a specific jurisdiction, it limits the generalisability of the findings to other countries but allows for opportunities for comparative studies.
⇒ By only relying on scientific literature, models that have an observable impact on the Canadian market, regardless of where they were developed, could be excluded.
⇒ The reliance on authors' affiliations with Canadian research institutions may exclude relevant studies where Canadian data was used but the researchers are affiliated with institutions outside Canada.
⇒ The method does not include a plan to address practical constraints related to the deployment and use of AI tools in healthcare settings.

INTRODUCTION

Difficulty of having a meaningful impact of artificial intelligence in healthcare

Artificial ntelligence (AI) can be defined as a machine's ability to perform 'human-like cognitive functions (eg, learning, understanding, reasoning or interacting)'.[1] AI has made significant progress in recent years and is attracting growing interest in a variety of fields.[2] The exponential growth of data and the significant evolution of computing power are key factors in this evolution. AI represents considerable potential in many areas of activity, including the economy, robotics, agriculture and healthcare.

When it comes to healthcare, AI has tremendous potential in this field[3] as it can help to reduce complications, prevent hospitalisations, ease administrative burdens,[1] diagnose diseases early[4] and assist in triage and patient management. It can also reduce diagnostic errors made by healthcare professionals.[5] This significant potential is leading researchers to take a greater interest in developing AI tools and algorithms to support healthcare practice.

Despite this growing desire to develop AI algorithms for healthcare and its progress in various fields of activity, the general observation is that, so far, its contribution has not lived up to expectations.[6] Indeed, the implementation of AI in healthcare still faces numerous difficulties[5] linked, among other things, to the specificity of the healthcare field, lack of maturity of the tools and algorithms developed and lack of studies of the obstacles to meaningful impact in healthcare based on empirical data.

Healthcare sector specificity

The specific nature of activities in the healthcare sector is one of the main obstacles to the meaningful impact of AI. This specificity can be highlighted by several aspects; these include the complexity and sensitivity of the healthcare field, issues associated with the availability of quality data or with data access policies and, finally, the problems associated with the strict ethical rules governing the protection of patient privacy.[2 5]

Healthcare is a highly sensitive and complex field. Patient safety remains one of the main concerns of healthcare professionals. The level of error tolerance is very low. And yet, models can often make serious errors, especially if they are learnt from unreliable data. These errors can lead to patient complications or even death. The stakes are even higher when it comes to public health. For example, IBM Watson for oncology, an AI model used to analyse data from patients' medical records and help doctors explore cancer treatment options for their patients, recently came under scrutiny for allegedly making 'risky and erroneous' suggestions for cancer prevention.[5] Another factor contributing to the limited impact of AI in healthcare is its restricted adoption due to the necessity of explaining algorithm results. Indeed, advanced AI models are black boxes. They can predict with very high scores but give virtually nothing about the logic behind their choices, apart from the data and the nature of the algorithm used.[2] As evidence-based medicine relies on the highest standards of explicability,[7] the lack of explicability poses a problem for the acceptance of AI by healthcare professionals.[2] The complexity and sensitivity of the healthcare field are therefore obstacles to the effective adoption of AI in this domain. However, they are not the only elements to be considered.

In addition to the specificity of the healthcare field, the availability of quality data is also an aspect to consider for healthcare AI. An AI model is only as safe as the data it has learnt from. Indeed, implementing AI models requires large datasets from several sources (pharmacies, electronic health records…),[5 7] representing a handicap to the development of AI models based on these real-world data. Furthermore, the models may assimilate biases from the data they have learnt from. If, for example, the data used to train an AI is mainly collected in academic centres, that AI will be less attentive to patients from populations that do not regularly visit these centres and, consequently, treat them less appropriately. Differences between images of racialised and non-racialised patients can implicitly introduce disparities in model decisions.[7] Thus, the availability of quality data is a key factor in the successful integration of AI in healthcare.

Together with the aforementioned obstacles to the meaningful impact of AI on healthcare, there are the politics of data access and patient privacy. Indeed, healthcare is one of the fields with the strictest privacy rules.[8] Patient medical records, for example, are protected by strict laws, so sharing this information, even for research purposes, could be challenging. Indeed, to guarantee access to information, the patient's consent must be obtained. It has to be said that doing this on a large scale can be a major logistical challenge.[5] Also, even de-identified data can often be re-identified when combined with other datasets.[7] These considerations create major risks for initiatives seeking to make healthcare data available for use in the development of AI models, particularly for cases where, in public health, data from very large segments of the population are required. Strategies to preserve patient privacy are central considerations for initiatives to implement AI algorithms for healthcare, but not the only ones.

Finally, considerations relating to the reuse of models developed in other environments must also be considered. Indeed, the problems associated with the widespread use of AI algorithms and tools are not the least of the obstacles to the meaningful impact of AI in healthcare. It represents a major challenge. Most tools and algorithms are specific to the environments in which they were developed. This makes them difficult to transpose from one country to another or even from one establishment to another. To enhance the contribution of AI in healthcare, the development and implementation of AI algorithms must consider the specificity of the healthcare field (jurisdiction and organisation specificities). This is a key consideration but is not enough on its own to solve the problem of integrating AI in healthcare.[9]

Lack of maturity of tools developed in the healthcare field

In addition to the problems associated with the specificity of the healthcare field and generalisation, there is also the problem of the maturity of AI tools and applications.[10] Indeed, in response to the pandemic, several tools and algorithms have been developed around the world.[11] BlueDot[12] in Canada and HealthMap[13] in the USA are examples of software based on AI algorithms used as 'epidemic alert' tools. XrAI,[14] developed by the Canadian company 1Qbit, and COVID-Net, a convolutional neural network developed by Wang *et al*,[15] are diagnostic tools. They raised great expectations when they were first introduced. Most of these AI tools generated enthusiasm and hope about their potential to provide significant help in response to the pandemic. However, it has to be said that their contribution has not lived up to expectations.[11] This modest contribution of AI to the fight against the pandemic is partly due to the fact that very few of the tools developed have reached maturity.[16] The lack of data but also, paradoxically, the excess of data, especially from social networks (often biased), has progressively worked against the predictive capacity of these tools and algorithms and, at the same time, led to a regression in their contribution to the fight against the pandemic.[17]

Lack of empirical data on barriers limiting the meaningful impact of AI in healthcare

As we have just discussed, there are several obstacles to having a meaningful impact of AI in healthcare (specificity of the healthcare field, difficulty of generalisation, lack of maturity of the developed models). Several studies in the literature are devoted to these difficulties,[18] but, despite the abundant literature, we do not yet have a global viewpoint, based on empirical data, of the obstacles for AI to have the expected impact in healthcare. Most studies are based on anecdotal evidence, narrative or analytical commentary and lack empirical data.[18] Consequently, the determinants of these limits are still insufficiently understood.[5] If the healthcare system is to be adequately transformed to meet new needs, we need a clear typology of the characteristics of the AI algorithm being developed to identify ways of improving their impact on healthcare in general and on the Canadian healthcare system in particular. To address the need for empirical data in a Canadian context, we propose to conduct a scoping review to identify characteristics of AI algorithms developed by Canadian researchers or researchers with affiliations in Canadian research institutions to support the clinical management of patients. Its aim is to identify areas for improvement in the Canadian context for AI algorithms in the clinical field. The aim is to identify levers for action to improve their contribution to the provision of quality care.

Research question

This study aims to answer the following research question: What are the characteristics of the developed AI algorithms in a Canadian setting, and which of these characteristics can be essential as leverage points for AI algorithms to better impact Canadian healthcare?

- Population: AI algorithms developed by researchers affiliated with Canadian institutions.
- Concept: characteristics of AI algorithms, including (but not limited to) their purpose, clinical application, validation processes, data sources for development, testing and implementation, etc.
- Context: impact of AI algorithms on Canadian healthcare systems.

METHOD AND ANALYSIS

To meet the research objective, a scoping review will be carried out, consisting of retrieving AI algorithms developed by researchers with affiliations in Canadian research institutions, available in the literature, for patient triage, diagnosis and care management. This protocol was developed in accordance with the JBI Scoping Review Methodology Group's best practices for scoping review protocols.[19] The Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines[20] will be followed for the scoping review. The various studies will thus be divided according to the main characteristics identified (sources and types of data, calculation method, analysis objective, level of data integration, etc).

Identification of relevant articles

The research strategy aims to identify sources of evidence on AI algorithms developed by researchers with affiliations with Canadian research centres. The MEDLINE (PubMed) and CINAHL (EBSCO) databases and Web of Science (Clarivate) are the sources of information. The search strategy was developed in consultation with a university librarian specialising in health sciences and consisted of the combination of three concepts: (1) AI, (2) clinical management of patients and (3) Canadian context (see online supplemental appendix 1). The words contained in the titles and abstracts of the relevant data sources, together with the indexing terms used to describe the data sources, were used to develop a comprehensive search strategy for the selected databases (online supplemental appendix 2).

Eligibility criteria

After extracting the articles using the built query, the following inclusion and exclusion criteria will be used to sort the identified studies:

Inclusion criteria: (1) the article concerns an AI algorithm developed for the triage, diagnosis or care management of patients, (2) the language of publication of the article is French or English, (3) the date of publication of the article is between 2014 and December 2024. An update is planned for summer 2025 to include articles published after this period.

Exclusion criteria: (1) the article's full text is not open access or not available by academic subscription, (2) the article presents fundamental algorithm development that does not directly address a clinical activity need, (3) the article is a review, (4) the article is a commentary or editorial, (5) the article is an abstract and (6) the objectives of the authors of the article are other than to make predictions (eg, exclude the article if the methodology/algorithm is used to determine characteristics only).

Data selection

After the search, all identified articles from each source will be imported into Covidence, and duplicates will be removed. Titles and abstracts will be reviewed by two reviewers against the study's inclusion and exclusion criteria. A more detailed evaluation based on the full text of the selected data sources will then be carried out, still in Covidence, according to the inclusion criteria, by the two evaluators. Reasons for excluding full-text data sources that do not meet the inclusion criteria will be recorded and reported in the scoping review. Disagreements between the two reviewers at each stage of the selection process will be resolved by discussion or by a

Table 1 Data extraction grid

Article information	Information on the algorithms used	Information on the clinical data support for the algorithm development
► Author affiliation ► Place of publication (province and city) ► Publication date ► Clinical domain (cardiology, oncology, radiology, etc)	► Type of developed algorithm (machine learning, deep learning, large language model, expert systems, etc) ► Targeted users (patients, clinicians) ► Targeted usage (triage, diagnosis and treatment, etc) ► Evaluation criteria identified (performance metrics, benchmarks, ethical aspects)	► Data source (international open-source database, public databases, hospital records, primary care, clinical studies, medico-economic data, etc) ► Data type (medical images, clinical texts, physiological signals, etc) ► Sample size ► Level of data integration

third reviewer. The results of the search and the process of inclusion of evidence sources will be reported in full in the final version of the scoping review and presented in a PRISMA-ScR flowchart.[20] To date, the query retrieves 5000 articles from each source database (online supplemental appendix 2).

Data extraction

Once the list of final articles to be included is approved by all reviewers, data will be extracted from the evidence sources included in the scoping review by two people using the data extraction tool provided by Covidence. The extracted data will include specific details on the authors, the algorithms and the training data used in the algorithms (table 1).

Data summaries and results synthesis

Data analysis will consist of a descriptive analysis. Results will be presented in tabular form. A narrative summary will accompany the results, describing how the results relate to the objective of the scoping review.

Patient and public involvement

A dissemination workshop will be conducted towards the conclusion of the scoping review. This workshop will bring together researchers, patients and other key stakeholders to (1) present the findings, (2) develop the recommendations and (3) collect other insights and feedback to refine the conclusion of the study.

ETHICS AND DISSEMINATION

This study does not require ethical approval, as it involves the review and collection of data from published and/or publicly available articles. It is expected to be completed by November 2025. The dissemination strategy includes a publication of the results of the scoping review, as well as presentations at conferences on AI and care practice. The results of the study will map, according to previously defined criteria, AI algorithms developed for triage, diagnosis and care management by researchers with affiliations in Canadian research institutions. In particular, it will identify levers for action to better integrate AI algorithms into Canadian care practice. A dissemination workshop will be conducted towards the conclusion of the scoping review. This workshop will bring together researchers, patients and other key stakeholders to (1) present the findings, (2) develop the recommendations and (3) collect other insights and feedback to refine the conclusion of the study.

DISCUSSION

This study will enable us to map the trends in health research in Canada around AI algorithms. It should allow us to highlight the challenges that need to be addressed to achieve a greater impact of AI algorithms in everyday healthcare. The review will help identify areas for improvement and provide relevant recommendations within the Canadian context, showing how the conditions enabling the development of these algorithms can be significantly improved to support their implementation.

The study is limited to the Canadian context as it ensures feasibility given the high productivity of the AI field and allows for an in-depth analysis within a jurisdiction. It will allow a comparison of the situation in its provinces that share similar contexts. It does not extend to other countries, which may have different healthcare systems. The specificity of the healthcare domain and the need to reconcile data realities in the development of AI algorithms necessitate jurisdiction-specific analyses. Comparisons with other jurisdictions can be performed in a subsequent analysis.

The study is in an early stage, but several points have already been achieved. We developed a concept plan and formulated a search strategy, which was refined through consultation with a librarian. Data sources were identified, and research was conducted within these sources. The collected data were imported into Covidence, and the data are being integrated to remove redundancy.

This study has certain limitations. One limitation is the failure to account for constraints related to the deployment and use of the tools implemented. Additionally, the selection process was based on authors' affiliations; some authors who work with Canadian data may not be affiliated with Canadian research centres, which could influence the comprehensiveness of the study.

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