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Advancing Health Equity through AI-Powered Medical Imaging: A Case Study of HealthAI and the Challenges of Accessibility and Bias

Dev R Gupta

Horace Mann

Abstract

This paper explores how artificial intelligence, specifically through the application HealthAI, can be used to address healthcare disparities and advance health equity in medical imaging. The study begins with a literature review focused on diagnostic accuracy, implementation challenges, digital divide issues, and ethical concerns such as bias and data representation. HealthAI is then presented as a case study to show how an AI-powered diagnostic tool can bridge gaps in access to care, especially in underserved regions where radiologist shortages are common. The research analyzes HealthAI's design, accuracy, and implementation through the lens of health equity frameworks from the World Health Organization. Results show that while HealthAI demonstrates high diagnostic accuracy and ease of use, challenges remain around regulatory approval, digital literacy, and ensuring representative data. The discussion connects these findings to broader themes in the literature, emphasizing the need for transparency, inclusivity, and ongoing evaluation to prevent AI from reinforcing existing disparities. The paper concludes that AI has significant potential to make healthcare more equitable, but this depends on careful attention to accessibility, bias mitigation, and real-world feedback from diverse populations.

Keywords: Artificial Intelligence, Health Equity, Medical Imaging, Healthcare Disparities, Digital Divide

Introduction

Artificial intelligence is emerging as a transformative force in healthcare, with the potential to significantly impact health equity and accessibility across diverse populations. In medical imaging diagnostics, AI's pattern recognition and machine learning applications enable it to deliver quick and accurate diagnoses, offering innovative solutions to address critical gaps in healthcare delivery (Pinto-Coelho, 2023). In underserved areas where access to healthcare professionals is limited, AI's ability to automate diagnostics is addressing critical challenges like radiologist shortages and delayed diagnoses. Such AI-powered diagnostic tools, particularly those focused on health equity, offer transformative potential to improve healthcare accessibility and reduce disparities in underserved communities.

Chest X-ray diagnostics powered by AI are especially impactful in advancing health equity, enabling faster identification of diseases such as pneumonia, which remains a leading cause of mortality worldwide (Curtin et al., 2024). HealthAI is one such tool that analyzes X-rays in underserved areas and, using its machine learning capabilities, offers diagnosis for pneumonia while addressing fundamental issues of healthcare accessibility and digital equity. By bridging gaps in healthcare delivery, AI-powered tools like HealthAI demonstrate the potential to advance equity and efficiency in global healthcare systems, particularly when examined through established health equity frameworks.

Medical imaging is a vital part of healthcare, and has become essential for diagnosing a range of diseases such as certain types of cancer, stroke, tumors, among others (Kumar, 2023). However, depending on radiologists to interpret X-rays leads to bottlenecks in healthcare systems, especially in low-resource settings where healthcare disparities are most pronounced (Karera et al., 2024). AI diagnostic tools offer an avenue to address these disparities, with many exceeding 84.8% accuracy in their diagnoses, which is higher than the average for radiologists (Shelmerdine et al., 2022). The digital divide in healthcare, characterized by unequal access to technology and digital literacy, poses significant challenges to equitable healthcare delivery (Li et al., 2025). HealthAI, which has an accuracy of 90% on pneumonia detection and costs nothing to use, exemplifies how such tools can help bridge both the healthcare gap and the digital divide in underserved regions.

Despite the growing adoption of AI in medical imaging, there is limited research connecting recent advancements in AI to health equity frameworks and their practical applications in addressing healthcare disparities. Existing literature provides valuable insights into themes such as diagnostic accuracy, healthcare accessibility, and AI-enabled data-driven environments (Bennani et al., 2023), yet fails to systematically examine these developments through the lens of established health equity frameworks. While many studies focus on the technical performance of AI models or theoretical discussions on their potential, there is insufficient analysis linking these themes to specific case studies that demonstrate real-world relevance to health equity goals. This paper addresses this gap by analyzing recent literature on AI in medical imaging through a health equity lens and presenting HealthAI as a case study to illustrate how emerging AI technologies can either advance or hinder health equity goals. It also showcases HealthAI's role as an accessible diagnostic tool for pneumonia detection in underserved regions, examining its impact on healthcare disparities and digital accessibility.

This paper will evaluate recent themes in AI-powered medical imaging through a systematic literature review and a case study on HealthAI's application for chest X-ray diagnostics, specifically focusing on health equity implications. It will analyze how HealthAI aligns with key health equity frameworks, including the World Health Organization's Health Equity Framework, examining diagnostic accuracy, healthcare accessibility, and AI-enabled data-driven environments through the lens of equity and inclusion. The study will also address critical issues of digital divide, infrastructure requirements, and accessibility barriers that may either promote or hinder equitable healthcare delivery.

By synthesizing insights from existing research and analyzing case study data on the HealthAI app through established health equity frameworks, this paper seeks to provide an extensive overview of AI adoption in medical imaging while demonstrating how accessible tools like HealthAI can either contribute to or detract from equitable healthcare delivery globally. The analysis will specifically examine how AI tools can address healthcare disparities while considering the challenges posed by digital divides, infrastructure limitations, and accessibility barriers that may prevent equitable implementation.

Methods

The methodology for this paper integrates a literature review with a thematic case study of HealthAI, a chest X-ray AI diagnostic app, to develop synthetic insights combining themes in the literature with their real-world applications through a health equity lens. This approach allows for examination of how AI technologies can either advance or hinder health equity goals in practice.

Literature Review

An intensive literature review was conducted to identify and analyze established and emerging themes in the adoption of AI in healthcare, with a specific focus on health equity, accessibility, and digital divide considerations.

In terms of keywords, the Primary Terms employed were:

- "Artificial Intelligence" OR "AI"
- "Machine Learning" OR "Deep Learning"
- "X-ray diagnostics" OR "Radiology" OR "Medical Imaging"
- "Healthcare accessibility" OR "Global health equity"
- "Diagnostic accuracy" OR "Sensitivity and specificity"

Secondary Terms were expanded to include health equity-specific terminology:

- "Bias mitigation" OR "Algorithmic fairness"
- "Ethics in AI" OR "Regulatory frameworks"
- "Low-resource settings" OR "Underserved populations"
- "Digital divide" OR "Health equity"
- "Infrastructure requirements" OR "Accessibility barriers"

To develop a robust search strategy which gave relevant papers, the primary and secondary terms were discussed in combinations using boolean operators such as:

- ("Artificial Intelligence" AND "X-ray diagnostics")
- ("Machine Learning" AND "Healthcare accessibility")

- ("Diagnostic accuracy" AND "Bias mitigation")
- ("Health equity" AND "Digital divide")
- ("AI" AND "Healthcare disparities")

To further refine the papers included, inclusion and exclusion criteria were formed. The inclusion criteria were dependent on 4 factors: timeframe, study types, focus areas, and language the paper was written in. In terms of timeframe, only studies published in the last 5 years, i.e., 2019-2024, were considered relevant for inclusion. The reason for this is that studies before 2019 do not accurately reflect the development and growth of AI in healthcare and AI abilities in general, particularly in addressing health equity concerns. With the advent of new AI tools in the last 5 years, the landscape of AI in healthcare has changed dramatically, and this paper aims to show the current landscape reflected by the developments in the last 5 years. Secondly, only peer-reviewed articles, systematic reviews, meta-analyses, clinical trials, and guidelines were considered in the literature review. This comprehensive list covers most forms of academic writing that can inform the literature review. Other forms lack credibility or focus in the area of the literature review. The third aspect of the literature review is the narrowing down of the focus areas of the papers considered. More specifically, papers were only included if they matched on one or more of these focus areas:

- AI/ML applications in X-ray diagnostics
- Ethical considerations, bias, or equity in AI healthcare tools
- Real-world implementation challenges in low-resource settings
- Digital divide and accessibility barriers in healthcare AI
- Health equity frameworks and measurement approaches

The reason for this expanded focus is that by covering these areas, the literature review can thoroughly analyze and identify the recent themes of AI in healthcare through a health equity lens. By constraining the focus to AI/ML applications in X-ray diagnostics, the papers found will be able to address topics such as accuracy, implementation, and how such tools relying on AI/ML are working in X-ray diagnostics as well as offering a parallel to HealthAI which also relies on AI/ML applications for its diagnostics. By considering the ethical considerations, the literature review can address one of the biggest worries and barriers to real-world implementation of AI in healthcare while examining how digital divides may exacerbate existing inequities. By considering papers that focus on real-world implementation challenges, especially in low-resource settings, the literature review will be able to address the practical process and restrictions of AI in healthcare in these settings where equity concerns are most pronounced. The addition of digital divide and health equity framework focus areas ensures comprehensive coverage of accessibility barriers and measurement approaches that are central to evaluating equitable healthcare delivery. Lastly, the inclusion criteria requires the paper to be in English.

Apart from inclusion criteria, there are also exclusion criteria that had to be addressed for a paper to be considered a part of the literature review. As part of the exclusion criteria, any papers published before 2019 were excluded, this is in line with the inclusion criteria and the reasoning is the same—recent advancements in AI over the last 5 years render papers published before as not accurately reflecting the current state of AI adoption in healthcare and its impact on health equity. Similarly, any non-peer reviewed articles were also excluded; the literature review only wants to consider works which are credible and academic in nature to ensure the review is as comprehensive and relevant as possible. Papers focused on other topics around AI such as AI in finance or engineering were also not considered as that does not pertain to the discussion of this paper. Lastly, studies which arise from regions where the reliability of the data is an issue, for example warzones, were also excluded as without reliable and credible data, the extrapolations the study draws might also be flawed.

The last part of the search strategy for the literature review is the databases and journals that were used. The primary databases that were used are:

- Academic Search Ultimate
- ScienceDirect
- ProQuest Central
- JSTOR
- PubMed/PMC

Apart from the primary databases mentioned above, other open access sources were also used. They are:

- Journal of Medical Internet Research AI
- Nature Partner Journals Digital Medicine
- BMC Medical Informatics and Decision Making
- BMJ

The reason behind picking these databases and journals is two-fold. Firstly, the primary databases used are selected because those were the ones the researcher had access/membership to. All of the primary databases chosen also have relevant papers in relation to the topics discussed in this research paper. These databases are reputable journals and publications which further makes their content more useful and reliable for literature analysis. To supplement the primary databases, secondary databases which were open access were also used. The reason for supplementing the primary databases with these open-source ones is because all the primary databases, while very credible and large, are not exclusively focused around AI in healthcare or healthcare in general (e.g., JSTOR, ScienceDirect). By also including open access journals whose main focus lies in AI in healthcare or healthcare in general, there is a higher chance of finding relevant studies for the literature review. All the supplemental journals chosen are also highly acclaimed in the healthcare field and are extremely credible sources of information, therefore including them enhances the literature review.

Case Study

As part of addressing the gap in current research as mentioned before, a case study-based approach that converges with the literature review was used, specifically focusing on health equity implications. A case study approach involves analyzing a practical application and how it relates to the themes of the research paper through established health equity frameworks. Therefore, in this case, the case study-based approach involved analyzing HealthAI, a practical application of AI in medical imaging, and how AI is being used to address gaps in healthcare systems, especially in low-resource settings, while examining its impact on health equity and digital accessibility.

The reason for using a case study-based approach is to address the research gap identified in current literature surrounding AI's use in healthcare and its impact on health equity. The research gap is insufficient analysis linking emerging themes of AI in healthcare to specific case studies that demonstrate real-world relevance to health equity goals and digital accessibility. Thus, to fill this gap, a case study-based approach was required as through that, themes discussed in the literature review could be connected to a real-world application and evaluated through health equity frameworks. Further, as described by Robert K. Yin in his book "Case Study Research: Design and Methods, Edition 3," case study-based approaches "are the preferred strategy when 'how' or 'why' questions are being posed," and "when the focus is on a contemporary phenomenon within some real-life context" (Yin, 2014). In the case of this research paper, the focus is on addressing how AI in healthcare can either advance or hinder health equity goals and how it can help bridge healthcare disparities while navigating digital divides and accessibility barriers. Furthermore, the paper discusses this within the real-life context of healthcare equity as well as the practical application of AI in healthcare with HealthAI.

HealthAI

HealthAI is an AI-powered diagnostic tool specializing in pneumonia detection and diagnosis that addresses critical health equity challenges in underserved populations. HealthAI was developed by Dev R Gupta and Anay Sharma. The initial model for HealthAI that diagnoses pneumonia was made in the month of January 2025, with the service going live a month after. The development of the model took 3 months. The aim of HealthAI is to bridge gaps in healthcare in underserved areas and address digital divide issues that prevent equitable access to diagnostic services. It does so by diagnosing X-rays in underserved areas free of cost, allowing people to receive diagnostic care who otherwise may not have the resources to do so, thus directly addressing economic barriers to healthcare access. The model itself is a DenseNet CNN model that has been trained on images of both normal X-rays and infected X-rays which have pneumonia. The model is trained on a dataset of pneumonia images and normal images by the University of California San Diego. Due to the reliable nature of the source of the dataset, it is a highly credible and reliable source of information. The use of HealthAI relies on users inputting their X-ray examinations into the HealthAI website, which then uses its machine learning model to give a percentage chance of the X-ray having pneumonia, for example: 87% chance of having pneumonia.

To connect the emerging themes from the literature review to practical applications through a health equity lens, an analysis of HealthAI was conducted using established health equity frameworks, particularly the WHO Health Equity Framework. Factors such as how applications like HealthAI serve to bridge diagnostic gaps in underserved areas while addressing digital divide issues, how they serve as an example of how AI can advance health equity goals, accessibility barriers and infrastructure requirements, as well as more technical aspects such as data around the accuracy of HealthAI, the datasets it uses, and their potential for bias, were analyzed through the lens of health equity measurement and evaluation frameworks. Here is a link to access HealthAI- https://startups-and-service-med-bobm.onrender.com/

Results

The following 27 Research Papers were used for the literature review -

Table 1.

Summary of Research Papers

Title	Paper Number	Authors	Year Pub.	Date Accessed	Summary

Artificial intelligence in healthcare: transforming the practice of medicine	1	Junaid Bajwa et al.	2021	28 March, 2025	Outlined recent breakthroughs in the application of AI in healthcare, described a roadmap to building effective, reliable and safe AI systems, and discussed the possible future direction of AI augmented healthcare system
Real-world testing of an artificial intelligence algorithm for the diagnosis of chest X-rays in primary care	2	Queralt Miró Catalina et al.	2024	28 March, 2025	Researchers validated an AI chest X-ray algorithm against radiologist diagnoses using 278 images in

					Catalonia. The algorithm showed high accuracy (0.95) and specificity (0.98) but low sensitivity (0.48), requiring additional training for effective clinical use in primary care.
Development and validation of open-source deep neural networks for comprehensive chest x-ray reading: a retrospective, multicentre study	3	Dicente Cida et al.	2024	28 March, 2025	Researchers developed X-Raydar, an open-source AI system for chest X-ray interpretation, using 2.5 million studies from six UK hospitals (2006-2019). The

					system achieved strong performance with mean AUC of 0.919 on auto-labelled data and outperformed historical radiologists on 27 of 37 findings, demonstrating robust generalization across datasets.
GAO Report: AI in Medical Diagnostics	4	U.S. Government Accountability Office & National Academy of Medicine	2022	28 March, 2025	The U.S. Government Accountability Office and National Academy of Medicine jointly published a

report examining AI/ML technologies in healthcare diagnostics, focusing on benefits like earlier disease detection and challenges including technological and regulatory questions. The report addressed the critical need for healthcare system efficiency as annual spending approaches $6.8 trillion by 2030.

Redefining Radiology: A Review of Artificial Intelligence Integration in Medical Imaging	5	Reabal Najjar	2023	28 March, 2025	This comprehensive review traced AI's integration into radiology from X-ray discovery to modern machine learning applications, examining AI's roles in image segmentation, computer-aided diagnosis, and workflow optimization across multiple medical disciplines. The review identified key challenges including data

					quality issues, the "black box" problem, and ethical implications, while advocating for continued research and collaboration between radiologists and AI developers.
A translational perspective on clinical AI fairness	6	Liu et al.	2023	28 March, 2025	This perspective paper examined AI fairness in clinical contexts, arguing that traditional fairness approaches focused on equality across demographic

subgroups are misaligned with healthcare needs where clinical differences may be justified. The authors advocated for "equity" rather than "equality" as the appropriate objective, emphasizing the need for multidisciplinary collaboration between AI researchers, clinicians, and ethicists to develop clinically relevant fairness frameworks.

Ethical and Social considerations of applying artificial intelligence in healthcare: A Two-Pronged Scoping Review	7	Ratti et al.	2025	28 March, 2025	This scoping review examined ethical and social considerations of AI in healthcare using a novel two-pronged approach: one reviewing recent academic literature (2021-2023) and another analyzing systematic reviews over a longer timeframe (2014-2024). The authors found that general ethical principles become inadequate for addressing the nuanced ethical issues arising as

					AI transitions from theoretical discussion to real-world healthcare applications.
Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations	8	Seyyed-Kalantari et al.	2021	28 March, 2025	This study examined algorithmic bias in chest X-ray AI systems across multiple datasets, finding that state-of-the-art computer vision classifiers consistently underdiagnosed diseases in under-served populations including female, Black, and low

					socioeconomic status patients. The researchers discovered higher underdiagnosis rates for intersectional groups like Hispanic female patients, raising concerns about AI systems potentially exacerbating existing healthcare disparities.
Federated learning for multi-center imaging diagnostics: a simulation study in cardiovascular disease	9	Akis Linardos et al.	2022	28 March, 2025	Researchers conducted the first federated learning study for cardiovascular MRI diagnosis

					using deep learning, demonstrating that AI models trained across four medical centers with privacy-preserving distributed learning achieved comparable performance to centralized approaches in detecting hypertrophic cardiomyopathy.
GPT-4 in Radiology: Improvements in Advanced Reasoning	10	Rajesh Bhayana, Robert R. Bleakney, Satheesh Krishna	2023	28 March, 2025	Researchers evaluated ChatGPT's performance on

radiology board-style examinations, finding that GPT-4 significantly outperformed GPT-3.5 and exceeded passing thresholds by over 10%, demonstrating improved AI reasoning capabilities and contextual understanding of radiology-specific terminology, though reliability concerns persist due to occasional "hallucinations."

Deep Chest: an artificial intelligence model for multi-disease diagnosis by chest x-rays	11	Hakan Şat Bozcuk et al.	2024	28 March, 2025	Researchers developed Deep Chest, an AI model using EfficientNetB0 and transfer learning to diagnose multiple thoracic diseases from chest X-rays using 453 images, the model achieved 0.98 AUC, 0.98 sensitivity, and 0.83 accuracy. The tool was deployed as a free web application, demonstrating high diagnostic accuracy for

					pulmonary pathologies including masses and nodules, particularly valuable where expert radiological support is limited.
Development and Validation of a Deep Learning-Based Automated Detection Algorithm for Major Thoracic Diseases on Chest Radiographs	12	Eui Jin Hwang et al.	2019	28 March, 2025	Researchers developed and validated a deep learning algorithm to automatically detect major thoracic diseases on chest radiographs using 89,834 images from 62,019 individuals. The algorithm achieved

					0.979 AUC for classification and 0.972 for localization, significantly outperforming all physician groups including thoracic radiologists. When physicians used the algorithm assistance, their diagnostic performance improved substantially across all experience levels.
The Role of Artificial Intelligence in	13	Olena Strubchevska et al.	2024	28 March, 2025	The authors explored artificial intelligence's

Diagnostic Radiology		significant impact on radiology through a comprehensive analysis of eight articles published between 2018 and 2024. They evaluated AI's diagnostic accuracy in radiological image interpretation, examined its advantages and disadvantages, assessed future development prospects, and considered GPT-4's potential for radiology image analysis. The study

					concluded that AI represents a revolutionary medical tool capable of transforming diagnostic strategies to improve healthcare quality.
Radiologists Outperformed AI in Identifying Lung Diseases on Chest X-Ray	14	Plesner et al.	2023	28 March, 2025	Researchers compared four commercially available AI tools with 72 thoracic radiologists in interpreting 2,040 consecutive adult chest X-rays from four Danish hospitals. While

AI tools achieved moderate to high sensitivity (62-95%) for detecting airspace disease, pneumothorax, and pleural effusion, radiologists outperformed AI systems by producing fewer false-positive results and maintaining better diagnostic accuracy in complex, real-life clinical scenarios with multiple findings present.

AI-Driven Thoracic X-ray Diagnostics: Transformative Transfer Learning for Clinical Validation in Pulmonary Radiography	15	Md Abu Sufian et al.	2024	28 March, 2025	Researchers evaluated advanced AI methodologies using DenseNet121 and ResNet50 on 108,948 chest X-ray images from 32,717 patients to enhance diagnostic accuracy in pulmonary radiography. DenseNet121 achieved 94% AUC for pneumothorax and edema detection, surpassing expert radiologists' performance. The

					study integrated natural language processing techniques including LDA, NER (92% precision, 88% recall), and sentiment analysis, reducing processing times by 60% and annotation errors by 75%.
Comparison of Chest Radiograph Interpretations by Artificial Intelligence Algorithm vs Radiology Residents	16	Joy T Wu et al.	2022	28 March, 2025	Researchers compared AI algorithm performance with five radiology residents in interpreting 1,998

chest radiographs using a novel deep learning architecture trained on 342,126 images. The AI achieved comparable sensitivity (0.716 vs 0.720) but superior positive predictive value (0.730 vs 0.682) and specificity (0.980 vs 0.973) compared to residents, demonstrating AI's potential to reach resident-level performance for preliminary chest radiograph

					interpretations in emergency department workflows.
Role of radiologist with the advent of artificial intelligence in medical imaging	17	Anitha Boregowdanapalya	2024	29 March, 2025	The author explored artificial intelligence's transformative role in healthcare radiology, examining how AI enhances diagnostic precision and workflow efficiency through automated analyses and reduced subjectivity. While AI provides

objective, quantitative assessments enabling faster disease detection and lesion classification, the study emphasized that current AI performance remains task-specific, requiring human oversight for accuracy. The research highlighted challenges including algorithm bias, ethical considerations, and regulatory hurdles that must

					be addressed for responsible AI implementation in clinical workflows.
Using AI to Improve Radiologist Performance in Detection of Abnormalities on Chest Radiographs	18	Souhail Bennani et al.	2023	29 March, 2025	Researchers evaluated AI assistance (ChestView; Gleamer) impact on 12 radiologists of varying expertise levels interpreting 500 chest radiographs with 522 abnormalities. AI assistance significantly improved sensitivity for

detecting pneumothorax (26% increase), consolidation (14%), lung nodules (12%), pleural effusion (8.5%), and mediastinal masses (5.9%), while also increasing specificity for most conditions and reducing reading time by 31% from 81 to 56 seconds across all radiologist experience levels.

Deep learning improves physician accuracy in the comprehensive detection of abnormalities on chest X-rays	19	Pamela G. Anderson et al.	2024	29 March, 2025	Researchers developed and evaluated an FDA-cleared AI system using deep learning for comprehensive chest X-ray abnormality detection and localization. The AI achieved high accuracy (AUC: 0.976) and generalized well to public datasets (AUC: 0.975). When physicians used AI assistance, their abnormality detection significantly

					improved (AUC difference: 0.101, p < 0.001), with non-radiologist physicians achieving radiologist-level accuracy while evaluating chest X-rays faster, demonstrating AI's potential to improve diagnostic access and quality.
Diagnostic Performance of Artificial Intelligence in Chest Radiographs Referred from the	20	Julia López Alcolea et al.	2024	29 March, 2025	Researchers evaluated AI software (Arterys MICA v29.4.0) performance against a radiology resident in

Emergency Department	interpreting 784 emergency department chest X-rays, using senior radiologist assessment as gold standard. AI achieved high sensitivity for fractures and pneumothorax (100%), moderate for pulmonary opacity (76%), acceptable for pleural effusion (60%), but low for pulmonary nodules (33%). The study found AI's high negative predictive values (>95%) suggest screening

					utility, though additional training is needed for broader clinical applicability.
Change or No Change: Using AI to Compare Follow-up Chest Radiographs	21	Julianna Czum	2023	29 March, 2025	This editorial discussed a deep learning AI algorithm developed by Yun and Ahn et al that assessed stability between baseline and follow-up paired chest radiographs using 3.3 million chest X-rays from 329,036 patients over seven years. The AI achieved

AUC of 0.77-0.80 for discriminating change versus no change, with 88-90% specificity at higher triage rates. While the author acknowledged AI's potential to help manage radiologist burnout and increasing workloads, limitations included exclusion of device changes and single-institution data raising generalizability concerns.

AI-based radiodiagnosis using chest X-rays: A review	22	Yasmeena Akhter et al.	2023	29 March, 2025	The authors provided a structured review of AI/ML-based chest X-ray analysis systems for diagnosing various lung diseases including pneumonia, tuberculosis, pneumoconiosis, COVID-19, and lung cancer. Despite 2 billion CXRs performed annually worldwide, workforce limitations particularly affect developing

nations. The review examined challenges facing AI diagnostic systems including small sample sizes, data privacy, poor quality samples, adversarial attacks, and model interpretability requirements, while providing an overview of existing datasets, evaluation metrics, patents, and identifying key open research problems.

Deep Learning for Automated Triaging of Stable Chest Radiographs in a Follow-up Setting	23	Jihye Yun et al.	2023	29 March, 2025	Researchers developed and validated a deep learning algorithm using thoracic cage registration and subtraction to triage paired chest radiographs for longitudinal follow-up, utilizing 3.3 million chest X-rays from 329,036 patients over eight years. The algorithm achieved AUCs of 0.77-0.80 across validation and test sets, with 88-90% specificity at 40% triage

					threshold for identifying "no change" cases. For urgent findings like consolidation, pleural effusion, and pneumothorax, specificity ranged from 78.6%-100%, demonstrating potential for automated triaging in emergency and ICU settings.
Generative Artificial Intelligence for Chest Radiograph Interpretation in the Emergency Department	24	Jonathan Huang et al.	2023	29 March, 2025	Researchers evaluated an AI model's ability to generate chest X-ray reports in emergency

					departments. The AI produced reports with similar clinical accuracy and quality to radiologist reports, while outperforming teleradiology reports in textual quality across 500 patient cases.
Association of Artificial Intelligence–Aided Chest Radiograph Interpretation With Reader Performance and Efficiency	25	Jong Seok Ahn et al.	2022	29 March, 2025	Researchers tested whether AI assistance improved radiologists' performance in interpreting chest X-rays. Six

					radiologists evaluated 497 chest radiographs with and without AI support. AI assistance significantly improved detection sensitivity for all findings and reduced reporting time by 10%.
Artificial Intelligence Applied to Chest X-ray: A Reliable Tool to Assess the Differential Diagnosis of Lung Pneumonia in the	26	Davide Ippolito et al.	2023	29 March, 2025	Researchers tested an AI system's ability to differentiate between COVID-19 pneumonia, bacterial pneumonia, and

Emergency Department					healthy patients using chest X-rays in emergency departments. The AI achieved 93.8% accuracy with excellent sensitivity and specificity, demonstrating strong performance comparable to experienced radiologists.
Performance of a Breast Cancer Detection AI Algorithm Using the Personal Performance in	27	Yan Chen et al.	2023	29 March, 2025	Researchers compared AI algorithm performance against human readers using the

Mammographic Screening Scheme	PERFORMS mammographic screening test sets. The AI showed comparable diagnostic performance to average human readers, with similar sensitivity (84-91%) but higher specificity (89% vs 76%) in breast cancer detection.

Throughout the paper, along with citations, paper numbers will be used to communicate which paper is being referred to.

Literature Review

Diagnostic Accuracy and Implementation Through a Health Equity Lens:

All studies in the literature review discussed how diagnostic accuracy is one of the main themes of AI in healthcare, with particular implications for health equity and accessibility. The reason for this is that AI is extremely well versed in pattern recognition making it useful in the radiology/imaging world where AI can diagnose diseases from medical images with high accuracy. Due to the predicted shortage of healthcare professionals and short supply of radiologists, many believe that AI can help address these gaps by one of two things: firstly, replacing the need for radiologists as a whole or secondly acting as a supplementary tool for radiologists to use to increase their overall efficiency. From a health equity perspective, this diagnostic capability has significant implications for addressing healthcare disparities, particularly in underserved communities where radiologist shortages are most acute.

Upon analysis, no paper thought that the first was a possibility in the upcoming future citing ethical and technical limitations to AI. In this case the diagnostic capability of AI is not a problem, in fact, a study said "Studies have demonstrated AI's ability to meet or exceed the performance of human experts in image-based diagnoses from several medical specialties including pneumonia in radiology" (Bajwa et al., 2021). As discussed, the paper talks about how AI has achieved greater or similar accuracy to human radiologists in studies which could allow its replacement of radiologists. Rather, the issue in this case is that AI itself needs to be monitored and requires oversight to be effective. As paper 18 stated, "Radiologists play a pivotal role in validating AI tools and advocating for their responsible implementation, ensuring that AI enhances clinical workflows without compromising the essential human connection in healthcare" (Bennani et al., 2023). However, from a health equity standpoint, even with required oversight, AI tools can serve as significant equalizers by providing diagnostic capabilities to areas where radiologist access is limited or non-existent.In a timeline drawn up by a study for the next 10 years, the authors only predicted complete AI integration but not replacement of radiologists (Bajwa et al., 2021).

AI as a Partner to Radiologists in Advancing Health Equity:

The second way of AI addressing gaps in radiologists by acting as a supplementary tool for radiologists to increase the efficiency of workflows is far more likely and already in motion, with significant health equity implications. On this topic, paper 5 brought to attention a study that shows "AI significantly streamlines the acquisition of radiologist analyses on chest X-rays, as evidenced by a study wherein an AI system reduced interpretation delivery times from 11.2 days to a mere 2.7 days, reinforcing the potency of automated triaging systems in streamlining healthcare workflows and amplifying patient care standards" (Najjar, 2023). This efficiency improvement is particularly valuable in underserved settings where delayed diagnoses can have disproportionate impacts on vulnerable populations. As shown by the results of the study and opinions of other papers on AI, the current thought is that AI with its diagnostic accuracy should be used as a supplement to radiologists where radiologists provide key oversight to make sure the tool is effective while also extending diagnostic capabilities to historically underserved communities.

Implementation Hurdles and Digital Divide Considerations:

However, there are also other issues regarding the implementation of AI in healthcare that have particular relevance to health equity. This is shown in paper 4 which outlined some of the challenges in the actual implementation of AI technologies. The main problems while implementing these technologies were FDA approval, trust and education, and data access (United States Government Accountability Office et al., 2022). From a health equity perspective, these challenges are compounded by the digital divide, which creates additional barriers for underserved populations in accessing AI-powered healthcare solutions.

In terms of the first problem, the "Reluctance of healthcare providers ("HCPs") to adopt technologies that have not been reviewed by FDA or adequately validated," renders many algorithms moot. Paper 4 showed that "The GAO cited a review of 516 studies evaluating image-based AI algorithms that found that 94% of these studies were inadequate to validate the algorithms" (United States Government Accountability Office et al., 2022). As this quotation indicates, many algorithms do not have FDA approval and without that it makes healthcare providers not implement these technologies in their own practice. The digital divide further exacerbates this issue, as safety-net organizations and underserved communities may lack the resources to properly evaluate and implement AI technologies even when they receive regulatory approval.

Further, healthcare providers are found to be hesitant in implementing technologies if they are not able to understand the limitations and biases of the tool or are not presented with "clinical evidence about the technology's performance". This concern is particularly acute in the context of health equity, as algorithmic bias can systematically disadvantage certain demographic groups, potentially worsening existing healthcare disparities. Thirdly, there are issues around data accessibility to actually be able to build out these AI powered models, like Paper 4 said there are challenges in accessing high quality, real world data to actually train and test models on (United States Government Accountability Office et al., 2022). These data challenges are particularly problematic for ensuring health equity, as underrepresented populations may be excluded from training datasets, leading to AI systems that perform poorly for these groups.

Ethical and Bias Concerns in Health Equity Context:

A concern on the forefront of AI in healthcare is the ethical and bias concerns that come with the adoption of AI, with particular implications for health equity. Concerns around the bias of AI models is a main theme of AI in healthcare. The main sources of bias as discussed in papers 6 and 7 have significant health equity implications. First is data underrepresentation, this topic revolves around the lack of data for certain subgroups of people which influences AI models making them biased (Liu et al., 2023). This underrepresentation particularly affects marginalized communities and can lead to AI systems that systematically underperform for these populations, potentially exacerbating existing health disparities.

Secondly, as explained in paper 6, "any historical (and existing) bias in medical practice can be reflected in medical records, e.g., underdiagnosis and undertreatment of postpartum depression has been observed among minorities on Medicaid, which will bias the resulting prediction models in similar ways if not carefully handled" (Liu et al., 2023). This historical bias embedding is particularly concerning from a health equity perspective, as it can perpetuate and amplify existing healthcare disparities through AI systems. Research has shown that AI algorithms can systematically underdiagnosed diseases in underserved populations, including female, Black, and low socioeconomic status patients, with even higher underdiagnosis rates for intersectional groups like Hispanic female patients.

Thirdly, there are concerns around data preprocessing where mistakes around the data entered for the model could result in bias, for example, not accounting for overlapping subjects when mixing datasets. Apart from some of the main concerns around bias, there are also significant ethical concerns that arise with AI in healthcare from a health equity perspective. Apart from some of the main ethical concerns like accountability, privacy, and transparency there are also other important concerns discussed in paper 7 such as the potential deskilling of healthcare professionals, and unequal access to resources in underserved areas due to issues like internet access (Ratti, 2025). The digital divide in healthcare access is particularly problematic, as many underserved communities lack the necessary digital infrastructure to benefit from AI-driven healthcare solutions.

In terms of accountability, concerns arise around AI offering wrong diagnosis with no one being held accountable in such a situation. Similarly, there are issues around transparency of AI models, the low transparency on most models make identifying issues and biases of the algorithm difficult. These transparency issues are particularly concerning from a health equity perspective, as they make it difficult to identify and address biases that may disadvantage certain populations. Further, there are concerns around the privacy of patients both who use the AI and those whose data is being fed into the AI. Moreover, if AI is widely implemented there may be a shortage of healthcare professionals due to the reliance on AI, people may be discouraged to work as radiologists or professionals. This would be a harmful scenario because as discussed in the last section AI needs oversight to be effective and without skilled radiologists AI may become obsolete.

Lastly, ethical concerns around the unequal access to AI models exist, for example, people in underserved areas may not have access to resources like the internet which may hamper their access to AI care. Unfortunately, these areas need AI the most due to the lack of radiologists in these areas. This creates a paradox where AI tools that could help reduce health disparities may actually exacerbate them if not implemented with careful attention to digital equity and accessibility.

Solutions and Safeguards Through Health Equity Frameworks:

To address these issues, several solutions have to be implemented with particular attention to health equity considerations. First and foremost, robust regulatory frameworks must be implemented which regulate how AI is used in healthcare while ensuring equitable access and performance across demographic groups. Secondly, papers 6 and 7 outline how gaps between clinicians and developers of AI tools cause several of the bias problems listed above. With more conversation between the multiple stakeholders involved with the AI and patients such concerns can be mitigated. This is particularly important for health equity, as it ensures that the perspectives and needs of underserved communities are incorporated into AI development processes.

Thirdly, concerns around data and bias in data must be solved, this could be through procurement of additional data, more regulation etc. From a health equity perspective, this means ensuring that training datasets are representative of diverse populations and that AI systems are validated across different demographic groups. The WHO Health Equity Framework provides guidance on how to systematically assess and address these data representation issues. Lastly, AI developers and radiologists must be educated more on the ethical concerns of AI and how to use AI effectively for the future while considering health equity implications (Liu et al., 2023).

Case Study on HealthAI Through Health Equity Analysis

Diagnostic Accuracy and Implementation in Health Equity Context:

As mentioned in the methods section, HealthAI does image analysis on X-rays, diagnosing them for pneumonia, with particular relevance to health equity goals. Patients upload their X-ray into the platform and then HealthAI can inform them about the chance of them having a disease, in this case pneumonia. HealthAI is able to come to a diagnosis of a X-ray using its pattern recognition skills. More specifically, HealthAI at its core is a DenseNet CNN model with both "relu" and "sigmoid" activation that has been trained on images of both normal X-rays and X-rays with pneumonia. In this case, HealthAI has an accuracy of 93.1% on its training dataset and a 86% accuracy on a new dataset that it was not trained on. Further, the false positive rate of the model is 0.0451.

In terms of implementation from a health equity perspective, HealthAI is extremely useful for use in underserved areas such as low-middle income countries where access to radiologists or the supply of radiologists is scarce. According to the WHO Health Equity Framework, such tools can help address fundamental barriers to healthcare access that contribute to health disparities. It further extends to even first world countries in places where there might be delays in accessing diagnostic care. The reason why HealthAI is useful in these underserved areas where access to diagnostic care is limited is the simple design and process of using HealthAI as well as HealthAI's capability, which aligns with digital health equity principles that emphasize accessibility and usability.

Firstly, the use of HealthAI is very simple, all that is needed is an X-ray and device, the user has to only upload the image of the X-ray to receive a diagnosis. Secondly, since the process relies on a machine learning model and not a radiologist's input it is useful without any external resources. This approach is particularly impactful because it enables a broader reach for diagnostic services, especially in settings where healthcare infrastructure is lacking, directly addressing the social determinants of health that contribute to health inequities. The simplicity of the upload process, requiring only a digital image of the X-ray and an internet connection, means that even users with minimal technical skills can benefit from the system, though digital divide considerations remain important.

The high accuracy rates of 93.1% on the training set and 86% on an external dataset underscore the reliability of HealthAI in detecting pneumonia from X-ray images. However, from a health equity perspective, it is crucial to examine whether these accuracy rates are consistent across different demographic groups, as research has shown that AI systems can exhibit differential performance based on race, gender, and socioeconomic status. The low false positive rate of 0.045 further supports the model's clinical utility, minimizing unnecessary anxiety or follow-up procedures for patients who do not actually have pneumonia. This is especially important in resource-constrained environments, where every diagnostic and treatment decision carries significant weight and where false positives can strain limited healthcare resources.

AI as a Partner to Radiologists in Advancing Health Equity:

HealthAI as discussed previously is very impactful in underserved areas where access to radiologists is limited, however, a very prominent use case of HealthAI is to be used in partnership with radiologists to make their process/workflow quicker and more accurate, leading to both more lives saved and overall efficiency in their workflows. In this way HealthAI can serve as a valuable partner for radiologists in their processes while also being a valuable tool in areas without radiologists, directly supporting the WHO's goal of achieving health equity through improved access to healthcare services.

By being a partner to radiologists, HealthAI could also undergo many advantages such as increased accuracy of its program as well as better use of the algorithm as it would be manned by skilled radiologists and not just patients. This could reduce the risk of incorrect diagnoses harming patients and adds another safety net to the program. From a health equity perspective, this partnership model can help ensure that AI tools are appropriately validated and calibrated across different populations, reducing the risk of perpetuating healthcare disparities. Similarly, it adds a safety net to radiologists' diagnoses as well as it gives them a second opinion, which improves their decisions as well.

This point around providing a second assessment is extremely impactful because this is a very frequent and emphasized problem that many radiologists sometimes suffer through. In high volume areas especially, radiologists need a second decision many times as due to fatigue and tiredness they may make mistakes, further AI is trained to detect anomalies that even skilled radiologists might miss. By giving a second decision radiologists can bypass these issues of fatigue and high volume as well as be able to know of subtle anomalies which they themselves might not be able to pick up but HealthAI can. This is particularly important in underserved settings where radiologist workload may be higher and resources more limited.

Implementation Hurdles and Digital Divide Considerations:

In terms of implementation hurdles, HealthAI has faced a few major implementation hurdles that have particular relevance to health equity. The first one is regulatory approval from the FDA, the reason this is a hurdle is because it is a time and money intensive process. HealthAI is in the process of applying for FDA approval to be able to implement it widely around the world. From a health equity perspective, regulatory approval processes must ensure that AI systems are validated across diverse populations and do not perpetuate existing healthcare disparities.

The second major hurdle is getting hospitals and patients who could use HealthAI to understand what it is and how to use it, which is particularly challenging in underserved communities where digital literacy may be lower. On this end, many video tutorials, explanations and other materials have been prepared for users and posted on the HealthAI website. There are also plans of having more research oriented materials for healthcare professionals to better understand the strengths and limitations of HealthAI. The digital divide poses significant challenges here, as many underserved communities may lack the digital infrastructure or literacy needed to effectively use AI-powered healthcare tools.

The very intuitive and relatively simple process of getting a X-ray diagnosed on HealthAI which only involves clicking a picture of your X-ray and then uploading it to the platform to get a result further makes it very easy to understand and use for both radiologists and normal patients. However, ensuring digital equity requires addressing infrastructure barriers, language barriers, and digital literacy gaps that may prevent equitable access to these tools. Lastly, getting data around X-rays is an implementation hurdle that HealthAI used to face, however it has combated with access to various validated, declassified X-ray datasets which allow for high-quality results.

Ethical and Bias Concerns Through Health Equity Lens:

HealthAI has a few ethical and bias concerns with the main one being underrepresentation in terms of the data being fed to the model and the data the model is trained on, which has significant health equity implications. The dataset used by HealthAI has a larger focus towards women and children as well as those from Asia primarily, this means that the model may not be that accurate when detecting pneumonia when it comes to men or people from other continents. This type of demographic bias in AI systems is a well-documented concern that can perpetuate healthcare disparities.

However, when tested on images of men and people from other continents, HealthAI did not have a significant drop in accuracy, only dropping by .7%. This suggests that while demographic representation in training data is important, the model may still perform reasonably well across different populations. However, to even better address this issue of bias in the model's training dataset towards women and children, HealthAI plans on integrating more datasets of pneumonia that cover different demographics so that it is better able to generalise between all people. This approach aligns with health equity principles that emphasize the importance of inclusive and representative datasets.

Another major concern is privacy, and using customer data which they feed into the platform to further train models. To avoid issues like this, HealthAI does not download any images that the customer uploads making sure that there are no breaches in privacy, customers also sign a waiver form that further ensures that the customer understands what's happening and can make an informed decision for themselves. From a health equity perspective, privacy protections are particularly important for vulnerable populations who may be more susceptible to discrimination or harm from data breaches.

This is also beneficial for the model in terms of what data it's being trained on, if customer data was being used then that might lead to imbalances in the representation of data in the training dataset which could in fact lead to lower accuracy in other cases. Thus, HealthAI does not use customer data while training its models as its beneficial from both an ethical and bias standpoint, supporting health equity goals by avoiding further skewing of demographic representation in training data.

Use Cases Through Health Equity Framework:

HealthAI has two main use cases as described above, which are being used from the customer standpoint in underserved areas where access to radiologists and other diagnostic services is limited or not available. In this use-case, HealthAI is being embraced by customers with over thousands of website visits, and recommended by doctors in the field. An example is this comment made by Dr. Peter Berardo, a renowned radiologist, "HealthAI is well suited for providing assistance in diagnostic imaging interpretation, particularly in the setting of remote and underserved locations where access to a radiologist is not immediately available".

This use case directly addresses health equity goals by providing diagnostic capabilities to populations that have historically been underserved by healthcare systems. As the comment shows, due to the scarcity of radiologists in many areas where there is a high volume of patients who lack access to diagnostic care, HealthAI can help radiologists be more efficient and also act as a radiologist in certain situations. In this way it can alleviate the burden in these underserved settings by providing highly accurate diagnostics for pneumonia while addressing fundamental barriers to healthcare access.

The second use case is partnering with radiologists themselves to act as a safety net for the algorithm and for radiologists, improving the accuracy of radiologists and making them more efficient by being able to analyze X-rays quicker. In this use case, HealthAI acts as a second opinion to the radiologist which leads to better outcomes overall. From a health equity perspective, this partnership model can help ensure that AI tools are appropriately validated across different populations and do not perpetuate existing healthcare disparities.

Discussion

In this discussion section, the literature review will be applied and looked at through the lenses of the HealthAI case study, with particular focus on health equity implications and the application of established health equity frameworks. One of the main themes covered in the literature review was diagnostic accuracy and implementation, especially considering the data on AI's implementation and benefits in healthcare. From a health equity perspective, HealthAI exemplifies how AI tools can address fundamental barriers to healthcare access that contribute to health disparities.

On this note, HealthAI is a great example of the point around high accuracy due to the benefits machine learning/AI programs have in pattern recognition. It is due to this advantage that HealthAI has a very high accuracy rate of around 93.1% as tested on the training dataset. However, when analyzed through the WHO Health Equity Framework, it becomes crucial to examine whether this accuracy is consistent across different demographic groups, as research has shown that AI systems can exhibit differential performance based on race, gender, and socioeconomic status.

As the literature review discussed in its sections around AI as a partner to radiologists and diagnostic accuracy and implementation, the main use case of AI in healthcare especially medical imaging seems to be as a partner to radiologists instead of an outright replacement of them. In this manner, HealthAI is a tool that acts as a partner to radiologists by giving them a second opinion, thereby acting as a safety net to the radiologists' diagnoses. This partnership model is particularly important from a health equity perspective, as it can help ensure that AI tools are appropriately validated and calibrated across different populations, reducing the risk of perpetuating healthcare disparities.

However, apart from just acting as a partner to radiologists, HealthAI plans on acting as a tool for normal patient use, with a focus on underserved and understaffed areas where access to radiologists and diagnostic care is limited. This approach directly addresses health equity goals by providing diagnostic capabilities to populations that have historically been underserved by healthcare systems. In such places, the simple process of using HealthAI which only involves uploading an image and its quick response time of less than 10 seconds, allows accurate and simple diagnostics. However, the digital divide remains a critical consideration, as many underserved communities may lack the digital infrastructure or literacy needed to effectively use such tools.

Going even further, as the literature review section on use cases commented, full applications that can diagnose various diseases from chest X-rays present an opportunity for models like HealthAI to serve an even larger patient base and provide even more benefits to radiologists. Currently, HealthAI only works for pneumonia but is being developed for a larger model that can diagnose a larger variety of diseases from chest X-rays. From a health equity perspective, expanding diagnostic capabilities while ensuring equitable performance across demographic groups will be crucial for maximizing the tool's impact on reducing healthcare disparities.

The next major theme discussed in both the literature review and case study was implementation hurdles, with particular relevance to health equity. The biggest ones are getting the relevant approval to use these applications as well as the training and education of healthcare professionals on how this tool could be used effectively. However, these challenges are compounded by the digital divide and infrastructure barriers that disproportionately affect underserved communities. On this note, HealthAI is currently in the process of applying for regulatory approval and understanding how other similar solutions are navigating this implementation hurdle.

In terms of education and training, HealthAI's simple interface and diagnosis process allow it to better help patients and professionals understand how they can best use HealthAI addressing a significant barrier to implementation. However, ensuring digital equity requires addressing infrastructure barriers, language barriers, and digital literacy gaps that may prevent equitable access to these tools. Further better data sharing around HealthAI and its performance further helps in strengthening how professionals interact and understand HealthAI.

Data availability and issues with data bias and underrepresentation were also major concerns addressed in the literature review, with significant health equity implications. However, by using a clearly labeled and described dataset from a reliable source HealthAI can address this issue well. The Health Equity Measurement Framework provides guidance on how to systematically assess and address these data representation issues. Further HealthAI conducted tests to see whether the model would end up having a much lower accuracy in X-rays where there was underrepresentation in the demographics of the person whose x-ray it was, for example, males in America. However, the data showed that there was only a minor decrease in the accuracy of HealthAI, showing that in this case, the underrepresentation of certain demographics did not have an outsized impact on the model's accuracy when being used on people of those demographics.

While existing literature covers many topics like diagnostic accuracy and implementation hurdles in great detail, one place where there was a lack of information is how patients themselves are using these applications online and what their views are, particularly from underserved communities. This gap is particularly concerning from a health equity perspective, as understanding patient experiences and barriers to access is crucial for ensuring equitable implementation. Further research around how they interact with such applications and how they use them are valuable pieces of information that can help in better informing the use of AI in healthcare, especially in addressing healthcare disparities.

Previously, research also lacked how to link emerging themes of AI in healthcare to specific case studies that demonstrate real-world relevance, however, this research paper is being addressed. However, even more research should be conducted in this area to better demonstrate different case studies of how AI is being used in the real world as it helps in better informing those making such models. From a health equity perspective, this research should specifically examine how AI tools perform across different demographic groups and settings, and how they can be designed and implemented to reduce rather than exacerbate healthcare disparities.

The analysis of HealthAI through established health equity frameworks, particularly the WHO Health Equity Framework, reveals both opportunities and challenges in leveraging AI to address healthcare disparities. While HealthAI demonstrates significant potential for improving diagnostic access in underserved areas, careful attention must be paid to ensuring equitable performance across demographic groups, addressing digital divide issues, and implementing appropriate safeguards to prevent the perpetuation of existing healthcare disparities.

Conclusion

This case study and analysis of HealthAI are extremely helpful because it is significantly generalizable to other models and uses of AI in medical imaging. While not completely generalizable due to its unique model and use case of patient-driven and radiologist-driven rather than just radiologist lead to some limits to how generalizable it is, to a great degree this analysis of HealthAI applies to other programs in healthcare. Through the literature review, leading themes of AI in healthcare were analyzed and discussed in context with a real-world applicable AI. These themes were diagnostic accuracy and implementation, ethical and bias concerns, use cases of AI in healthcare, and more. As discussed throughout the research paper, AI has a very big impact on healthcare especially as we step into a new era of AI creation and use. AI's pattern recognition skills allow it to be of extremely usability in the medical imaging space as both a supplement and oftentimes replacement to radiologists. There are several concerns about such technology being implemented which range from ethical and bias concerns such as lack of representation to implementation hurdles like lack of knowledge around how to use AI in healthcare. However, the benefits AI delivers in healthcare, especially in medical imaging are too drastic to ignore. HealthAI in particular has a great opportunity to contribute to diagnostics in underserved areas where access to any diagnostic care including radiologists is scarce, thus showing how AI can be used to help in providing access to healthcare around the world.

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