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Authors: Yifan Zhang, Sarah Newbery, David W. Savage, & Brian M. Ross

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Artificial Intelligence and Rural Health Equity: Perspectives from Northern Ontario

Yifan Zhang
Northern Ontario School of Medicine University
Thunder Bay, Ontario, Canada
yifzhang@nosm.ca

Sarah Newbery
Northern Ontario School of Medicine University
Thunder Bay, Ontario, Canada
snewbery@nosm.ca

David W. Savage
Northern Ontario School of Medicine University
Thunder Bay, Ontario, Canada
dsavage@nosm.ca

Brian M. Ross
Northern Ontario School of Medicine University
Thunder Bay, Ontario, Canada
bross@nosm.ca

Abstract

Healthcare is becoming increasingly reliant on artificial intelligence (AI). However, marginalized people, including those in rural and remote communities, risk being bypassed or ignored by the AI revolution. This paper presents findings from a mixed-methods study exploring the perspectives of healthcare workers in Northern Ontario, a vast and mostly rural region of Canada, characterized by cultural diversity and an under-resourced healthcare system. We collected data using an anonymous online survey. The data suggested that participants had concerns about readiness, infrastructure, resourcing, cultural competence, language availability, workforce education, and the importance of local community representation during AI development and implementation. Some participants expressed optimism about AI's potential, but also warned against an urban-derived, one-size-fits-all implementation. Our study highlights that healthcare AI must be contextualised, guided by equity considerations and shaped by the actual experiences of rural practitioners. These findings contribute to a broader understanding of how inclusive healthcare AI should be developed to meet rural and remote community needs.

Keywords: Artificial intelligence, rural and remote, healthcare workers

Intelligence artificielle et équité en matière de santé rurale : perspectives du nord de l'Ontario

Yifan Zhang
Northern Ontario School of Medicine University
Thunder Bay, Ontario, Canada
yifzhang@nosm.ca

Sarah Newbery
Northern Ontario School of Medicine University
Thunder Bay, Ontario, Canada
snewbery@nosm.ca

David W. Savage
Northern Ontario School of Medicine University
Thunder Bay, Ontario, Canada
dsavage@nosm.ca

Brian M. Ross
Northern Ontario School of Medicine University
Thunder Bay, Ontario, Canada
bross@nosm.ca

Résumé

Le système de santé dépend de plus en plus de l'intelligence artificielle (IA). Cependant, les personnes marginalisées, notamment celles des communautés rurales et éloignées, risquent d'être laissées pour compte ou ignorées par la révolution de l'IA. Cet article présente les résultats d'une étude utilisant des méthodes mixtes qui explore les perspectives des professionnels de la santé du Nord de l'Ontario, une vaste région essentiellement rurale du Canada, caractérisée par une diversité culturelle et un système de santé sous-financé. Nous avons recueilli des données au moyen d'un sondage anonyme en ligne. Les données suggéraient que les participants étaient préoccupés par la préparation, les infrastructures et les ressources, la compétence culturelle, la disponibilité linguistique, la formation de la main-d'œuvre et l'importance de la représentation des communautés locales lors du développement et de la mise en œuvre de l'IA. Certains participants se sont montrés optimistes quant au potentiel de l'IA, mais ont également mis en garde contre une mise en œuvre uniforme, inspirée des communautés urbaines. Notre étude souligne que l'IA dans le domaine des soins de santé doit être contextualisée, guidée par des considérations d'équité et façonnée par les expériences réelles des praticiens ruraux. Ces résultats contribuent à une meilleure compréhension de la manière dont l'IA dans le domaine des soins de santé inclusifs devrait être développée pour répondre aux besoins des communautés rurales et isolées.

Mots-clés : Intelligence artificielle, zones rurales et isolées, professionnels de la santé

1.0 Introduction

Artificial intelligence (AI) is transforming many aspects of society. This includes healthcare, where AI has the potential to enhance diagnostic accuracy, streamline administrative tasks, and personalize patient care (Kumar et al., 2023; Malik & Solaiman, 2024; Schork, 2019). For example, AI applications include algorithms that analyze medical imaging to detect early signs of disease, predictive models for patient risk stratification, and natural language processing tools that assist in clinical documentation. These tools have been suggested as a means to improve care for underserved populations, including those living rurally (Khalifa & Albadawy, 2024; Perkins et al., 2024; Smit et al., 2023). Despite its potential, the integration of AI into healthcare systems presents challenges. These include ethical concerns about privacy and accountability, implementation barriers, and varying levels of professional acceptance (Allen et al., 2024; Li et al., 2022; Nair et al., 2024). While significant attention has been given to the technical development and clinical applications of AI, far less is known about the attitudes of healthcare workers toward these technologies. Existing studies have primarily focused on physicians in urban and resource-rich settings, reporting a mix of optimism for AI's potential and concerns about its impact on workload and patient care (Allen et al., 2024; Al-Medfa et al., 2023; Oh et al., 2019; Perrier et al., 2022; Mat reffien et al., 2021). However, there remains a gap in understanding how healthcare workers in rural, remote, and underserved communities view AI's effect on their practices, particularly in areas with unique sociocultural and infrastructural challenges.

Northern Ontario provides an ideal context for exploring these attitudes. This vast region, spanning over 800,000 square kilometres, contains two small cities, Thunder Bay and Sudbury, and a predominantly rural and/or remote population. It is home to a diverse demographic, including a significant proportion of Indigenous and Francophone residents, whose cultural and linguistic needs add complexity to healthcare delivery (Strasser et al., 2013). The region is served by the Northern Ontario School of Medicine University (NOSMU), founded in 2002 to address the healthcare needs of northern and underserved populations, with many, but not all, healthcare workers affiliated with the University (Ross & Cervin, 2020). The diversity of geographic types within the region also allows a comparison between those who live in urban and rural, and remote and non-remote communities. In this study, we present opinions about AI of healthcare-associated workers in the region, from a variety of community types, and explore the implications for culturally appropriate care in this unique region.

2.0 Methods

2.1 Design

We conducted a mixed-methods, cross-sectional study using an anonymous, web-based survey of healthcare-associated workers in Northern Ontario. The survey included both structured (ordinal) and open-ended questions, allowing for quantitative analysis of attitudes and experiences as well as qualitative thematic exploration of narrative responses. The primary outcome was to identify healthcare workers' perceived barriers and enablers to AI implementation in healthcare settings, with a focus on contextual factors such as geographic remoteness, rurality, language, training, infrastructure, and cultural safety. A secondary aim was to describe the level of AI knowledge, usage, and interest among participants across different types of communities.

2.2 Survey Development

The survey included ordinal ratings and open-ended text responses. The questions asked in the survey were developed by considering other studies about attitudes to AI in healthcare (Chomutare et al., 2022; Oh et al., 2019; Perrier et al., 2022; Mat reffien et al., 2021), and in discussions between the researchers. The survey included questions on participants' self-reported professional roles, geographic location, knowledge and interest in healthcare AI, and implementation barriers. We asked participants to self-report the type of community they lived in using the categories: small rural, large rural, small urban, or large urban, and to indicate whether they considered their community geographically remote. These were self-reported rather than externally classified, in keeping with the study's focus on lived experience and perceptions. Given the subjectivity of how AI may be perceived and applied in different contexts, we aimed to capture how participants understood their own environments, rather than impose potentially arbitrary or externally defined labels. In addition to structured items, the survey included open-ended questions: one asked participants to describe any barriers to AI implementation in their community, and the other asked what they believed was most important to ensure their communities benefited from the AI revolution. These free-text responses formed the basis of the thematic analysis.

2.3 Recruitment of Participants

Participants were recruited using a combination of invitations by email, advertisements in newsletters and on social media during the 2024 calendar year. Potential participants were invited to click a web link that led to an online informed consent form. Those who consented were then directed to the survey, which was administered using the Qualtrics system. All participants who completed the survey indicated that they lived and/or worked in Northern Ontario and were involved in healthcare in roles such as practicing clinicians (e.g., physicians, nurses), clinical trainees (e.g., residents or students), healthcare administrators or support staff, and non-clinical researchers or educators.

2.4 Data Analysis

For quantitative data, intergroup differences in survey responses were compared using a Fisher's Exact Test (FET).

We analyzed textual data using thematic analysis, following an iterative process of coding, researcher discussions, and reflexivity to ensure rigour (DeMarrais & Lapan, 2017). The data were systematically coded, with meaningful segments labeled to capture key patterns and emerging concepts. Initial codes were generated inductively, allowing themes to emerge directly from the data. These codes were then grouped into higher-order themes through an ongoing comparative process (Ibrahim, 2012).

To provide transparency in how themes were developed, we constructed a narrative codebook based on inductively derived codes clustered into five overarching categories. Cultural and Geographic Relevance emerged from codes such as "Indigenous needs," "poverty and access," "local language," and "urban assumptions," all reflecting concerns that healthcare AI must be adapted to the cultural, linguistic, and geographic realities of Northern Ontario. Additional resourcing was built around codes like "need human support," "clinic is too busy," "no internet," and "underfunded." Involvement in technology development incorporated codes such as "not consulted," "rural afterthought," "tailored to local population," and "co-design," representing a clear desire for early and meaningful inclusion of local healthcare workers and communities in AI design. Education and Training for an AI-Integrated Future combined codes like "staff need training," "training is key," "worried for students," and "AI could shortcut learning," expressing both the immediate need for workforce upskilling and deeper anxieties about how AI may alter the teaching of medicine itself. Finally, policy and ethics reflected higher-level concerns captured by codes such as "equity first," "ethical use," "Indigenous data sovereignty," "adapt for disabilities," and "policy vacuum," pointing to participants' call for inclusive, accountable, and socially responsible governance of healthcare AI. The final themes were validated through peer debriefing and iterative refinement, ensuring that they accurately represented the underlying narratives within the dataset (Williams & Moser, 2019).

3.0 Results

3.1 Participants

In total, 68 participants completed the survey. All participants indicated that they lived within Northern Ontario and were involved in healthcare in some capacity, including clinicians, clinical trainees, healthcare administrators, or researchers. We also asked about the community that participants resided in, asking them to self-report as living in a large rural, small rural, large urban, or small urban community, and whether they viewed their locale as geographically remote. A summary of demographic and community details is described in Table 1.

Table 1. *Participant Characteristics*

Measure	**Value**
Age (median ± IQR)	39 ± 22
Gender (n)	38 female 27 male 1 non-binary 2 preferred not to answer
Role	29 practicing clinicians 24 clinical trainees 12 healthcare administrators/staff 3 non-clinical researchers

Table 1 continued

Years in role (Median ± IQR)	7 ± 14
Language(s) spoken (n)	68 English 19 French 6 Indigenous languages 1 other
Community type (n)	17 small rural 14 large rural 32 small urban 5 large urban
Remote community? (n)	30

Note: All responses are self-reported, including those for community type and remoteness.

3.2 Knowledge and Attitudes to Healthcare AI Between Those Identifying as Living in Remote and Non-Remote Communities

Most participants reported moderate to significant technological change in healthcare during their time in their role. Only 28% of respondents reported using at least one AI tool in their primary role, while 31% were unsure. Speech recognition and transcription were more widely adopted, with 67% of respondents using them at least several times per week. Sixty percent reported at least a little knowledge of AI in healthcare, and nearly all were at least moderately interested in the topic, while 90% expressed interest in receiving more AI training (see Table 2). Only 10% had previously been asked their views on healthcare AI. While 49% were unsure whether AI-related data was being collected in their community, just 7% confirmed it was (see Table 2).

In terms of opinions about AI, it was noticeable that many participants were uncertain, answering ‘don’t know’ to many questions (see Table 3). Most participants (71%) were not worried about AI replacing them (see Table 2), though clinical trainees expressed more concern or uncertainty (FET; $p < 0.05$). When asked to elaborate, most viewed AI as augmentative rather than replacing roles. A clinician stated, “Primary care may be augmented, but not replaced,” while a clinical trainee noted, “Radiologists might be replaced, but psychiatry seems safer.” Regarding AI’s impact (see Table 3), 58% agreed AI would improve their job performance. Some respondents answered that AI will not be appropriate for local needs (52%), had unclear legal liability (41%), and there was insufficient regulation (41%). Only 31% believed AI would reduce workloads, and 25% thought it would make their jobs more enjoyable. Other statements received less than 20% agreement.

No statistically significant differences in responses for the data shown in Tables 2 and 3 were found between those living in remote or non-remote communities, between rural and urban communities (FET; $p > 0.05$).

Table 2. *Knowledge Attitudes to AI in Healthcare*

Question	**All (n=68)**	**Not remote (n=38)**	**Remote (n=30)**
How much has technology changed how you carry out your primary role in the healthcare system? (None/Changed a little/Changed a lot)	6/34/40 [21]	7/38/35 [19]	5/27/47 [22]
What has the impact been of healthcare technological changes on how you carry out your primary role in the healthcare system? (Very negative/Somewhat negative/Neither positive nor negative/Somewhat positive/Very positive)	0/3/25/41/12 [20]	0/4/23/38/14 [22]	0/0/27/43/11 [18]
How many applications of AI have you used in your primary role in the healthcare system? (None/1-2/3-4/ > 5)	40/21/3/5 [31]	46/16/3/8 [27]	35/26/3/0 [36]
How often do you use speech recognition or transcription applications? (Never/Occasionally/Few times a week/Daily)	4/24/32/35 [4]	3/22/38/33 [5]	7/25/27/37 [3]
How would you rate your knowledge of AI use in healthcare? (Very little/A little/A a lot/Expert)	40/43/13/4	35/49/14/3	47/37/10/7
How would you rate your interest in the uses of AI in healthcare? (Not interested/Interested a little/Very interested)	2/29/69	0/27/73	3/33/63
Have you ever been asked your opinions about AI and healthcare previously? (No/Yes)	88/10 [2]	92/8 [0]	86/10 [3]
Do you know of any data being collected about the healthcare system in your community which is being used to develop AI technology? (No/Yes)	44/7 [49]	41/13 [46]	50/3 [50]
Would you be open to participating in training programs to enhance your understanding and skills related to AI in healthcare? (No/Yes)	4/78 [18]	8/73 [19]	0/84 [17]
How worried are you that AI will replace you in your primary role in the healthcare system? (Not at all/Mildly/Moderately/Extremely)	71/19/0/0 [10]	71/22/0/0 [8]	71/17/0/0 [13]

Note: The table shows the percentage of respondents giving the answer options for each question. Numbers in [parenthesis] give the percentage of those answering, 'don't know.' No statistically significant differences were found between those who self-reported as living in geographically remote and non-remote communities (FET, $p > 0.05$).

Table 3. Attitudes to AI in Healthcare

Statement (agreed with)	**All (n=68)**	**Not remote (n=38)**	**Remote (n=30)**
AI will make me better at my job	58/10 [32]	57/13 [30]	57/7 [35]
AI technology will not be appropriate for local needs	52/19 [30]	47/18 [33]	58/17 [26]
The legal liability is unclear if AI technology fails	41/6 [53]	47/5 [47]	32/7 [60]
There is insufficient policy/regulation in place to allow deployment of AI systems in healthcare	41/12 [47]	35/15 [51]	49/7 [42]
AI will reduce my workload	31/16 [53]	32/8 [60]	30/27 [44]
AI will make my job more enjoyable	25/9 [66]	21/8 [70]	30/10 [61]
AI technology will reduce patient privacy and confidentiality*	20/26 [53]	16/29 [55]	25/23 [51]
Decisions made by AI systems are untrustworthy as they are not properly explained or transparent	18/40 [43]	20/40 [39]	15/37 [48]
AI will divert resources from other priorities	16/50 [34]	17/50 [34]	17/43 [40]
AI will add to healthcare workers existing workload	16/41 [43]	15/39 [45]	17/43 [40]
AI will reduce my stress level	15/19 [66]	13/16 [71]	18/23 [60]
AI will impair the ability to provide compassionate patient-centred care	15/59 [26]	11/61 [28]	20/57 [23]
AI will take away attention from other needed changes to the healthcare system**	12/59 [30]	15/50 [35]	8/70 [24]
Decision-making using AI will be poorer than that of a human worker	12/40 [49]	7/39 [53]	18/40 [44]
AI will impair communication with patients	10/54 [25]	12/61 [27]	7/70 [22]
AI technology will be unreliable	7/43 [50]	9/47 [44]	5/37 [58]

Note: The Table shows the percentage of participants who 'agreed'/'disagreed' with each statement with the data ordered from highest to lowest agreement. The number in parenthesis is the percentage who answered, 'don't know'. No statistically significant differences were found between those who self-reported as living in geographically remote and non-remote communities (FET, $p > 0.05$).

3.3 Thematic Analysis of Barriers to Implementation of AI in Healthcare

Participants identified key barriers to AI implementation in healthcare (see Table 4), with the need for training (69%) and lack of suitability for their workplace (56%) being the most common. Only 12% believed technology needs were uniform across Northern Ontario. Those who viewed themselves as living in remote communities were significantly more likely to cite language (63% vs. 35%) and poor internet (60% vs. 30%) as barriers (FET, $p < 0.05$), though no significant difference ($p > 0.05$) was found between those identifying as residing in urban or rural communities.

Table 4. Barriers to Implementation of AI in Healthcare

Factor	**All (n=68)**	**Not remote (n=38)**	**Remote (n=30)**
Need for training	69/31	68/32	67/33
Not designed for your type of workplace or practice	56/44	54/45	57/43
Language barriers*	49/51	35/66	63/37
Difficulty getting systems maintained	48/51	41/58	53/47
Poor internet connectivity*	43/57	30/71	60/40
Mistrust of new tech by healthcare workers	40/60	43/58	33/67
Too costly	39/60	38/63	40/60
Mistrust of new tech by patients	30/71	32/68	27/73
Too difficult to use	12/88	11/89	13/87

Note: The Table shows the percentage of participants who 'agreed'/'disagreed' that each factor would be a barrier to implementation ordered from highest to lowest agreement (using all participants). The relative proportions of each possible answer were compared between those who had stated they lived in a remote community and those who had not, using a FET with statistical significance shown as *: $p < 0.05$.

We asked participants to comment more on potential barriers in their community, and also what the most important thing or things that needed to happen to ensure that the healthcare system in Northern Ontario communities benefited from the AI revolution. The two questions generated qualitatively similar responses, which we combined prior to conducting a thematic analysis. Five key themes emerged.

*3.3.1. Theme 1. Cultural and geographic relevance***.** Many participants identified the need to make healthcare AI applications relevant to the specific context of the region in terms of place, culture, and language. For example, a physician in a large rural community said, "Rurality is a bit different, and AI needs awareness (of that)." Many participants made reference to the Indigenous peoples of the area, such as a trainee in a small rural community who stated, "Making this work in First Nations communities will take a lot of discussion and development. I'm worried though that AI and healthcare will exclude Indigenous people." Concerns were also raised about the poverty of many in the regions, with a physician in a small rural community saying, “Some of my patients have no money and no access to computers and such. Another part of the great divide.”

*3.3.2. Theme 2. Additional resourcing***.** Many participants expressed the need for additional resourcing to be given to the clinical practices to help implement any new technologies. One clinician in a small rural community said, “AI would need a lot of human support. We are too busy here to add this tech to our clinic without a LOT of help.” Besides human resources and finances, the lack of internet access was also mentioned with one physician in a small rural community saying, “Many of my patients don't have access to the internet in their homes. That may be a barrier… .”

3.3.3. *Theme 3. Involvement in technology development.* A number of participants expressed the need for early and meaningful involvement of the communities and healthcare workers in Northern Ontario. One small rural community clinician identified the need to develop AI applications tailored to the local population, stating, “As a rural doc I just don’t want to be an afterthought that maybe someone will listen to if they have time.”

3.3.4. Theme 4. Education and training for an AI-integrated future. Many participants spoke of the need for training in any new AI technology, with one clinician in a large rural community stating, “Training is imperative, the facility I work for is very poor at staff training.” While most comments focused on upskilling the current workforce, one respondent raised a broader concern about how AI might reshape the educational landscape of medicine itself. A non-clinical support staff member in a large urban community reflected, “I think one of the biggest things we forget when it comes to AI is how we are teaching our learners…AI can have individuals cut corners. I worry about how we teach learners the foundations of medicine in the age of AI.” Though most responses related directly to training needs for current healthcare roles, this comment extends the conversation toward the future of clinical formation and the philosophical underpinnings of how medicine is taught. It reflects a wider conceptual horizon that, while beyond the immediate scope of this study, is deeply relevant to understanding the systemic implications of AI integration in healthcare.

3.3.5. Theme 5. Policy and ethics. Our participants mentioned many aspects of the policy and governance of AI and its ethical use. This included the need for equitable access to AI technologies. For example, a non-clinical researcher stated, “Health equity and social accountability needs to be at the forefront of all AI processes.” Similarly, a clinician in a small rural community said, “There should be a requirement to adapt tech for different peoples, disabilities, etc. and have it work well.” Several participants also highlighted the need for Indigenous data sovereignty within AI development and use in healthcare. A mandated need for equitable access was also mentioned with a clinical trainee saying that “each (healthcare professional) should be able to work anywhere and be able to use the technology.”

4.0 Discussion

This study aimed to explore healthcare-associated workers' perceptions of the opportunities and barriers related to the implementation of AI in Northern Ontario, with particular attention to geographic remoteness, infrastructure, and cultural and linguistic context. The study achieved this goal by identifying a set of common concerns and priorities expressed by participants across multiple roles and communities. Three major findings emerged: (1) widespread uncertainty and limited exposure to AI among participants, despite general interest and optimism; (2) significant perceived barriers to AI adoption, especially related to training, infrastructure, and equity; and (3) a clear call for culturally relevant and regionally grounded AI development that engages local communities. These findings are discussed below in relation to their implications for policy, implementation, and future research.

4.1 Attitudes Towards AI

The survey revealed that a small majority thought that AI would make them better at their job, although some skepticism was also evident, such as only a small minority believing that AI would reduce their stress level or workload. Many respondents also expressed concern about regulation and liability. Notably, many participants were unsure about AI's impact, perhaps suggesting a more 'wait and see' approach. Such findings are of importance with regard to ease of implementation, since the expectancy that a healthcare technology will improve aspects of a person's workplace role is a major predictor of its acceptance by clinicians (Barchielli et al., 2021; Ifinedo, 2012). Overall, participants' attitudes toward AI reflected a mix of cautious optimism and uncertainty, suggesting that successful implementation will require clear communication, demonstrated benefit, and training tailored to the needs of diverse healthcare roles and settings.

4.2 Barriers to AI Implementation

Our respondents also identified a number of barriers to the adoption of AI, consistent with those found in other studies, such as difficulties maintaining systems, poor internet access, mistrust of new technologies, high cost, and lack of usability (Chomutare et al., 2022; Hassan et al., 2024; Petersson et al., 2022). This may reflect prior experience with the introduction of new healthcare technologies such as electronic health records or telemedicine (Chomutare et al., 2022; Petersson et al., 2022), or general societal concerns related to trust and acceptance of new technologies due to either a lack of knowledge about what is being introduced, or a lack of transparency in their design and implementation (Sauchelli et al., 2023). As such, addressing the uncertainty about healthcare AI seen throughout our survey is of importance, as this is likely to impact adoption. Indeed, while most respondents were interested in additional training, the need for such was the most frequently reported barrier to AI use.

4.3 Cultural Safety and Geographic Barriers

The majority of our respondents viewed that there are barriers to implementation of AI technologies. Importantly, those working in geographically remote communities were more likely to report language and internet connectivity as barriers. This aligns with the realities of healthcare provision, where internet access is often inequitable, unreliable, or slow, and AI use may widen the digital divide. Even with satellite services like Starlink, cost and hardware access may remain a barrier without additional resourcing. Additionally, many of those living in northern and remote communities speak French or Indigenous languages, and the lack of availability of patient-focused AI tools using these languages may result in inequitable access and outcomes for non-English speakers (Arredondo et al., 2014). Moreover, given the resulting need for translation services (CanTalk, n.d.; Réseau du mieux-être francophone du Nord de l'Ontario, n.d.), it is not surprising that a large majority of those surveyed responded positively about the use of AI for such a purpose. However, the small number of speakers of languages like Ojibwe may make it unlikely that commercial developers will opt to incorporate them into their products without regulatory mandates. Indeed, our respondents highlighted the need for AI to be culturally safe with respect to Indigenous peoples and contextually grounded in the realities of rural practice. This aligns with calls for culturally competent and safe AI systems that reflect the lived realities of Indigenous and rural populations (Avellan et al., 2020; Sue & Torono, 2005; Zowghi & Bano, 2024). Our findings are similar to those regarding Māori healthcare in New Zealand, which also emphasizes the integration of Indigenous perspectives into AI development, suggesting parallels with Canada's Indigenous context (Whittaker et al., 2023; Yogaranjan et al., 2022).

4.4 Inclusion in Development

In addition to sociocultural barriers, for AI to be effective, most applications need to be trained and tested on the populations with which they shall be used (Loftus et al., 2024; Yogaranjan et al., 2022), as highlighted by our participants. It is concerning that few respondents were aware of AI development using data from their communities, and most had never been asked for their views on healthcare AI. This aligns with findings that AI research in Canada is rarely funded outside major urban universities (Anawati et al., 2024). Our data further supports the need to engage with rural and northern communities and workers to co-design AI applications, not least because they have the contextual knowledge which is likely to be key to its success (Loftus et al., 2024).

4.5 Limitations

The main limitation was the small sample size, representing only a fraction of eligible participants. Self-selection bias may also have influenced the results, attracting those with strong AI opinions, while social media recruitment may have also led to under-coverage bias, excluding non-users (Bethlehem, 2010).

5.0 Conclusions

Our findings highlight policy implications, emphasizing the need for inclusive healthcare AI that reflects cultural, linguistic, and geographic diversity, and that AI development should engage and empower Northern Ontario communities, promoting social accountability, a finding that may be applicable to all underserved communities. We suggest that this goal can be supported by applying implementation science principles such as stakeholder engagement, contextualization, and effective knowledge translation (Bauer et al., 2015). Secondly, given the low resource nature of the region, there is also a need for additional support for the cost of research, training, internet access and the new technologies that will be needed so that rural, remote, and culturally diverse regions like Northern Ontario are not left behind in the healthcare AI revolution.

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