# B: Environmental Scan Extended Results

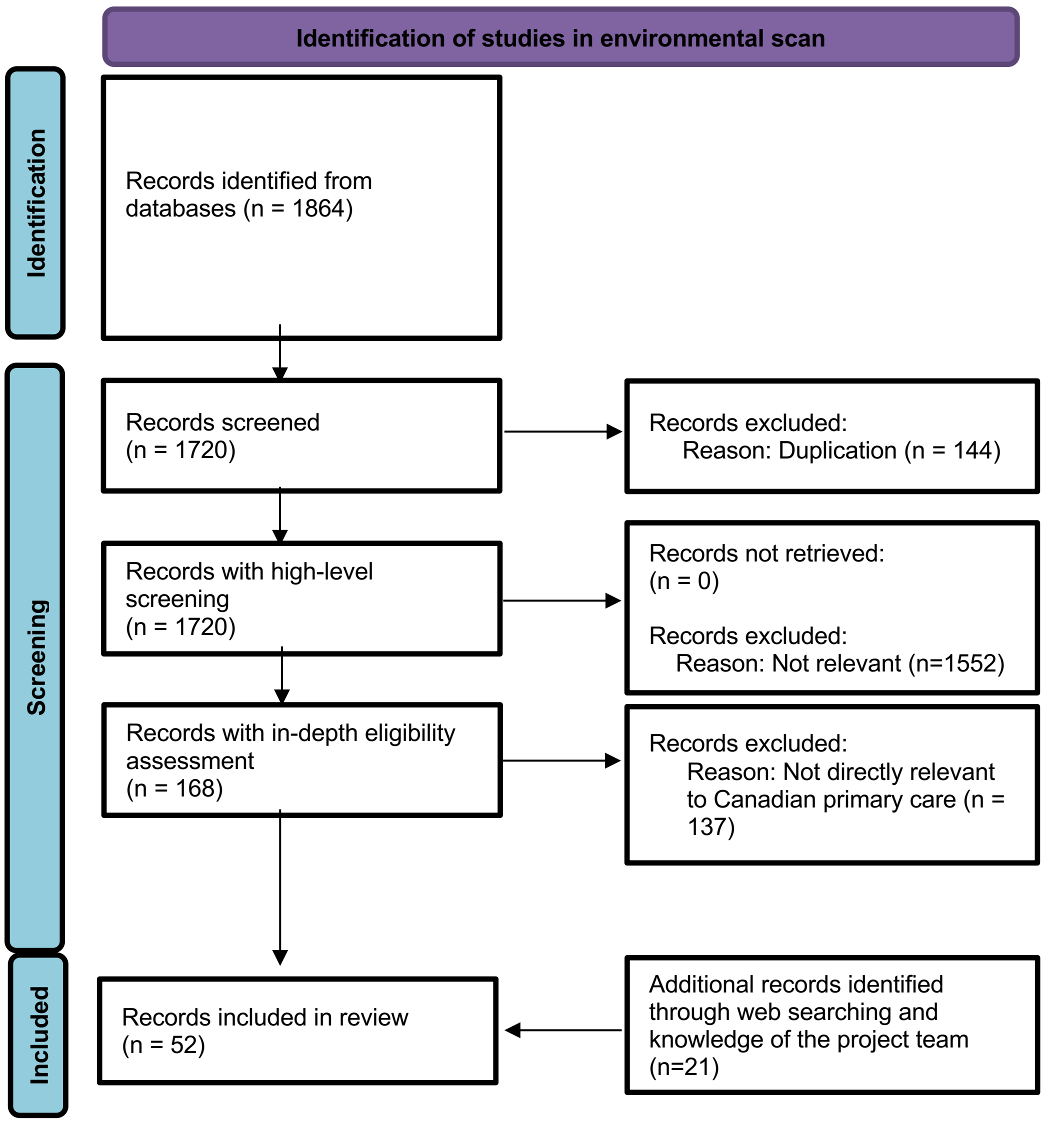


**Figure B.1.** Flow diagram of record identification for the environmental scan.

## B.1 Results Overview

A total of 52 research studies were included (Figure B.1). Findings are organized by type of research material:

- **Recent AI development research for specific application domains:** For example, development of predictive models with stated relevance to FM. Domains are described in Section 2.3 of main text and a summary of studies is below.

- **Field-level stakeholder engagement research**: Research that generated insights about AI for FM in general, such as priority applications and core values to uphold. Findings are summarized in Section 2.3 of main text with additional details below.
- **Challenges in AI for FM research:** Described below.
- **Additional materials of interest:** Key organizational reports and initiatives, guidelines on AI for health research, and commentaries and emerging discussions. Described below.

## B.2 Summary of Eligible AI Technology Development Research Organized by Major Domains of AI Applications in FM

**Preventive Care and Risk Profiling**
Recent prognostic modelling research focused on identifying patients who are likely to develop diabetes within the next eight years[1], and on assessing risk for early (within 4 years of diagnosis) and late premature (4 years or more from diagnosis) death in epilepsy[2].

**Physician Decision Support**
Studies on physician decision support targeted either diagnostic assistance or therapeutic decision support.

*Early diagnosis and signalling:* Recent research has been conducted to support AI use for the diagnosis of Chronic Obstructive Pulmonary Disease (COPD)[3], frailty[4], primary screening of otologic conditions[5], type 1 diabetes mellitus[6], initial voice disorder screening[7], alcohol-screening among high-risk patients[8], skin lesions[9], myopathy[10], cervical spinal cord compression[11], adult-onset epilepsy[2,12], cardiovascular disorders[13], hypertension[14], dyslipidemia[15], post-traumatic stress disorder[16], and cognitive impairment[17].

These types of research studies often state the potential utility of AI-based diagnosis tools to support increased scope of decision-making as a key motivation, especially in remote locations or other areas with limited availability of specialists, as family physicians often have the initial diagnosis and triage responsibilities.[5] For example, development of tools to support primary care providers' diagnostic accuracy for otologic abnormalities[5] may benefit people living in rural and remote areas with limited access to otolaryngology and lengthy waitlists. Similarly, AI tools can reinforce the evaluation of the severity of skin lesions and whether referral to dermatologists for further medical examination and treatment is necessary.[16] Overall, these types of AI-driven research can increase the scope of practice in primary care, and improve access to care for underserved populations.

While there are examples of high-quality research studies in the literature, similar trends persist from the previous scoping reviews where primary care is stated as the intended beneficiary of research, but there is little genuine collaboration with primary care researchers/providers/patients and "real world" primary care relevance is not demonstrated.

The Canadian Primary Care Sentinel Surveillance Network (CPCSSN) is one of the most consistently used data sources/repositories used in the aforementioned studies.[17] In terms of AI techniques, supervised machine learning (ML)[18] methods such as decision tree, random forest, and LASSO regression were the most common. For decision support research based on medical imaging Convolutional Neural Networks (CNN)[18] were the most popular AI technique. Few studies use Hidden Markov Models (HMM) for prognostic modelling and preventive care.[1]

While our review focuses primarily on academic research studies, it is important to note this is also an active area for technology industries. For example, 1QBit, a Vancouver-based software firm built XrAI using deep learning to detect COVID-19 from chest x-ray images.[19] XrAI is the first radiology AI tool to be authorized by Health Canada as a Class III Certified Medical Device.[19] Saskatchewan Health Authority has already adopted this computer-vision based radiology tool to optimize time and resources in the fight against the COVID-19 pandemic. The deployment of this AI technology can impact the role of family physicians, but whether family physicians are directly using the tool is unclear.

*Treatment/intervention recommendations:* To effectively use electronic medical record data, some researchers have attempted to develop AI to help classify cases. One such study worked on validating case definitions for frailty with CPCSSN data from Southern Alberta;[20] however, satisfactory performance was not achieved, highlighting the need for more work to investigate use of AI techniques to reliably identify heterogeneous diseases captured in electronic medical records.

Another study investigated patterns in prescribing antidepressants with respect to patients' weight status.[13] The findings of this research may support a rule-centric treatment approach for patients with depression and comorbid obesity. Another study proposed the integration of AI for optimal drug dosing and titration, but experiments have not yet been conducted to back up the proposed notions.[21]

Few studies we identified evaluated AI-based tools in practice. One of these few included both primary care physicians and psychiatrists in Montreal in a qualitative analysis to evaluate the perceived utility of Aifred, an AI-based tool for recommending major depressive disorder (MDD) treatment.[22] The findings of the study suggested that family physicians seemed to have the greatest utility in managing depression treatment protocols compared to psychiatrists.[22] Whether other tools exist that have reached suitable preliminary performance for pilot testing is unknown.

**Operational Efficiencies**

Studies have examined the potential and process for AI to improve operational efficiency in terms of laboratory and clinical work. Research has focused on identifying high-need patients. Little research, however, has directly addressed to what extent what type of tools or AI techniques may be most useful for primary care.

Disruptive innovation[23] indicates the paradigm shift from current clinical laboratory to next-generation primary care pathology, where some of the pathology tasks will be conducted at primary care facilities with AI enabled tools (e.g., visual analytics). The integration of AI-aided visual analytics tools can further aid the enhancement of precision diagnostics with cost efficiency, as per an existing review literature.[23] Furthermore, it is possible to optimize the laboratory resource utilization and management by deploying an AI platform called Pathology Laboratory Utilization Scorecards (PLUS)[24] to self-examine the test ordering patterns by primary care physicians.

Another research study developed a Maturity framework to adopt and integrate clinical analytics-based AI services into primary care.[25] This particular research study considers multi-level maturity assessment of AI services in primary care in terms of governance, IT infrastructure, data, analytics, capability, workforce skills, privacy, and security.[25]

One research study leveraged the Electronic Medical Record Primary Care (EMRPC) database, housed at ICES in Ontario, to predict patients who are likely to incur significant medical costs for various reasons, such as, chronic medical conditions.[26] This type of cost-prediction research can support operational efficiencies related to patient management and resource planning.

Despite expectations that AI could decrease physicians' administrative burden, no recent research related to family physician documentation support was found. The types of operational efficiency tools or underlying AI techniques that need to be primary care specific is unknown; potentially relevant research from other domains was not assessed.

**Population Health**

Researchers have attempted to use AI to identify prevalence of conditions to try and help with population segmentation and resource or intervention planning. One research study motivated by the COVID-19 pandemic used AI with EMR data to determine the prevalence of primary care provider-reported vaccine and polyethylene glycol (PEG) allergy.[27] AI algorithms have also been utilized to estimate the prevalence of physician-reported food allergy in Canadian children.[28] Another recent research study applied AI to estimate type 1 diabetes prevalence and incidence in primary care using primary care electronic medical record and administrative healthcare data from Ontario, Canada[29]. These types of population level predictions can help with population segmentation and resource or intervention planning.

**Patient Self-Management**

Researchers have examined how AI can assist patients in improving their own health. A collaboration with researchers from the United States and Canada designed an AI-assisted mHealth app to generate physical activity or training plans as per the characteristics of individual patients to prevent disability due to diabetes and depression.[30] However, it is noteworthy that this research study was mostly focused on USA-based case studies. Research related to AI-driven self-management applications exclusively in Canadian primary care is still underexplored.

## B.3 Summary of Field-Level Stakeholder Engagement Research

Studies to better understand potential uses and needs of AI for FM and primary care published since the previous reviews included: a three-part Delphi study with international participation of the IMIA Primary Health Care Informatics Working Group in 2018 (n=20)[31]; an international workshop hosted in Quebec during September 2019 (n=14)[32]; deliberative dialogues with primary care service users, providers, and health system leaders from across Canada in 2020 (n=48)[33]; a one-day collaborative consultation event in March 2021 with primary care and digital health stakeholders in Ontario (n=35)[34]; and semi-structured interviews with primary care and digital health stakeholders in Ontario (n=14)[35].

## B.4 Challenges in AI for Family Medicine Research

The paradigm shift towards AI-enabled FM faces obstacles like any other disruptive technology or research domain.[31] The following summarizes challenges identified by literature captured in our environmental scan:

**Lack of interdisciplinary collaboration:** The existing literature suggests limited engagement with clinical collaborators, and it is uncertain if researchers are currently aware of the importance of such collaboration.

**Disruption in temporal sequences of data:** FM provides care across the life course, addressing many different health concerns with variable frequency and intensity. The generalizability of AI research can depend on reliability and consistency in how care events are recorded in electronic medical records, and there is limited AI development tailored to such life course nuances. For example, alcohol-screening AI tools among high-risk patients may fail due to the unavailability of temporal alcohol consumption historical records of patients.[8]

**Comparison against standard of care and external model validation:** Many research studies do not appear to compare performance with existing clinical practice, follow-through to pilot testing of tools in practice settings, and/or are not approved by healthcare authorities. In general, our understanding of the comprehensive impacts of AI on FM and primary care practice is limited. Clinical trials and rigorous validation of AI models are needed to avoid harms. For example, the Babylon mHealth application has misdiagnosed a heart attack as a panic attack.[36]

**Biases against minority populations:** Beyond the general concern of data availability, the representativeness of training data can also significantly affect the performance of AI models across clinical populations. As an example, a research study on evaluating the severity of skin lesions emphasizes the necessity of including patients other than white skin toned.[9] Both representation in training data and decisions made throughout the development process can contribute towards biased performance.

**Privacy threats, security, and ethical considerations:** The privacy, security, and ethical use of patient's health data is a concern in AI research and continues to be an important consideration throughout the adoption of data-driven AI services.[9,31]

## B.5 Commentaries and Emerging Discussions

The past few years have also seen an increase in commentaries and discussion about AI for FM and primary care. Commentaries address expected impacts; challenges; social and ethical considerations; and economical, operational, and clinical utility questions.[37-43] Along with discussions about potential benefits, the need to mitigate potential risks and maintain compassion and positive interaction between patients and physicians has been emphasized.

## B.6 Additional Materials of Interest

### Key Organizational Reports and Initiatives

To support research working towards an end-goal of using AI and related digital technologies to improve compassionate and person-centered care, **AMS healthcare** developed **compassion and AI** funding programs.[44] The AMS compassionate care program sponsored the preparation of a briefing document by Dr. Ross Upshur on the potential impacts of AI on FM for the 2019 CFPC 2019 Annual Leaders Forum,[45] and sponsored the AI for Family Medicine Research Roundtable described in this report.

The **AI for Health Task Force** based out of the **Canadian Institute for Advanced Research (CIFAR)** published a report highlighting the landscape and potential benefits of AI for healthcare in Canada.[46] The report also provided recommendations related to encouraging strategic investments with responsible scaling in Canada's digital healthcare system. CIFAR has collaborated with AI Institutes—Amii in Edmonton, Mila in Montreal, and the Vector Institute in Toronto—to develop and lead a national **Pan-Canadian Artificial Intelligence Strategy**, supported by $125 million funding from the Government of Canada.

The **Royal College of Physicians and Surgeons of Canada** commissioned a task force to prepare a report on the impact of AI and digital technologies on the evolving landscape of technology in the healthcare industry.[47] Various initiatives such as literature reviews, interviews, surveys were used to arrive at a series of findings and recommendations about the potential impacts of AI on healthcare and the future roles and training needs of specialty physicians.

A white paper submitted to the New Digital Research Infrastructure Organization (NDRIO) provides an overview of various means to design and improve digital research infrastructure to advance AI enabled research in Canada.[48]

**Canada Health Infoway** developed an AI toolkit and held an associated webinar series in early 2022 to help healthcare organizations across Canada better understand key considerations and resource requirements for implementing AI into healthcare.[49] **Infoway Insights** is an open-source interactive data and analytics hub supporting large volumes of digital health and virtual care-related survey data collected from Canadian researchers and healthcare organizations.[50] **Infoway's Performance Analytics** team most recently conducted an AI literacy survey relating to digital health in Canada.[51]

The **American Board of Family Medicine** held a two-day virtual summit to discuss AI for FM, leading to the publication of the IDEAS framework.[52] The IDEAS framework presents the major domains for successful integration of AI into primary care: infrastructure upgrade, delivery transformation, evaluation modernization, algorithm marketing authorization and reimbursement, and social justice.[52]

### Guidelines on AI for Health Research

Several guidelines related to AI for healthcare research have been published.[53-64] To our knowledge, none are specific to FM or primary care, although there is a framework for the ethical use of AI with electronic health records in primary care.[65] While some principles are theoretically applicable across healthcare disciplines, FM may warrant special considerations. For example, the need to focus on breadth over depth and the need to provide care that spans across the patients' life course are two key principles that might require unique research principles.

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