Opinion

Artificial intelligence in improving access to healthcare for underserved populations

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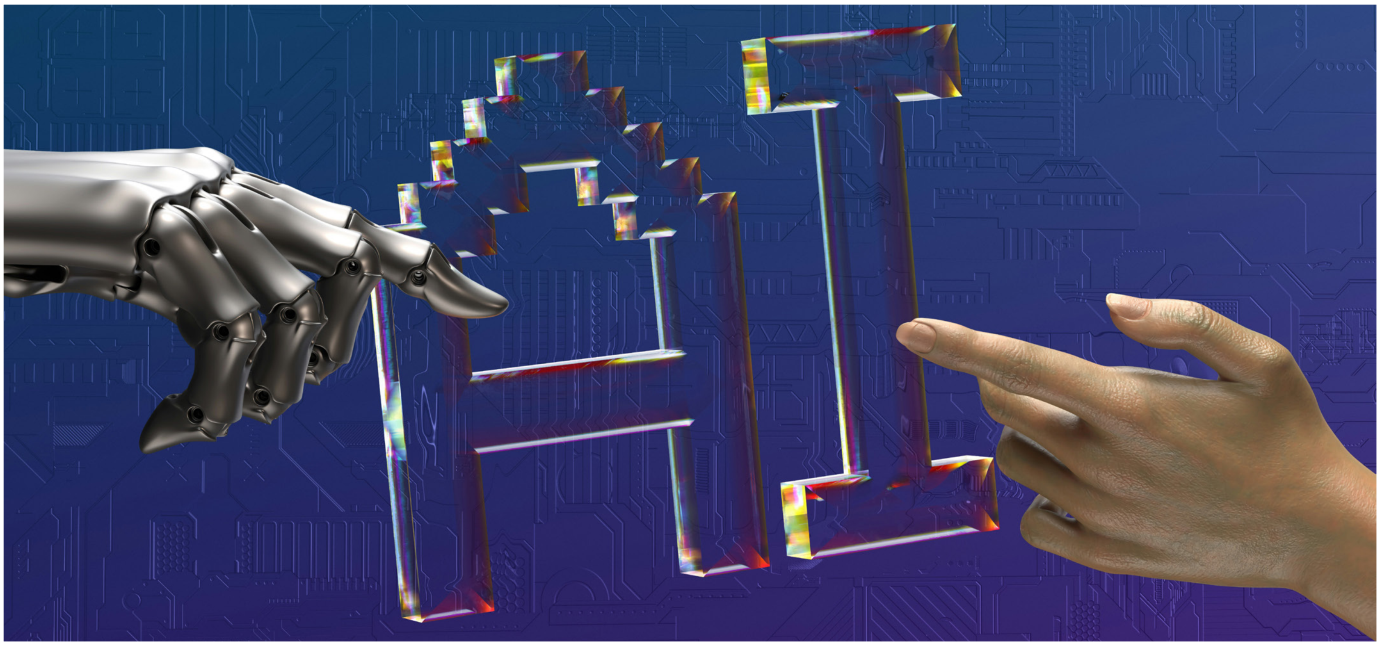

Abstract

Underserved populations experience barriers to timely, affordable and culturally appropriate healthcare. Artificial intelligence (AI), including machine learning (ML), deep learning (DL) and natural language processing (NLP) can mitigate these barriers by enabling and enhancing remote diagnostics, optimising service location and delivering scalable health education. Empirical examples include ML supported mobile computed tomography (CT) screening; ML based geospatial facility siting; DL diagnostic tools for cardiology, ophthalmology and dermatology; and NLP chatbots for maternal health and mental engagement. While these interventions show expanded reach to underserved populations, deployment is constrained by infrastructure gaps, dataset bias, limited external validation and uncertain cost- effectiveness. Inclusive data collection, rigorous multicentre evaluation, economic assessment and equity focused governance are required to ensure AI translates into equitable improvements in access to care.

Abbreviations

AI - artificial intelligence
AIATM - AI-assisted telemedicine
CT - computed tomography
DLAI – deep learning AI
DL- deep learning
ML - machine learning
NLP - natural language processing
NLPAI - natural language processing AI
ROP - retinopathy of prematurity

Introduction

Underserved populations face barriers to access of healthcare services, causing significant disparities in health outcomes.[1] These barriers often stem from key social determinants of health factors, encompassing poverty, geographic isolation, cultural barriers and social discrimination.[1,2] Artificial intelligence (AI) has emerged as a tool for supporting healthcare systems to improve efficiencies, across diagnosis, treatment and prevention of illness.[3] Harnessing AI may also contribute to improving health access and outcomes in underserved populations through data-driven evidence-based methods such as ML, NLP[4] and telemedicine applications.[5] This research explores how ML, NLP and telemedicine applications can improve access to healthcare for underserved communities.

Underserved populations

Underserved populations are people and communities who systematically face barriers to timely, culturally appropriate and affordable healthcare. Examples include people on low incomes, living in poverty, or living in remote or rural residents.[6] Racial and ethnic minorities such Black, Asian and other minority communities often face this challenge as well as refugees, asylum seekers and recent immigrants including those with limited English proficiency. Homeless and unstably-housed people and those with physical or mental disabilities can also be considered underserved. These groups often overlap, compounding disadvantage; for instance, the Office for National Statistics reports that people living in the most deprived areas have a life expectancy 9.5 years shorter than those in the least deprived areas, highlighting health inequalities driven by social and economic disadvantage.[7] These issues are closely linked to income, with 18% of the UK population living in absolute poverty.[8]

Many healthcare disparities experienced by underserved populations stem from historical and structural processes. Slavery, colonialism, forced displacement and discriminatory laws created and concentrated social and economic disadvantage for racial and indigenous communities. Industrialisation and ensuing deindustrialisation produced regional economic decline, leaving some communities with underinvestment in services. Policies such as segregation, criminalisation of poverty and discriminatory employment practices have limited opportunities for wealth, education and health for particular groups.[9,10] Modern policy decisions such as austerity, uneven infrastructure investment and underfunding of public services have reinforced these patterns.[11–13] The result is persistent geographic, economic and social exclusion, poorer transport and broadband access, fewer local health providers and lower health literacy,[14] all of which are barriers reducing access to healthcare. Moreover, members of the LGBTQIA+ community face barriers in the form of gaps in provider knowledge and variable access to culturally competent services.[15] Consequently, individuals exhibit decreased healthcare utilisation, leading to poorer health outcomes.[15] It is important to note that these factors can interact to multiply barriers to healthcare, for instance being an immigrant while earning low income in a rural area. Therefore, addressing the needs of underserved populations requires targeted and structural interventions which consider historical context and intersecting identities.

Machine learning AI

ML, a subdiscipline of AI, develops algorithms and statistical models that consolidate data and improve performance over time. Telemedicine is the diagnosis, treatment and monitoring of patients by means of remote telecommunications technology. AI-assisted telemedicine (AIATM) is the integration of AI applications into telemedicine platforms.

AIATM has shown great potential in addressing lack of access to healthcare by pairing powerful AI applications, such as ML models, with the advantages of telemedicine. A study by Toa et al demonstrates how ML can enhance lung cancer screening by facilitating remote diagnostic assistance, using remote CT with ML support. Mobile CT units were sent to three underserved community screening sites for two months, allowing registration of 28728 residents and screening of 19571 residents. ML algorithms performed the initial reviews of the CT scans. A retrospective cohort study encompassing individuals' demographics, health history and CT images was then conducted. The results showed high engagement, with 67% of registered individuals participating in the study. Of these, 2.68% were found to be at high risk for lung cancer, and the majority received timely treatment. This study demonstrated the high efficacy with which ML algorithms can improve access to care for underserved communities and potentially decrease disparities in health outcomes.[16]

This study contributes valuable evidence addressing healthcare disparities in lung cancer screening in resource-constrained settings. Deploying mobile CT units with remote AI assistance demonstrates a promising strategy to overcome geographical and infrastructural barriers prevalent in underserved communities in western China. The high participation rate suggests strong potential for community acceptance and engagement with such initiatives. However, the study has a limited observational period and relies on initial outcomes, which necessitates caution when interpreting long-term effects on cancer diagnosis and survival rates. Furthermore, the study lacks comprehensive cost-effectiveness analysis and may suffer from inconsistencies in screening protocols across different sites.[16] These limitations call for more rigorous evaluations such as longitudinal studies and cost-effectiveness analyses before widespread implementation. Additionally, researchers were unable to complete follow-up tracking for all participants, which could have contributed to biased results. Future research should focus on longitudinal studies to assess the long-term outcomes of AIATM, particularly cancer staging and patient survival rates over time. Investigating standardisation of screening protocols across different sites and assessing potential disparities in AI model performance due to infrastructural and demographic variability would further enhance reliability. Comprehensive cost-effectiveness analyses are also necessary to evaluate the sustainability and scalability of deploying AI-assisted CT units in underserved communities.

ML can also be used to improve access to healthcare through infrastructure planning. A study by Douard et al developed an ML-based geospatial methodology to identify suitable locations for new healthcare facilities in northern Ghana, aiming to improve equitable healthcare access.[17] The methodology used population density maps from sources like WorldPop and national statistics agencies, along with data on existing facilities, to label potential sites. They employed a fast and accurate ML classifier known as Light Gradient Boosting Machine to rank prospective locations, then used a clustering algorithm to group suitable sites. The cluster centres were surrounded by Voronoi polygons, which estimated the service area if a facility were built there. To assess how much a new facility would improve local access, measures such as travel time to the nearest existing facility, the number of people per facility, and combined scores were calculated within each polygon. Candidate sites were prioritized based on the model scores to identify those that most enhanced accessibility. Limitations include reliance on existing data, which may introduce bias since facility locations are used as a proxy for site suitability. Validation through field studies is necessary. The model also does not consider cost-effectiveness or optimise for both impact and affordability,[17] suggesting future inclusion of resource-allocation analysis.

Deep learning AI

Deep learning AI (DLAI) is a class of ML suited to analysing large, complex and unstructured healthcare data including clinical notes, electronic healthcare records and medical images. DLAI has shown remarkable efficacy in applications relevant to underserved populations.

Retinopathy of prematurity (ROP), and specifically plus disease, is a leading cause of childhood blindness that disproportionately affects underserved communities with limited access to ophthalmology specialists. Wagner et al developed and validated DLAI models for automated detection of plus disease. One bespoke model and one code-free model (usable without coding expertise) were trained on diverse retinal image datasets from premature infants in London and externally validated on data from the USA, Brazil and Egypt. Both models achieved high accuracy comparable to experienced clinicians in separating healthy retinas from pre-plus and plus disease. Results suggest potential for DLAI driven ROP screening in resource-limited environments. Strengths of the study include diverse training data and multi-country testing.[18] Limitations included poorer code-free performance for pre-plus disease, reduced accuracy across images from different devices, and small external validation datasets. There was also a lack of individual-level confounder data such as sex and ethnicity, as well as inter-observer variability between training image graders, particularly junior ophthalmologists.[18] Addressing these limitations requires large-scale, multicentre prospective validation, longitudinal assessments of clinical impact, and standardised grading protocols for training data. Evaluation of cross-device deployment is also important to further understand the efficacy of the DLAI models. These steps would help ensure the AI-driven ROP tools are both effective and equitable when deployed in the required healthcare environments.

In cardiology, a randomised controlled trial by Kumar et al shows that DLAI-enhanced ultrasound devices can improve access to quality cardiac imaging for underserved communities. DLAI aided clinicians without prior sonography training to acquire echocardiograms more efficiently. Thirty-eight internal medicine residents without prior sonography training used devices with or without DLAI guidance over two weeks. The DLAI software provided real-time instructions for probe placement and image assessment.[19] Results showed the DLAI group achieved higher image-quality scores and significantly faster scan times. This suggests DLAI-aided ultrasound can empower healthcare providers with limited training, thereby expanding diagnostic access. Limitations of this study include the use of a single hospital setting, short follow-up, potential bias from open-label design, and use of routine patients rather than patients with challenging cases.[19] Future research should involve large, multicentre blinded trials and long-term performance assessment to validate clinical utility and inform broader implementation.

DLAI has also shown promise in improving access to healthcare through diagnostic imaging in dermatology. A systematic review by Behara et al analysing 95 studies from Scopus, IEEE and MDPI, highlights DLAI's effectiveness in skin cancer detection. Using image processing and feature extraction, DLAI improves lesion classification, enabling faster diagnosis and broader dermatological care, especially in resource-limited settings with specialist shortages.[20] A study by Carvalho et al included in the systematic review demonstrated how DLAI allows patients to upload skin images for automated review, benefiting remote communities by reducing the need for in-person visits. While promising, further studies are needed to confirm these findings across diverse populations and settings.[20]

Natural language processing AI

Natural language processing AI (NLPAI) is a subdiscipline of AI which enables machines to interpret, generate and respond to human language. Advances in NLPAI chatbots also offer potential to improve access to healthcare to underserved populations.

A study by Khan et al explores the potential of NLPAI chatbots in primary care depression management, to improve accessibility, early detection and patient engagement. The study shows that NLPAI chatbots have simulated human like conversations, provided psychoeducation, offered behavioural support, and tracked mood and symptoms through ongoing interactions with users.[21] Chatbots were also able tailor interventions based on user responses, and flagged changes indicating worsening depression. In regard to underserved communities, access to depression care is enhanced by decreasing the need for in-person appointments with mental healthcare providers, particularly in areas where access to mental health services are more scarce.[21] A systematic review by Aggarwal et al supports results from Khan et al. The study shows more of the promising efficacy of AI chatbot algorithms in promoting health-behavioural changes in large and diverse populations. Of the 15 included studies, six showed high efficacy in promoting healthy lifestyles, four in promoting smoking cessation, two in promoting treatment adherence, and one in promoting reduction of substance abuse.[22] These studies are limited by the absence of a meta-analysis to statistically combine and synthesise findings. However, its current findings show promise and can act as a platform for randomised controlled trials to establish more definitive conclusions.

In addition, Guvava et al developed ZimHealthBERT, an Android- and iOS-compatible multilingual conversational NLPAI framework for mother-and-child health in Zimbabwe, aiming to address language barriers to healthcare access.[23] The model was trained with patient dialogue and expert-informed qualitative data, including a medical knowledge graph and cultural adaptation layer to provide contextually relevant responses in major local languages: Shona, Ndebele and English. In a pilot study involving 30 clinicians and 60 patients, interviews and surveys reported a 21% increase in prenatal attendance, a 20.6% rise in medication adherence, and a 35.5% improvement in patient comprehension.[23] While ZimHealthBERT showcased promising results, several limitations are important to consider. The study's focus on urban areas restricts generalisability to rural communities with distinct challenges,[23] and its short time frame limits understanding of long-term impacts. Self-reported data on patient and provider satisfaction could introduce bias, and the AI model's reliance on technology excludes some individuals. Critically, a cost–benefit analysis is needed to assess economic viability. Despite these limitations, ZimHealthBERT offers valuable insights into AI's ability to provide a nuanced approach to improving access to healthcare.

Current challenges and future directions

Implementation of AI technologies may face technological and infrastructure barriers that can hinder their effectiveness and accessibility. Individuals in underserved populations may lack adequate internet access and necessary computing hardware and software.[24] This can hinder access to applications such as telemedicine and remote monitoring. This can be addressed by government and private investment in broadband infrastructure in underserved areas and by upgrading existing facilities such as computers and servers to support AI systems.

Data bias may also be a challenge when implementing AI technologies for underserved populations. AI algorithms learn from historic data; therefore, inherent biases may be reflected in results. Historic data are more likely to represent less-deprived socioeconomic groups due to lack of healthcare access for underserved populations. As a result, AI algorithms may yield less accurate results for underserved communities if trained on unrepresentative data, potentially perpetuating disparities in treatment, diagnosis and health outcomes.[25] This issue can be addressed by collecting data from diverse populations to account for various demographics, including underserved groups. Technologists and healthcare providers should also involve underserved communities in data collection to gain insight into specific needs and cultural contexts that may be overlooked.

Conclusion

AI presents an opportunity to mitigate unequal healthcare access for underserved populations through enhancement of diagnostic capacity, facilitation of remote care delivery, augmentation of health education, and service planning.

Empirical evidence from DL, ML and NLP has shown efficacy against a range of barriers to healthcare access. Nonetheless, the translation of these innovations into equitable public-health impact requires rigorous safeguards, such as further validation and cost-effectiveness studies. Deliberate efforts must also be made to mitigate algorithmic bias to prevent exacerbation of existing inequalities. Investment in digital infrastructure and workforce capacity, alongside regulatory frameworks that embed ethical and accountability mechanisms, is also required to support sustainable implementation. When deployed with methodological rigor and equity-centred governance, AI can serve as a scalable enhancer to conventional health systems for narrowing entrenched disparities in access to care.

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Hi, I'm a second-year medical student and a co-founder and President of the Health and Medical Technology Society. My interests include surgery, medical technology, and healthcare innovation. I am also interested in exploring and addressing healthcare disparities through research and practical efforts.