Diagnosing Inequality: The Promise and Limits of AI in Bridging Healthcare Gaps

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Abstract
Healthcare disparities in the United States continue to disproportionately affect low-income individuals, ethnic minorities, migrants, and people with disabilities due to systemic barriers such as limited access to care, provider shortages, and financial constraints. This paper evaluates the effectiveness and limitations of artificial intelligence (AI)-based diagnostic tools in addressing these inequities. Drawing from a comprehensive literature review, AI simulation testing, sensitivity analyses, and qualitative case studies, the study assesses diagnostic accuracy across diverse demographic profiles. Findings indicate that AI systems perform well in identifying single-cause conditions when provided with detailed symptom inputs, but exhibit reduced accuracy in complex or multi-causal cases, especially when training data lack demographic diversity. Disparities in diagnostic outputs by race and age further underscore embedded algorithmic biases. Integration of mobile diagnostic devices and culturally representative datasets improves AI performance in under-resourced settings. The paper concludes with strategic recommendations for algorithm refinement, infrastructure investment, workforce training, and policy integration to ensure that AI technologies contribute meaningfully to healthcare equity.

Key Words: Healthcare disparities; artificial intelligence; diagnostic accuracy; social service integration; algorithmic bias; health equity; underserved populations; digital health ethics

Introduction
Structural Barriers in U.S. Healthcare
Healthcare disparities represent a persistent and urgent challenge in the United States, disproportionately impacting vulnerable populations such as low-income individuals, ethnic minorities, migrants, and people with disabilities. These groups encounter systemic barriers, including high healthcare costs, insufficient insurance coverage, limited access to

specialists, and fragmented care delivery systems. Approximately 8.4% of the U.S. population lacks health insurance (U.S. Census Bureau, 2022). Consequently, underserved populations experience a 40% higher prevalence of chronic conditions, such as diabetes and hypertension, compared to more privileged groups (CDC, 2020). This disparity is reflected in elevated mortality rates; for example, Black adults face a 23% greater risk of premature death from preventable conditions compared to White adults (Office of Minority Health, 2021). In rural areas, these inequities are further compounded by infrastructure deficits, with 14% of rural clinics reporting significant shortages of primary care providers, resulting in delayed diagnoses and suboptimal disease management (National Rural Health Association, 2022). Additionally, food insecurity has been strongly correlated with higher rates of chronic conditions such as diabetes and hypertension, with risk increasing as the severity of food insecurity worsens (US Department of Health and Human Services, 2024).

Economic constraints further impede access to timely care. National healthcare data reveal that 16% of heart failure patients delay essential treatment due to financial limitations. Such delays contribute to an average annual increase of over $8,000 in healthcare expenditures per patient. These challenges affect both elderly and non-elderly populations, underscoring the Systemic impact of financial barriers on health outcomes.

Surveys and national health reports also highlight persistent access issues, including provider shortages and financial instability, which disproportionately affect marginalized communities. For instance, 8.5% of individuals reported delaying medical attention, while 14.7% postponed dental care due to cost. These delays can significantly hinder chronic disease management, emphasizing the need for accessible, affordable healthcare solutions.

While numerous studies have explored AI applications in clinical diagnostics, few have systematically simulated large language models' diagnostic capabilities under data sparsity and demographic variation. This study contributes to the existing literature by modeling how LLMs behave in constrained, low-resource diagnostic environments where patients often present with vague symptoms and incomplete histories. Additionally, the integration of food insecurity as a contextual variable reflects an emerging but underrepresented axis of health inequality in AI evaluation. By exploring model behavior under these conditions and across racial and socioeconomic lines, this paper aims to identify structural biases and limitations that may otherwise go undetected in standard AI benchmarking protocols.

The Role of Artificial Intelligence in Advancing Health Equity

Artificial intelligence (AI) has emerged as a promising short-term strategy to address healthcare disparities. By leveraging large-scale datasets and advanced analytical tools, AI technologies have the potential to enhance

diagnostic accuracy, improve treatment efficiency, and optimize clinical workflows. AI-powered natural language processing (NLP) and computer vision systems have demonstrated strong performance in clinical settings. For example, NLP algorithms can interpret unstructured clinical notes with up to 90% accuracy, aiding in the timely diagnosis of conditions such as cancer and diabetes (Jiang et al., 2021). Similarly, computer vision models now match or surpass human radiologists in identifying abnormalities like tumors or fractures, with AI-assisted mammography reducing false positives by 5.7% and false negatives by 9.4% (Rodriguez-Ruiz et al., 2019).

For underserved populations, these technological advancements offer meaningful opportunities to increase diagnostic consistency, enable earlier detection, and provide access to specialized expertise in low-resource environments. However, several challenges remain. These include algorithmic bias due to unrepresentative training data, infrastructural limitations in underfunded health systems, and ethical concerns related to transparency and data privacy. Overcoming these obstacles is essential to ensure that AI-driven innovations contribute to more equitable healthcare delivery. Prior work by Rajpurkar et al. (2018) demonstrated that deep learning models could match radiologist-level performance in chest X-ray interpretation, underscoring the potential for diagnostic accuracy at scale. Similarly, Esteva et al. (2017) showed optimal performance in skin cancer classification, illustrating how computer vision in dermatology may reduce disparities in access to specialist care.

This paper examines the application of AI in medical diagnostics and its potential to reduce healthcare disparities. Through a review of current methodologies, empirical performance assessments, and real-world case examples, this research identifies both the limitations and opportunities of AI deployment in resource-constrained contexts. Finally, the paper offers policy and research recommendations aimed at expanding representative datasets, refining algorithmic fairness, and fostering interdisciplinary collaboration to realize AI's potential in promoting health equity.

Evaluating Diagnostic Accuracy Across Demographics
Simulation Protocol

To improve the clarity and rigor of our simulation methodology, we implemented a structured, repeatable framework to guide AI-based diagnostic testing using large language models (LLMs) such as ChatGPT and Google Gemini. Each simulation followed a consistent format: a defined patient demographic profile (age, sex, ethnicity), a set of primary symptoms, symptom duration, and limited medical history when applicable.

The diagnostic input was initially minimal—typically one to two key symptoms without detailed history—to reflect conditions commonly seen in low-resource or fragmented care settings. Subsequent iterations of the

same case incrementally included additional relevant symptoms and contextual data. This approach allowed for an observation of how diagnostic suggestions evolved as the model was exposed to more complete information.

Inputs were selected based on published case study patterns and clinical heuristics, with conditions such as malaria revised to include more realistic combinations of symptoms, such as fever, chills, and recent travel to endemic regions. The purpose of this framework was not to establish definitive performance benchmarks, but to simulate plausible clinical encounters in under-resourced scenarios and identify how AI models respond to variations in data availability and specificity. All diagnostic cases used in this study were simulated and did not involve real patient data. No protected health information was used, and all scenario designs were based on published case patterns and publicly available guidelines.

While overall sensitivity and specificity values were captured for general diagnostic performance, further stratification across race, gender, and age was conducted. For example, AI systems yielded a 90% sensitivity in malaria detection for White patients versus 82% in comparable Black patient simulations, suggesting that even in high-performance cases, diagnostic parity was not fully achieved. These discrepancies underscore the need for performance benchmarking disaggregated by demographic group.

The accuracy and equity of AI diagnostic tools were assessed using a multi-method approach that included literature review, AI simulation testing, sensitivity analyses, and real-world case studies.

Literature Review

A comprehensive review of scholarly and institutional sources—such as publications from the Centers for Disease Control and Prevention (CDC), World Health Organization (WHO), and peer-reviewed journals—was conducted to identify key demographic variables influencing diagnostic outcomes, including age, gender, ethnicity, and socioeconomic status. Case studies involving conditions such as Familial Mediterranean Fever and PTSD provided contextual benchmarks for evaluating AI-generated diagnoses. Statistical methods, including chi-square analyses, quantified disparities in diagnostic accuracy across diverse populations.

AI Simulation Testing

Diagnostic scenarios were developed and tested using established AI platforms, including ChatGPT and Google Gemini. Each scenario began with minimal symptom input and incrementally expanded to evaluate the effect of additional clinical detail on diagnostic precision. To assess algorithmic bias, demographic parameters—such as age, ethnicity, and gender—were systematically varied. Cross-platform comparisons were also conducted to evaluate consistency, reliability, and reproducibility.

Sensitivity Analysis

Robustness testing involved the variation of symptom combinations and demographic characteristics to determine their influence on diagnostic outcomes. All datasets were anonymized in accordance with ethical research guidelines to ensure privacy and compliance.

Qualitative Interviews and Case Studies

To complement quantitative evaluations, qualitative data were collected through interviews with healthcare professionals, missionaries operating in resource-constrained regions, and patients from underserved communities.

These perspectives highlighted the diagnostic challenges associated with limited infrastructure and access to care. A representative case study involved a 78-year-old male who was initially misdiagnosed due to limited symptom input. Upon the inclusion of additional details, such as widespread rashes, persistent nausea, swollen joints, severe headaches, and chest pain, the AI system correctly identified tuberculosis as the underlying condition.

Limitations of AI Diagnostics in Diverse and Complex Contexts

Language and Health Literacy Barriers

AI simulation testing demonstrated that language differences, limited health literacy, and cultural variation significantly impair effective communication between patients and healthcare systems. These barriers reduced the quality of symptom descriptions, which in turn diminished AI diagnostic accuracy. However, the inclusion of detailed and specific symptom information consistently improved diagnostic performance, underscoring the need for educational and technological strategies that bridge communication gaps.

While the simulations provided useful insight into diagnostic model behavior, their generalizability remains limited. The scenarios were constructed to reflect plausible presentations but were not validated against actual patient outcomes. Future studies should incorporate clinical validation trials to confirm the consistency and safety of AI-assisted diagnostic tools in real-world care settings.

Demographic Representation and Diagnostic Bias

Simulation results revealed substantial variability in diagnostic accuracy based on patient demographics. For example, a 25-year-old White male presenting with numbness symptoms received a 30% likelihood of a diabetes diagnosis, while comparable Black and Asian individuals were assigned substantially lower probabilities (~10% and 5–10%, respectively). Similarly, among 65-year-old females experiencing

urination issues and numbness, White patients received the highest likelihood estimates (50–60%) relative to Black (40–50%) and Asian (30–40%) patients. These disparities reflect underlying algorithmic biases associated with non-representative training datasets.

Challenges in Diagnosing Multi-Causal Conditions

AI systems showed reduced accuracy when addressing complex, multi-causal clinical cases. One example, reported through qualitative interviews with healthcare professionals in Tanzania, involved a patient who presented with high fever and was initially suspected of having malaria.

Further evaluation, using integrated digital auscultation, revealed a concurrent pneumonia diagnosis. In this case, AI systems demonstrated an 85% sensitivity rate, indicating diminished performance in scenarios involving coexisting conditions. These limitations are consistent with findings in the existing literature, which highlight the difficulty AI systems face in diagnosing overlapping pathologies (Lee et al., 2021; Smith et al., 2020).

Strategies for Enhancing Diagnostic Accuracy and Equity

Applications in Single-Cause Diagnoses

AI-driven diagnostic systems demonstrate strong performance in cases involving singular, well-defined conditions. In one representative case described by healthcare professionals in Tanzania, a patient presented with high fever and was initially suspected of having malaria. While this early suspicion aligned with regional disease prevalence, it lacked sufficient clinical detail for accurate diagnosis. Subsequent evaluation, after incorporating additional symptoms and contextual risk factors such as travel history, chills, and persistent respiratory distress, revealed a concurrent pneumonia diagnosis.

In earlier simulation trials, cases like this were intentionally modeled with minimal symptom input to assess how LLMs perform under constrained clinical conditions. However, these inputs have since been revised for greater realism and consistency with diagnostic standards. By systematically enriching symptom sets in later iterations, the updated design more accurately reflects clinical workflows and allows for clearer assessment of AI responsiveness in multi-causal diagnostic contexts. As expected, AI sensitivity remained limited in scenarios involving overlapping pathologies, reinforcing existing concerns about model performance in complex real-world cases (Lee et al., 2021; Smith et al., 2020).

Alignment with Existing Research

Empirical findings closely reflect patterns documented in the current literature. Previous studies affirm AI's accuracy in detecting single-cause

diseases. Similarly, challenges in diagnosing patients with overlapping pathologies align with findings from Lee et al. (2021), who noted limitations in AI's ability to differentiate between coexisting conditions.

Literature on mobile diagnostic tools also supports recent innovations; the integration of digital stethoscopes and mobile health technologies has shown promise in improving diagnostic capacity, particularly in underserved environments (Jones et al., 2022).

Integrating Mobile Diagnostic Tools

To address AI limitations in complex cases, diagnostic workflows incorporated devices such as the 3M Littmann CORE Digital Stethoscope. Field evaluations indicated that pneumonia detection accuracy improved by approximately 20% when using the stethoscope compared to traditional methods. The addition of automated blood pressure monitors further enriched diagnostic assessments with real-time hemodynamic data, enabling frontline providers to detect and monitor conditions without immediate access to in-person clinical support. These enhancements are supported by recent studies emphasizing the potential of mobile health tools in expanding diagnostic reach and reliability.

Strategic Directions for Equitable Implementation

To maximize AI's impact on health equity, several key areas of development must be prioritized:

1. Expanding Training Datasets: Diverse and representative datasets reflecting underserved populations' demographic and socioeconomic characteristics are essential to reducing bias and improving diagnostic accuracy.
2. Algorithm Refinement: AI models must be continuously improved to account for demographic and cultural variability, ensuring more equitable diagnostic outcomes.
3. Infrastructure Development: Public and private investment in healthcare infrastructure, particularly in rural and resource-limited regions, is necessary to support the deployment of AI tools.
4. Provider Education and Training: Healthcare professionals must receive training in cultural competency, digital literacy, and AI integration to effectively use these technologies in clinical practice.
5. Longitudinal Impact Studies: Ongoing evaluations of AI diagnostics over time are required to assess sustained health outcomes and inform evidence-based policy development.
6. Policy and Systems Integration: Technological innovation alone is insufficient to resolve systemic healthcare inequities. Effective implementation depends on integrated policy efforts that expand community health initiatives, improve healthcare affordability, and build digital infrastructure. When combined with social service

interventions, such as mobile clinics, telemedicine programs, and community-based care, AI diagnostics can become part of a broader, more responsive healthcare system capable of addressing long standing disparities.

Conclusion

Toward Equitable Implementation of AI Diagnostics

AI technologies hold significant promise in addressing healthcare disparities, particularly for populations affected by economic hardship and limited access to care. When supported by detailed symptom inputs and demographically representative data, AI-driven diagnostic systems can improve early disease detection, promote timely intervention, lower long-term healthcare expenditures, and contribute to greater health equity. The integration of advanced diagnostic technologies with targeted social service initiatives offers a comprehensive strategy to close the gap between innovation and accessibility.

However, critical barriers remain. Algorithmic biases rooted in non-representative training datasets continue to produce unequal diagnostic outcomes across racial and age groups. Infrastructural limitations—especially in low-income and rural communities—further restrict access to AI-enabled tools. Ethical concerns, including data privacy, transparency, and accountability, also require careful and ongoing attention. Moreover, despite their technical capabilities, AI systems cannot replace the role of human clinical expertise, particularly in nuanced decision-making and patient-centered care.

Overall, the responsible deployment of AI in healthcare requires a coordinated effort across research, policy, and practice. Improvements in data diversity, algorithmic fairness, healthcare infrastructure, and interdisciplinary collaboration are essential for AI to fulfill its potential as a tool for promoting health equity. Through these integrated efforts, a more sustainable, equitable, and responsive healthcare system can be realized—one that meets the needs of society's most underserved populations.

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