The Impact of AI on Marginalized Communities

INAF 5706: Global Health Policy

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November 27, 2025

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Introduction

For several years, artificial intelligence (AI) has been rising globally. AI is a form of computer science that allows computers to perform tasks and duties that usually require human intelligence. AI systems do so by learning from a large volume of data, identifying patterns to make predictions or decisions (Google Cloud, n.d.). AI encompasses several key areas, including machine learning (ML). It is reflected almost everywhere in our day-to-day lives, such as face recognition, web applications, fitness tracking and more. As AI integrates into society, it contributes to the performance and improvement of sectors such as healthcare. The healthcare sector is being reshaped by AI as it is seen as a tool across every level of the medical ecosystem, particularly from research and clinical documentation to treatment and patient engagement. AI in healthcare is in its most advanced state, given its ability to scan patients to detect illnesses like cancers and heart diseases. It is also able to capture electronic health records and improve clinical trials (Barth, 2025).

Patients are the central figure of the healthcare system; they receive diagnosis, medication and treatment that corresponds to their needs. The medical care that patients receive is expected to be at an adequate level of quality that ensures their health and well-being. As much as patients are invited to engage with their primary caregiver, make crucial decisions about their health and build a lifestyle promoting health, they need to feel like they are seen and heard. With the presence of AI, it can be difficult for some patients to build that sense of trust.

Specifically, marginalized communities in healthcare face barriers such as systemic racism, biases and a lack of awareness for cultural care. It is proven that AI does not consider the needs of marginalized communities, which may affect their health and well-being. With that, this research paper raises the following question: How does the use of AI in the healthcare sector impact marginalized communities? Several literature reviews explain how the use of AI in healthcare affects the experience and health of marginalized communities. Through my thesis, the most prevalent key concepts when addressing this issue are health equity, bias, and AI systems. These key concepts can explain the gaps within these issues, particularly the lack of awareness of ethnic differences and the understanding of AI systems within the healthcare sector. The following lines will provide an in-depth explanation of each key concept and policy implications for this topic.

Development

Several literatures were identified and analyzed to gain a better understanding of how health and AI can interact. A wide range of topics were covered in these various literature review papers, and this current paper discusses the ones that incorporate and discuss the impact left on marginalized communities regarding AI in the healthcare sector. Some literature reviews may be mentioned more than once – that is, because they address more than one key concept covered by this paper. The paper will begin with the concept of health equity, followed by bias, and finally, AI systems. Each key concept will hold an analytical review of the themes, including the findings and any gaps highlighted.

    A) <u>Health Equity</u>

To begin, health inequity is a major issue that affects many countries on a large scale. The World Health Organization (WHO) describes it as "the unfair and avoidable or remediable systematic differences in health among population groups defined socially, economically, demographically or geographically. Health inequities arise fundamentally from the unequal allocation of power, money and resources, which manifest in the unequal distribution of social determinants" (WHO, 2025, p.5). They stem from social injustice and leave a long-lasting and generational impact. According to the WHO, they are reflected in the differences that are avoidable and unjust. Thus, it is the handling of social determinants of health that seems to account for most of the health inequities between various social groups (WHO, 2025). With the presence of health inequity and the evolution of AI, it is crucial to examine how the use of AI can alleviate and support the promotion of health equity within marginalized communities. The WHO defines health equity as "the absence of unfair and avoidable or remediable differences in health among population groups defined socially, economically, demographically or geographically", and many researchers have examined the role of AI when it comes to promoting equity in the healthcare sector (WHO, 2025, p.5). The following lines present three papers that address health equity and the use of AI in healthcare.

Firstly, the peer-reviewed paper titled, *AI Impact on Health Equity for Marginalized, Racial, and Ethnic Minorities* written by Nchebe-Jah Iloanusi and Soon Ae Chun, addresses health inequities and how health disparities are reflected through structural injustices shaped by racism, bias and

social determinants (Iloanusi & Chun, 2024). This study examines AI models and applications in healthcare settings, all while focusing on the impacts they have on marginalized and disadvantaged populations. At the beginning of the paper, the authors highlighted that to address AI and health equity, there must be a balanced perspective to allow AI to promote health equity rather than reinforce the status quo (Iloanusi & Chun, 2024). By enforcing the status quo, it may risk preventing innovation and growth and rather disable systems and communities from adapting to ever-changing environments. The status quo can lead to stagnation, which is why it must be challenged, especially for the purpose of improving healthcare. Also, the authors believe that to achieve health equity with AI, there must be technical mitigation and diverse community engagement, collaboration, as well as social and cultural contextual understanding that is centred around patients coming from marginalized communities (Iloanusi & Chun, 2024). Doing so could limit or reduce the risks of discrimination and promote fairness and transparency when engaging with patients for any type of issue or problems they are facing, such as a cancer diagnosis or a mental health treatment (Iloanusi & Chun, 2024).

Furthermore, the authors conducted a study where the methodology was to systematically identify, evaluate and synthesize relevant studies on the intersection of emerging technologies, health equity and marginalized groups. The authors used a standardized form to extract key data from included studies, and they took a narrative synthesis approach to analyze the extracted data (Iloanusi & Chun, 2024). As a result, the findings illustrated the challenges in health equity, particularly the key datasets that were used to quantify and characterize algorithmic biases in healthcare AI systems. AI models such as Large Language Models (LLMs), ChatGPT or Gemini have shown risks of negatively affecting health inequities (Iloanusi & Chun, 2024). Equally, the authors enumerated AI's potential and risks for health equity. Potential includes how AI can expand access to care through automating tasks and reaching undeserved areas. In addition, AI could analyze diverse health data to identify determinants driving disparities, target interventions, and promote system equity through optimized resource allocation, ensuring fair distribution across groups. Whereas the risks of AI perpetuating inequity include an algorithmic bias resulting from learning stereotypes and prejudices ingrained in training data; a lack of diverse data causing blind spots in model performance for marginalized groups; and the process of automating without ethics potentially increasing disparities and removing human judgment

(see Figure 1) (Iloanusi & Chun, 2024). Overall, the authors of this peer-reviewed paper depicted and set the foundation for the essential elements when examining health equity and AI, along with the impacts it can leave on marginalized communities.

A second literature titled, *Health and AI: Advancing responsible and ethical AI for all communities*, written by Nicol Turner Lee, Malaika Simmons, and Michael Crawford, highlights discussions held between Working Group Experts (WGEs) over AI, and the strategies implemented on ways to engage with AI in healthcare. Health experts held four online sessions over a two-month period with the objective of identifying opportunities and best practices for AI in healthcare. The authors highlighted AI's revolution taking place in healthcare and considered the risks and concerns it may pose to the sector. They also highlight the importance of ensuring AI is safe, effective and that the use of technology may benefit communities. Finally, the authors raised the importance of collaboration between the government, companies and the healthcare industry to form AI governance structures.

In terms of health equity, this article covers AI in the healthcare sector and the way it is transforming service delivery, administration duties and patient care. Although they believe that AI in healthcare can improve access to quality of care for medically vulnerable communities and patients, the authors did not neglect to mention how medically vulnerable communities and even local health institutions are at risk of being left behind in the AI revolution "due to not having basic access to high-speed broadband, data, resources and education" (Turner Lee et al., 2025). Indeed, to promote health equity, one must recognize the gaps in relation to the level of accessibility of resources marginalized communities may or may not have and the contribution AI may bring to fill in those gaps.

Moreover, public policies ensure that the development and deployment of AI technologies exist to advance health equity (Turner Lee et al., 2025). Indeed, the influence of political leaders, including the government, can further advance policies that can be implemented to the benefit of vulnerable populations. Political actors can push for amendments and measures that can ensure AI tools and systems are equitable across all communities. To add, health equity needs to be reflected in the AI design and development process. The authors believe this could be done by

enhancing the diversity of training datasets, establishing comprehensive evaluation mechanisms and developing robust AI protocols to better assist clinicians and users to understand AI decisions (Turner Lee et al., 2025). All in all, this literature covered the various strategies put in place to guarantee that the use of AI promotes the health of all, including marginalized communities.

The final paper covering health equity is titled, *Health Equity and Ethical Considerations in Using AI in Public Health and Medicine*, written by Irene Dankwa-Mullan. Dankwa-Mullan provides an overview of the critical roles of health equity and ethical considerations in the deployment of AI. The author defined health equity in the context of AI as "the fair and just distribution of health technologies and their benefits" (Dankwa-Mullan, 2024). The author also noted that for health equity to be considered, all individuals should have access to the same high-quality healthcare services, despite their socioeconomic status, sex, race, gender, ethnicity, disability status or geographic location. Additionally, for health equity and AI in the healthcare systems to work in favour of all communities, AI needs to bridge existing health disparities rather than widen them. Globally, it is evident that health disparities can be life-threatening in various communities, particularly when large-scale infections such as COVID-19 take place. The COVID-19 pandemic has had a profound impact on the world, resulting in nearly 20 million deaths since 2020. In fact, life expectancy declined in 84% of countries during the pandemic (IHME, 2025). Equally, many communities are ignored and neglected when it comes to their health. As a result, this form of negligence can trickle down within the marginalized community and negatively impact their lives and the lives of future generations. As such, authors like Dankwa-Mullan and the ones mentioned previously signal the importance of appropriately manipulating AI tools and systems within the healthcare sector to allow marginalized communities to receive proper care and ultimately promote health equity.

B) <u>Bias</u>

The second key concept is the presence of bias in healthcare. The term bias refers to an idea, whether negative or positive an individual may have about someone or something. This idea can affect interactions with other people belonging to certain groups (Haghighi, 2023). Biases are shaped in different forms – they can be implicit, hence a bias that a person is unconscious of, or

they can be explicit, a conscious and deliberate bias. In healthcare, biases are very common and come in different forms, such as sexual identity, education, age, ableism, and racial bias. With the implementation of AI in the healthcare sector, bias cannot be left unobserved, which is why several authors discuss the importance of AI to recognize and mitigate bias in healthcare.

In addition to examining health equity, Iloanusi and Chun highlighted that AI alone cannot resolve systemic biases and discrimination. Since most AI systems rely on the detection of statistical patterns and correlations in data, they inevitably inherit biases that are embedded in their training data. Consequently, AI systems absorb these biases (Iloanusi & Chun, 2024). Nonetheless, there are several alarming examples demonstrating unconscious biases in healthcare algorithms. For example, algorithms that predict patients' health risks exhibited significant racial bias by assigning higher risk scores to Black patients compared to White patients who carry identical clinical profiles (Iloanusi & Chun, 2024). Equally, bias is seen implemented in AI platforms such as ChatGPT and LLMs. Although there are ways to adjust algorithm techniques, they unfortunately remain underdeveloped.

On the other hand, Turner Lee et al. (2025) raise the risks of AI in healthcare, such as algorithmic bias and data privacy concerns. Algorithmic bias refers to systematic errors in machine learning which produce unfair or discriminatory outcomes. It often reinforces existing biases and can be concerning when detected within AI systems that support life-altering decisions in sectors like healthcare (Jonker & Rogers, n.d.). With healthcare algorithms relying on underrepresented data, this leads to biased outcomes as it amplifies health disparities among patients of colour and other demographics. Regarding bias mitigation and health equity, data that trained AI models most likely stem from medical records, which most of them are filled with implicit and explicit biases (Turner Lee et al., 2025). Although biases are unavoidable in healthcare, it is important to learn how to distinguish valid and relevant information from conceptualized ideas.

Furthermore, in the paper titled, *Examining inclusivity: the use of AI and diverse populations in health and social care: a systematic review*, the authors set an objective which involves "understanding the impacts of the AI systems used in health and social care on diverse and

marginalized populations" (Marko et al., 2025, p.2). Based on their computer-assisted qualitative data analysis study, AI models frequently rely on datasets that fail to reflect the diversity of global patient populations, specifically in areas like medical imaging. For example, AI models can diagnose skin conditions in light-skinned individuals but perform poorly for those with darker skin due to underrepresentation in data training (Marko et al., 2025). Such biases can affect the allocation of resources based on demographic factors. It could also initiate errors in language models used in clinical environments. This disparity illustrates the gravity level biases in AI models can have. Considering low- and middle-income countries (LMICs), the lack of recognition of different skin complexion or other demographic factors could gravely impact the care patients in LMICs may receive with AI implemented in healthcare.

To add, when discussing the importance of health equity, Dankwa-Mullan addresses the sources and risks of bias within AI. AI data biases can arise from the processes of data access, collection, acquisition, preparation, processing, development, and validation (Dankwa-Mullan, 2024). The author flags various forms of biases, such as experience and expertise bias, which refers to the various levels of expertise among individuals involved in developing AI systems. There is also exclusion bias, which occurs when certain groups are systematically left out of the data collection and analysis processes. Exclusion bias can be illustrated through underrepresentation, which is what is often seen with marginalized communities – they are not considered when data is being gathered, which adversely affects them. Also, environment bias, empathy bias and evidence bias are forms of biases that can affect AI data in healthcare (Dankwa-Mullan, 2024). Overall, biases can be extremely dangerous to the health of marginalized communities if not handled correctly and especially if those communities are not taken into consideration when AI systems are being developed and improved.

C) AI Systems

A third and final key concept is AI systems. Article 3(1) of the *EU Artificial Intelligence Act* defines an AI system as a "machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments"

(EU, 2025). AI systems can take various forms, and they are implemented in individuals' daily lives. They act as virtual assistants, such as Siri. They can also act as chatbots, as seen with ChatGPT, Google's Gemini and Microsoft's Copilot. In this context, AI systems in healthcare contribute to facilitating the role of physicians and practitioners, along with assisting patients efficiently through record keeping and promoting innovation in medical practices (Barth, 2025). Nonetheless, there is still room for improvement for AI systems as they contribute to the inequity that resonates in marginalized communities. AI systems are founded on data that is fed to them to build their intelligence from that specific data. This leaves many communities feeling unacknowledged, which can undermine their health and well-being.

AI systems can facilitate people's lives, but they can also create a level of dependency for those using the tools. Nonetheless, AI failing to account for social risk by misattributing health disparities solely to individual behaviours or genetics could enhance the external barriers and structural racism that marginalized communities are facing. In fact, Iloanusi and Chun (2024) stated that most AI systems rely on the detection of statistical patterns and correlations in data, which makes them inherit biases within their training data. In their findings, they discovered that AI systems lack diverse and inclusive data. Consequently, to improve data collection and sampling, enhanced recording of race, ethnicity, gender identity and other demographic factors to support disaggregation in AI systems would be considered useful (Iloanusi and Chun, 2024). Disaggregated data can provide sub-categories of information by different categories such as ethnic groups, gender, and age. As a result, disaggregated data reveal inequalities in relationships between categories, further illustrating systemic oppression that marginalized groups are experiencing (BCOHRC, 2021). Although the authors proposed this strategy, it is crucial that disaggregated data is well manipulated; otherwise, it could harm marginalized communities by reinforcing systemic oppression (BCOHRC, 2021). Consequently, various participatory design processes are advocated by researchers to develop and govern AI systems to promote equity and justice. The authors highlighted the importance of centring the voices of disadvantaged groups in the governance of AI systems, as it helps align technology with community values and priorities.

In the same token, the authors of, *Managing a "responsibility vacuum" in AI monitoring and governance in healthcare: a qualitative study*, conducted semi-structured interviews. They asked participants about how AI/ML tools factor into their work, the applications of models they

believe are the most promising and/or challenging, and how they view issues surrounding AI/ML, including safety, governance, maintenance, and bias (Owens et al., 2025). The researchers found that while AI/ML-based healthcare technologies are widely acknowledged to degrade over time, the structures necessary to maintain and monitor these tools remain underdeveloped. This could be due to strategic ignorance where institutions benefit from not knowing when AI systems fail, thus shielding themselves from liability and regulatory scrutiny (Owens et al., 2025). The fact that institutions prefer not to address the failure of AI systems is one of the biggest harms that could be imposed on the healthcare sector. The tools used in the healthcare sector should be precise and as transparent as possible to deliver services to patients, particularly marginalized communities. Similarly, Turner Lee et al. (2025) highlighted that some international studies demonstrate how medical AI systems can propagate disparities based on race, gender, age and other factors through subtle pathways beyond just training data biases. Also, AI systems tend to perform poorly for underrepresented groups for several reasons, including insufficient data from those populations or a lack of context from AI companies. If companies prefer avoiding the issues that AI systems can introduce, these companies should not be contributing to healthcare, given how vital this sector is and how vulnerable marginalized communities are.

i. The Case of Rwanda and the Global South

The paper titled, *Artificial intelligence in medical imaging: Utilization, challenges, and practitioner perceptions in Rwanda* studies AI's utilization patterns and implementation challenges across Rwanda's healthcare system (Mukandayisenga et al., 2025). Rwanda is classified as a low-income country and faces several challenges, particularly in healthcare. Although it is one of the first African nations to implement an AI policy, Rwanda faces severe challenges, such as shortages of medical imaging professionals. The cross-sectional study consisted of surveying over 100 medical imaging practitioners across teaching, provincial and district hospitals (Mukandayisenga et al., 2025). The authors collected data on AI utilization, implementation barriers and practitioner attitudes. The challenges the practitioners faced varied from knowledge gaps, lack of training, poor data and limited access to technology. Consequently, the authors concluded that AI is useful in some areas; however, there is uneven AI integration, which could be due to infrastructural limitations and a lack of training. Additionally, as a low-

income country, Rwanda's application of AI remains basic compared to high-income countries where AI utilization is more advanced (Mukandayisenga et al., 2025). Ultimately, AI developers and non-governmental organizations (NGOs) should facilitate cost-effective AI deployment, and they should extend AI tools beyond teaching hospitals to ensure equitable healthcare access.

In parallel, if we examine specifically the Global South, AI systems are influencing the region. Nevertheless, AI systems are not as significant as other regions. In fact, there are significantly fewer published studies that have observed AI systems in deployments with patients and healthcare professionals and even fewer in the context of the Global South (Okolo, 2022). Furthermore, Okolo, who authored *Optimizing human-centered AI for healthcare in the Global South*, discovered that AI systems for healthcare continue to be commercialized. Without rigorous oversight, it could bring harm to communities within healthcare. Considering these issues, the developers and designers of AI systems should build them in a manner that those systems can adapt to the contexts where they will be used and ensure that users are educated on the effective use of AI systems in a way that leverages their autonomy. Okolo (2022) raised that these findings indicate that fully autonomous AI systems may harm patient-provider relationships and could degrade the levels of healthcare that are provided in the Global South. In consequence, AI systems could greatly affect marginalized communities if they are conceptualized to adapt to a single environment and can only rely on one form of data rather than a diversity of data.

Policy Implications

The evolution of AI is influencing healthcare, leaving many benefits in promoting and supporting the sector. However, the establishment of AI systems does not fully consider marginalized communities and their needs. On a policy perspective, this is a massive issue, especially in regions where marginalized communities are more prevalent or in LMICs where the rights of marginalized communities are undermined. Nevertheless, there are opportunities for improvement through policy (Parthasarathy & Katzman, 2024). To address these issues, accountability needs to be taken by institutions and governments that are establishing AI systems and allocating funds to build those systems. The policy implications that should be considered involve visible disparities between groups and a lack of trust and privacy for marginalized communities.

Institutions developing AI systems for the healthcare sector should consider the group of individuals who are using their tools and provide efficient and diverse data to further enhance the AI system. According to Botha et al. (2024), there are no specific regulations on AI use in healthcare to respond to the scope and direction of liability for 'professional misconduct' of AI machines. As a result, it is unclear where accountability lies. By gaining awareness of the communities and groups of people that will use those AI tools, institutions could customize their datasets and promote a diversity of data, which could ultimately increase the level of representation and accountability within in AI systems.

With the third Sustainable Development Goal (SDG) under the UN, hence the promotion of healthy lives, healthcare is prioritized globally, and so the equipment and tools should accommodate everyone equally (UN, 2025). Similarly, it is important that NGOs, institutions and governments recognize the disparities that could undermine or harm the care that is provided to marginalized communities. To illustrate, the *Pan-Canadian AI for Health (AI4H) Guiding Principles*, highlight trust as a key enabler of AI adoption as it fosters engagement with underserved populations, patients and healthcare professionals (Government of Canada, 2025). An AI system that is trustworthy and that can mitigate privacy issues would raise the level of trust patients develop for the healthcare sector. Also, robust privacy safeguards are crucial in protecting patient privacy and preventing violations that disproportionately affect vulnerable populations (Marko et al., 2025). All in all, policymakers must be prepared to think creatively, attuning regulations not only to technical characteristics of AI products but also to those products' equity impacts in real-life scenarios (Parthasarathy & Katzman, 2024). These policy implications must be considered when building AI systems to provide a holistic approach that promotes and supports the well-being of everyone equally, despite the community they belong to.

Conclusion

In conclusion, this research paper examined how the use of AI in healthcare impacts marginalized communities. This is observed through three main key concepts – health equity, bias and AI systems. Several studies have raised the disparities that have become common in AI systems, making it difficult for patients from marginalized communities to receive accurate and high-quality care. With data being the main driver and source of AI systems, the lack of data

diversity puts marginalized communities at harm's risk and ultimately, could become life-threatening if physicians and primary care providers gain great dependence on AI systems. As a society that is becoming more digital, it is important for users to feel like they can trust the system that holds their personal information and to learn about these AI tools so they can become more educated and aware of AI. In the hopes that, as AI continues to evolve, marginalized and vulnerable communities will feel included in the advancement process of AI.

Word count of Research Paper: 4,360 words

Word count including Search Strategy: 1,128 + 4,360 = 5,488 words

Appendices

Appendix A: Paper's Search Strategy

This section covers the search strategy undertaken to conduct research on AI in healthcare and its impact on marginalized communities. To ensure the research process is as structured as possible, an Inclusion and Exclusion table was used to provide guidance (see Table 1). The table includes a description of the article type, the methodology, the geographic scope and the time frame. These elements were tracked throughout the process. Records such as peer-reviewed journal articles and reports from international organizations were included in the paper. The methodology within these documents covered qualitative and quantitative studies.

The geographic scope was limited to marginalized communities with a reference to Rwanda and the Global South since findings from those regions illustrated experiences faced by marginalized communities. Finally, the time frame dates from 2020 onwards; this ensures that the research process wasn't based on outdated papers discussing AI, given that it is an evolving topic. Thus, by selecting articles written as early as 2020, it ensured a recent literature review on the topic, all while considering the technological advances of AI in the healthcare system.

	Included	Excluded
Article Type	- Peer-reviewed journal articles - Reports from governmental provinces and international organizations - Articles from medical organizations, the federal	- Blogs - Wikipedia

	• government and tech companies such as IBM • Grey literature from national organizations, i.e., Brookings • Laws and charters	
Methodology	• Qualitative studies • Quantitative studies	
Geographic Scope	• Marginalized communities • The Global South • Rwanda	Non-marginalized communities
Time Frame	• 2020 and onwards	Older than 2020

Table 1: Inclusion and Exclusion Table completed to guide the paper's search strategy

Appendix B: Investigation of the research question

To investigate the research question, records were identified and selected through several databases. The databases included, but were not limited to, Google Scholar, PubMed, and the WHO. The search terms varied throughout the searching process, especially where a few searches were directed for specific concepts.

In addition, manual searches were conducted on medical as well as federal and provincial databases to seek the definition of specific terms. There are some articles that were found by conducting a Google search; nonetheless, they provided valuable knowledge to the paper. The search process is illustrated in the tables below, which contain several columns (see Tables 2 and 3). The database, the search terms, and the total number of articles are indicated in each table.

Date of Search	Database Used	Search Terms	Total # of Articles	Reviewed Articles
1 November 2025	Google Scholar	AI marginalized communities healthcare	17,400 results	Opened 3 articles based on relevance: *AI Impact on Health Equity for Marginalized, Racial, and Ethnic Minorities*
	PubMed		277 results	*Managing a "responsibility vacuum" in AI monitoring and governance in healthcare: a qualitative study*

	Brookings.edu	AI marginalized communities healthcare	9 results	Opened based on relevance: *Health and AI: Advancing responsible and ethical AI for all communities*
3 November 2025	PubMed	AI healthcare marginalized communities	102 results. Filter used: Peer-Reviewed Journals; Available Online	Opened 2 articles based on relevance: *Optimizing human-centered AI for healthcare in the Global South*
				Examining inclusivity: the use of AI and diverse populations in health and social care: a systematic review
5 November 2025	CDC	AI AND health sector AND marginalized populations	Over 1000 results. Literature found on the first page.	Opened 2 articles based on relevance: *Health Equity and Ethical Considerations in Using AI in Public Health and Medicine*
	Google Search/The Association for the Advancement of AI	AI AND health sector AND marginalized populations	Over 100 results – found this paper on page 3 of the search	*Promoting Equity in AI-Driven Mental Health Care for Marginalized Populations* *I did not use this paper.
Notes: • Most of these papers provided the key concepts explained in this research paper. • Barriers related to marginalized communities were addressed in most of the articles. • Policy implications were considered when conducting the research.				

Table 2: Breakdown of the Search Strategy conducted for a detailed overview of the research question.

Date of Search	Database Used	Search Terms	Total # of Articles	Reviewed Articles
8 November 2025	Google Cloud	Artificial intelligence	Over 100 results	Opened based on interest in topic: *Artificial intelligence (AI): a simple-to-understand guide*

9 November 2025	WHO	Health equity news	About 6,520 results. Found on page 1.	Opened based on relevance, and it led me to the subsequent report: *Health inequities are shortening lives by decades*
	The previous article led me to the report.			*World report on social determinants of health equity, 2025* (full report)
	MedicalNewsToday	Bias in healthcare	Over 100 results. Found on page 1. (I can only find it through a Google search.)	Opened based on relevance: *Biases in healthcare: An overview*
	Google Search/IBM	Algorithmic bias	1,195 results	Opened based on relevance: *What is algorithmic bias?*
11 November 2025	EU Artificial Intelligence Act	AI act		Opened based on relevance: *EU AI Act*
	British Columbia's Office of the Human Rights Commissioner	Disaggregation of data marginalized communities	221 results. Found on page 1	Opened based on relevance: *Disaggregated data: Summary of recommendations to prevent harm to communities*
12 November 2025	United Nations SDGs	SDG goals	The website displays all 17 goals.	Opened based on relevance: *Ensure healthy lives and promote well-being for all ages*
18 November 2025	Gale Academic One File	AI systems healthcare policy	3,308 results	Opened based on relevance: *Artificial intelligence in healthcare: a scoping review of perceived threats to patient rights and safety.*
21 November 2025	Government of Canada	AI in healthcare policy	1,186 results	Opened based on relevance: *Pan-Canadian AI for Health (AI4H) Guiding Principles*

22 November 2025	Google Scholar	use of AI marginalized communities policy response	About 217,000 results	Opened based on relevance: *Bringing Communities In, Achieving AI for All*
23 November 2025	Institute for Health Metrics and Evaluation (IHME)	COVID-19	533 results	Opened to provide an example on health equity/inequity: *COVID-19*
24 November 2025	Omni Library	AI AND healthcare AND marginalized AND communities AND bias AND LMICs	No records found	■■■■■■■
	JSTOR		7 results	No relevance to the paper.
	PubMed		1683 results	Opened based on relevance: *Applied artificial intelligence for global child health: Addressing biases and barriers* *I did not use this article.
	Omni Library	AI AND healthcare AND marginalized AND communities AND bias	51 results	None were relevant to the paper.
25 November 2025	PubMed	artificial intelligence AND healthcare AND Rwanda Filter – Publication Date: 5 years	32 results	Opened based on the interest of looking into a LMIC: *Artificial intelligence in medical imaging: Utilization, challenges, and practitioner perceptions in Rwanda*
Notes: • Most of these articles were used to understand specific concepts around AI, the healthcare sector and marginalized communities.				

Table 3: Breakdown of the Search Strategy conducted for specific concepts within the research question.

Appendix C: AI's Potentials and Risks

Table 3: AI's Potentials and Risks for Health Equity

Potentials of AI for Health Equity	Risks of AI to Perpetuating Inequity
• Expand access to care through automating tasks and reaching underserved areas [41, 43] • Enable personalized medicine tailored to individuals' uniqueness including genomics, behaviors, and environment [10] • Augment clinical decisions by detecting patterns human providers may miss, avoiding cognitive biases [41] • Analyze diverse health data to identify determinants driving disparities and target interventions [12] • Promote system equity through optimized resource allocation, ensuring fair distribution across groups [11]	• Algorithmic bias results from learning stereotypes and prejudices ingrained in training data [3, 48] • Lack of diverse data causes blind spots in model performance for marginalized groups [9, 40] • Focus on correlation risks confusing causal myths. For example, wrongly attributing health behaviors solely to individual choices while ignoring structural barriers faced by disadvantaged communities [17] • Automating without ethics may scale up existing disparities and remove human judgment [21] • Uncritical trust in AI's objectivity obscures how technologies inherit human biases [30, 44]

Figure 1: Table prepared by Nchebe-Jah Iloanusi and Soon Ae Chun illustrating the potentials and risks of AI for health equity.

The use of AI

This assignment utilized AI in the following ways:

- Reviewing grammar and spelling mistakes (i.e. Antidote and Grammarly)

- Providing definitions of concepts (i.e., the difference between grey literature and peer-reviewed articles)

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