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Towards a Non-Discriminatory Artificial Intelligence in Healthcare: Ensuring Equal Access and Utilization for Rural and Underdeveloped Areas

Menuju Kecerdasan Buatan yang Non-Diskriminatif dalam Layanan Kesehatan: Memastikan Akses dan Pemanfaatan yang Setara bagi Wilayah Perdesaan dan Tertinggal

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ABSTRACT: The enjoyment of the highest attainable standard of health is one of the fundamental human rights. Artificial Intelligence (AI) is a ground-breaking innovation with huge potential to accelerate multisectoral progress, including in healthcare. Yet, its reliance on data availability, governance structures, infrastructure, and technical expertise can perpetuate biases against underrepresented communities and exacerbate existing inequalities. This paper explores strategies to develop a just, inclusive, and humane AI framework that enhances healthcare services while ensuring equal access and utilization for people in rural and underdeveloped areas (RUAs). A narrative review was conducted through targeted searches in scientific databases and verified sources from April to June 2024 using relevant keywords such as "health as a human right," "AI and health," "AI in rural areas," "AI and inequality," "rural development," and "AI and social determinants of health,". The review highlights the profound impact of AI on RUA residents, who are disproportionately marginalized by the interplay of spatial and socioeconomic limitations. These challenges are amplified by uneven technological progress and the demand for specialized skills across different regions. Health data equity for RUAs could be enhanced by promoting social innovation, together with active community participation and human capital development. In this context, targeted training initiatives and coordinated efforts among educational institutions, employers, healthcare facilities, and labor unions can empower workers in RUAs to engage with evolving AI-driven systems. Ultimately, ideal and unbiased AI should safeguard health as a human right by ensuring inclusivity and non-discriminatory frameworks, becoming sustainable in its respective communities, and upholding ethical conduct.

***ABSTRAK**: Hak untuk menikmati derajat kesehatan setinggi-tingginya merupakan salah satu hak asasi manusia yang paling mendasar. Kecerdasan buatan (artificial intelligence/AI) merupakan inovasi revolusioner dengan potensi besar untuk mempercepat kemajuan lintas sektor, termasuk dalam bidang kesehatan. Namun demikian, ketergantungan AI terhadap ketersediaan data, tata kelola, infrastruktur, serta kapasitas teknis berpotensi melanggengkan bias terhadap kelompok yang kurang terwakili dan memperdalam kesenjangan yang telah ada. Tulisan ini membahas berbagai strategi untuk membangun kerangka kerja AI yang adil, inklusif, dan berorientasi kemanusiaan, yang tidak hanya meningkatkan mutu layanan kesehatan, tetapi juga menjamin kesetaraan akses dan pemanfaatan bagi masyarakat di wilayah perdesaan dan tertinggal (rural and underdeveloped areas/RUAs). Kajian ini menggunakan pendekatan tinjauan naratif melalui pencarian terarah pada basis data ilmiah dan sumber-sumber tepercaya dari April hingga Juni 2024, dengan kata kunci seperti "kesehatan sebagai hak asasi manusia", "AI dan kesehatan", "AI di wilayah pedesaan", "AI dan ketimpangan", "pembangunan pedesaan", serta "AI dan determinan sosial kesehatan". Hasil tinjauan menunjukkan bahwa pengaruh AI terhadap masyarakat di RUAs sangat luas, di mana mereka kerap mengalami marginalisasi akibat keterbatasan spasial dan sosial ekonomi. Kondisi ini semakin*

Keywords:
artificial intelligence; social determinants of health; rural and underdeveloped areas; marginalization; equity in development

Kata Kunci:
kecerdasan buatan; determinan sosial kesehatan; wilayah pedesaan dan tertinggal; marginalisasi; kesetaraan pembangunan

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diperparah oleh ketimpangan perkembangan teknologi dan kebutuhan akan keterampilan khusus di berbagai wilayah. Peningkatan kesetaraan data kesehatan di RUAs dapat dicapai melalui penguatan inovasi sosial yang disertai partisipasi aktif masyarakat dan pengembangan kapasitas sumber daya manusia. Dalam konteks ini, program pelatihan yang terarah serta kolaborasi antara lembaga pendidikan, penyedia layanan kesehatan, dunia kerja, dan serikat pekerja menjadi kunci untuk memberdayakan tenaga kerja di RUAs agar mampu beradaptasi dengan sistem kesehatan berbasis AI yang terus berkembang. Pada akhirnya, AI yang ideal dan bebas bias harus menjamin hak atas kesehatan melalui penerapan prinsip inklusivitas dan non-diskriminasi, keberlanjutan di tingkat komunitas, serta kepatuhan terhadap nilai-nilai etika.

1. Introduction

The Universal Declaration of Human Rights (UDHR) recognizes the inherent dignity and equal rights of all people. Article 25 of the UDHR affirms the right to health as part of an adequate standard of living, stating that "everyone has the right to a standard of living adequate for the health and well-being of himself and his family, including food, clothing, housing and medical care and necessary social services…"[1] This foundational right is further supported by the World Health Organization's (WHO) Constitution, which defines health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity."[2] Another key clause from the WHO Constitution underscores this right by stating that "the enjoyment of the highest attainable standard of health is one of the fundamental rights of every human being without distinction of race, religion, political belief, economic or social condition."[3]

Meanwhile, artificial intelligence (AI) refers to the mimicry of human cognitive functions in man-made machines. These systems are designed to handle tasks that typically require human intelligence, such as visual perception, decision-making, language translation, and speech recognition.[4] In healthcare, various forms of AI[5] — including chatbots, generative AI, agentic AI, and embodied robots — have been applied to accelerate technological development, for example, to improve the diagnosis and treatment of non-communicable diseases,[6] predict diseases transmission patterns,[7] and support preventive care through cognitive behavioral interventions.[8] Despite their differences, all types of AI are still reliant on representative data and adequate infrastructure.[9] Conversely, AI algorithms may perpetuate biases against underrepresented communities and exacerbate inequalities between populations where data and infrastructure are lacking.[10]

Marginalization may occur because the advancement of AI is tied to the data availability and governance, infrastructure limitations, technical skill gaps, and potential data discrepancies.[11] Kolfschooten et al.[12] argued that health discrimination can arise in three primary ways: (1) AI systems are trained with biased health data that are often not totally representative of all community; (2) the design of AI systems may hinder certain groups from

1 United Nations General Assembly, "Universal Declaration of Human Rights," (Paris: United Nations, 1948).
2 WHO, "Constitution of the World Health Organization," (New York: World Health Organization, 1946).
3 UN OHCHR, "Fact Sheet No. 31, the Right to Health," United Nations, https://www.ohchr.org/sites/default/files/Documents/Publications/Factsheet31.pdf.
4 Vivek Kaul, Sarah Enslin, and Seth A. Gross, "History of Artificial Intelligence in Medicine," Gastrointestinal Endoscopy 92, no. 4 (2020).
5 Zhuofan Kan et al., "Ai Types and Organizational Implications in Various Task Contexts: A Quantitative Review from China," Asia Pacific Business Review (2024).
6 G. Arora et al., "Artificial Intelligence in Surveillance, Diagnosis, Drug Discovery and Vaccine Development against Covid-19," *Pathogens* 10, no. 8 (2021).
7 R. Awasthi et al., "Vacsim: Learning Effective Strategies for Covid-19 Vaccine Distribution Using Reinforcement Learning," Intell Based Med 6 (2022).
8 Bandana Pandey, Sanchita Chakraborty, and Vineet Kumar, "Role of Artificial Intelligence in Health Communication," International journal of health sciences (2022).
9 Mirja Mittermaier, Marium M. Raza, and Joseph C. Kvedar, "Bias in Ai-Based Models for Medical Applications: Challenges and Mitigation Strategies," NPJ digital medicine 6, no. 1 (2023).
10 Isabella Backman, "Eliminating Racial Bias in Health Care Ai: Expert Panel Offers Guidelines," Yale School of Medicine, https://medicine.yale.edu/news-article/eliminating-racial-bias-in-health-care-ai-expert-panel-offers-guidelines/.
11 David B. Olawade et al., "Using Artificial Intelligence to Improve Public Health: A Narrative Review," *Frontiers in public health* 11 (2023).
12 IHA, "Ai Can Threaten Health Equity for Marginalised Populations: The Eu Must Act Now," (Netherlands: Health Action International, 2024).

accessing healthcare due to language barriers and/or limited digital literacy levels; and (3) the adoption of AI-based approaches may be restricted to stakeholders with sufficient financial resources to afford installations and routine maintenance costs. Additionally, Ghassemi et al. suggest that users may misunderstand the capabilities of their AI system and sometimes could only operate the technology on a basic functionality level that could not offer reliable explanations for any biases.[13]

Much of the current evidence on AI in healthcare reflects applications in urban contexts, where advanced hospitals, reliable internet connectivity, and highly skilled professionals enable its adoption[14]. For example, AI-assisted diagnostic imaging[15], generative analytics for electronic medical records[16], and digital health platforms[17] are more commonly piloted in metropolitan hospitals with the capacity to integrate such technologies. While urban areas are already leveraging AI to improve service delivery, the same opportunities remain limited for rural and underdeveloped areas (RUAs), which already face significant health-system deficits that contribute to poorer outcomes.

In most developing-country settings, rural populations have access to up to three to fourteen times fewer health workers than urban populations.[18] Evidence from pooled Demographic and Health Survey Data across 27 sub-Saharan African countries shows that only about one-fifth (22.4%) of women use maternal health services in rural areas, compared to over one-third (34.7%) in urban areas, with socioeconomic factors, such as wealth, education, and media exposure, explaining a large part of the gap.[19] National data from Indonesia likewise indicate higher proportions of primary health centers without general practitioners in underdeveloped areas, reaching 54.5% in the outermost regions.[20] Qualitative research from two underdeveloped regions in Mali further highlights how poor retention, unattractive working and living conditions, and weak local management limit the availability of qualified health workers in rural districts.[21]

While AI development has the potential to address these issues, these communities remain systematically marginalized, and their exclusion from AI system design and development process could further entrench existing inequities.[22] To address these concerns, this paper aims to provide a comprehensive examination of the risks posed by AI deployment in healthcare for RUA residents. Furthermore, this paper explores strategies for enhancing data equity for people in RUAs and proposes the development of a just, inclusive, and humane AI framework that is compatible with the specific conditions and challenges in the RUAs.

2. Method

This study employed a narrative review methodology to collect, organize, and analyze relevant data. Searches were conducted from April to June 2024 using targeted keywords, including “health as a human right,” “AI and health,” “AI in rural areas,” “AI and inequality,” “rural development,” and “AI and social determinants of health,”. The search was performed across peer-reviewed scientific databases, complemented by reputable grey literature sources, such as organizational reports and reliable popular websites with verifiable update logs and citable information. A snowballing approach was also used to review references cited in the identified literature.

Although the review aimed to capture a global perspective and provide insights from diverse RUAs settings, the search was limited to literature in English and Indonesian. The deliberate inclusion of Indonesian-language

13 M. Ghassemi, L. Oakden-Rayner, and A. L. Beam, “The False Hope of Current Approaches to Explainable Artificial Intelligence in Health Care,” *Lancet Digit Health* 3, no. 11 (2021).

14 Maxwell J. Smith et al., “Four Equity Considerations for the Use of Artificial Intelligence in Public Health,” Bulletin of the World Health Organization 98, no. 4 (2020).

15 Arora et al., “Artificial Intelligence in Surveillance, Diagnosis, Drug Discovery and Vaccine Development against Covid-19.”

16 C. Donnelly et al., “A Systematic Review of Electronic Medical Record Driven Quality Measurement and Feedback Systems,” *Int J Environ Res Public Health* 20, no. 1 (2022).

17 Chonnatee Rodsawang et al., “Designing a Competent Chatbot to Counter the Covid-19 Pandemic and Empower Risk Communication in an Emergency Response System,” Outbreak, Surveillance, Investigation & Response (OSIR) Journal 13, no. 2 (2020).

18 J. Guo and B. Li, “The Application of Medical Artificial Intelligence Technology in Rural Areas of Developing Countries,” Health Equity 2, no. 1 (2018).

19 Oduse Samuel, Temesgen Zewotir, and Delia North, “Decomposing the Urban–Rural Inequalities in the Utilisation of Maternal Health Care Services: Evidence from 27 Selected Countries in Sub-Saharan Africa,” Reproductive Health 18, no. 1 (2021).

20 Kemenkes RI, “Profil Kesehatan Indonesia Tahun 2023,” (Jakarta: Kementerian Kesehatan Republik Indonesia, 2024).

21 Mohamed Ali Ag Ahmed et al., “Factors Explaining the Shortage and Poor Retention of Qualified Health Workers in Rural and Remote Areas of the Kayes, Region of Mali: A Qualitative Study,” Rural and Remote Health 20, no. 3 (2020).

22 Bettina Bock, “Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection,” Sociologia Ruralis 56 (2015).; Elena N. Naumova, “Public Health Inequalities, Structural Missingness, and Digital Revolution: Time to Question Assumptions,” Journal of public health policy 42, no. 4 (2021).

sources was intended to highlight underrepresented viewpoints, particularly those concerning RUA communities that may not be visible in English-language publications. This choice draws on the authors' language competencies as a research asset to include valuable insights that would otherwise be excluded due to linguistic barriers.

All references were meticulously reviewed manually to minimize selection bias. The data extracted were categorized into themes related to AI, RUAs, policy considerations, and human rights. These themes formed the basis for exploring strategies to develop a just, inclusive, and humane AI framework that could enhance healthcare service in RUAs. Alongside this, legal frameworks such as the WHO Constitution, as well as the concept of social determinants of health, were used as analytical lenses to guide interpretation and assessment of the findings. On a broader scale, this review aims to contribute to the body of knowledge needed to effectively engage rural communities and ensure their data are accurately represented in AI-driven healthcare systems.

3. Findings and Discussion

3.1 AI from a Perspective of Human Right to Health

The fulfilment of the right to health is a continuous obligation, which ensures a state of well-being and the absence of disease.[23] Since health is interdependent with social engagement and the institutionalization of social values, realizing the right to health includes, *inter alia*, the fulfilment of other human rights.[24] These include access to education, employment, housing, and transportation, which influence one's ability to seek and receive care without compromising livelihood or mobility.[25]

Within these concepts, placing AI technologies within the framework of health as part of human rights is a complex and nuanced endeavor. AI, like all technologies, is constantly evolving, and universal access to its most advanced forms is neither practical nor currently achievable. Therefore, the right to health should not be conflated with equal access to every available AI system. Instead, AI should be recognized as a tool with the potential to advance health equality by addressing systemic gaps and barriers in healthcare delivery.[26]

The United Nations General Assembly (UNGA) in 2023 acknowledged the role of digital innovation, including AI, in supporting the realization of the highest attainable standard of health. AI technologies can enhance inclusion and mitigate long-standing inefficiencies in health systems, many of which were further exposed during the COVID-19 pandemic.[27] The pandemic marked a pivotal moment for AI in healthcare. AI supported diagnosis, treatment, epidemic trend evaluation, logistics management, and surveillance to become more efficient and effective in combating the pandemic.[28] For instance, numerous chatbots with AI and natural language processing (NLP) capabilities were developed to disseminate information, including preventive measures and symptom checking.[29] These and other ongoing advancements in AI have significantly reduced the necessity of human intervention in all aspects of healthcare.[30]

AI systems also show promise in reducing social barriers to care. For marginalized groups, whether due to economic status, geographical location, gender identity, or race, AI-enabled platforms can offer a degree of anonymity that may help reduce stigma in healthcare interactions. However, these benefits are not evenly distributed, and certain groups may still face exclusion due to structural or technological barriers. Therefore, the right to health in the AI era is not about entitlement to the technology itself, but rather the right to benefit from AI as a means of overcoming physical, social, and systemic barriers to health. Ensuring this right requires purposeful policies to guide the ethical and equal integration of AI into healthcare systems.

23 WHO, "Constitution of the World Health Organization."
24 Pratik Shah et al., "Artificial Intelligence and Machine Learning in Clinical Development: A Translational Perspective," NPJ digital medicine 2 (2019).
25 M. Marmot and R. Bell, "Fair Society, Healthy Lives," Public Health 126 (2012).
26 Nariman Noorbakhsh-Sabet et al., "Artificial Intelligence Transforms the Future of Health Care," *The American journal of medicine* 132, no. 7 (2019).
27 United Nations General Assembly, "Digital Innovation, Technologies, and the Right to Health: Report of the Special Rappoteur on the Right of Everyone to the Enjoyment of the Highest Attainable Standard of Physical and Mental Health," (Paris: United Nations, 2023).
28 S. Ashique et al., "Application of Artificial Intelligence (Ai) to Control Covid-19 Pandemic: Current Status and Future Prospects," Heliyon 10, no. 4 (2024).; Lian Wang et al., "Artificial Intelligence for Covid-19: A Systematic Review," Frontiers in medicine 8 (2021).
29 Hyojin Chin et al., "User-Chatbot Conversations during the Covid-19 Pandemic: Study Based on Topic Modeling and Sentiment Analysis," J Med Internet Res 25 (2023).
30 Zhoulin Chang et al., "Application of Artificial Intelligence in Covid-19 Medical Area: A Systematic Review," *Journal of Thoracic Disease* 13, no. 12 (2021).no. 12 (2021

3.2 AI and Marginalization

The reviewed literature generally examines how the advancement of AI technology in public health has been accompanied by numerous challenges, risks, and limitations. A significant concern involves the presence of bias within AI algorithms, which can manifest, persist, or even intensify in healthcare settings.[31] Bias is commonly reflected in variations in performance levels across different subgroups for a given predictive task and can emerge at various stages of AI model development, including data collection and preparation, model development, model evaluation, and clinical deployment.[32] When biased data is used, it becomes non-generalizable and can be particularly detrimental to marginalized groups.[33]

AI systems are also susceptible to issues related to missing data, which may result from malfunctioning equipment, errors in data handling processes, or the inaccessibility of certain populations.[34] While AI holds significant promise for reducing health inequities, it also has the potential to perpetuate, maintain, or worsen these inequities.[35] For individuals in RUAs, these challenges pose distinct barriers, particularly for populations experiencing deprivation and limited access to essential resources.

3.2.1 Marginalization of Rural and Underdeveloped Areas (RUAs)

The term "rural areas" is a complex and multidimensional concept lacking a universally accepted definition.[36] Generally, however, rural areas are defined as regions with fewer than 150 individuals per square kilometre.[37] Typically, rural populations consist of a higher proportion of elderly individuals and children, exhibit higher rates of unemployment and underemployment, and have lower population densities with higher percentages of poor and uninsured residents.[38] Compared to urban populations, rural communities are more susceptible to economic downturns due to their narrow economic specializations.[39] On the other hand, underdeveloped areas are characterized by persistent deprivation, irrespective of their geographical location.[40] While many underdeveloped areas are classified as rural, some are found within urban settings manifesting as urban poverty and metropolitan slum areas.[41]

Together, RUAs often serve as focal points for resource allocation in numerous health interventions due to the poorer life expectancies of their inhabitants.[42] Among the many social determinants of health, poverty and limited access to qualified healthcare stand out as the most immediate causes of poor health status in these areas.[43] A study conducted in China and Vietnam highlighted that factors such as low public health spending, shortages of healthcare professionals, inadequate training for health workers, transportation difficulties, and insufficient health insurance coverage collectively contribute to the substandard quality of healthcare in RUAs.[44]

There is general agreement among scholars that spatial and socioeconomic contexts are crucial for understanding the interplay between regional and local stakeholders that collectively influence RUA economies.[45] This suggests that beyond individual characteristics, a person's likelihood of experiencing deprivation can be influenced by residing in these areas − places with social structures that limit upward mobility for impoverished

31 Olawade et al., "Using Artificial Intelligence to Improve Public Health: A Narrative Review."
32 Mittermaier, Raza, and Kvedar, "Bias in Ai-Based Models for Medical Applications: Challenges and Mitigation Strategies."
33 Ziad Obermeyer et al., "Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations," Science 366, no. 6464 (2019).
34 Naumova, "Public Health Inequalities, Structural Missingness, and Digital Revolution: Time to Question Assumptions."
35 Stacey Fisher and Laura C. Rosella, "Priorities for Successful Use of Artificial Intelligence by Public Health Organizations: A Literature Review," BMC Public Health 22, no. 1 (2022).
36 L. G. Hart, E. H. Larson, and D. M. Lishner, "Rural Definitions for Health Policy and Research," Am J Public Health 95, no. 7 (2005).
37 Roger Strasser, Sophia M. Kam, and Sophie M. Regalado, "Rural Health Care Access and Policy in Developing Countries," Annual Review of Public Health 37, no. 1 (2016).
38 E. H. Larson et al., "State of the Health Workforce in Rural America: Profiles and Comparisons," (Seattle: University of Washington, 2003).
39 James Rourke et al., "Keeping Family Physicians in Rural Practice. Solutions Favoured by Rural Physicians and Family Medicine Residents," Canadian Family Physician 49 (2003).
40 Nasrin Mohammadiaghdam et al., "Determining Factors in the Retention of Physicians in Rural and Underdeveloped Areas: A Systematic Review," *BMC family practice* 21, no. 1 (2020).
41 Likke Prawidya Putri et al., "A Critical Review of Definitions of Rural Areas in Indonesia and Implications for Health Workforce Policy and Research," *Health research policy and systems* 20, no. 1 (2022).
42 Strasser, Kam, and Regalado, "Rural Health Care Access and Policy in Developing Countries."
43 Guo and Li, "The Application of Medical Artificial Intelligence Technology in Rural Areas of Developing Countries."
44 Xiaoyun Liu et al., "Can Rural Health Insurance Improve Equity in Health Care Utilization? A Comparison between China and Vietnam," *International journal for equity in health* 11 (2012).
45 Mark Shucksmith et al., "Urban–Rural Differences in Quality of Life across the European Union," Regional Studies 43, no. 10 (2009).

individuals.[46] Various conditions in different RUAs influence how income and other resources are distributed. These conditions include the rigidity of social hierarchies, the capacity of local institutions to provide education and healthcare, the industrial-occupational structure, and other labor market institutions that impact equal employment opportunities and fair compensation.[47]

RUAs also experience unique relationships with migrant residents. For example, in both the United Kingdom and the United States, RUAs have increasingly become destinations for migrants, both international and internal − many of whom live on the fringes of society, facing poverty and hardship.[48] Migrants often experience significant marginalization and exploitation, which is exacerbated by their lack of legal status and language barriers.[49] However, research in the UK indicates that legal residency does not necessarily protect migrant workers from discrimination and exploitation.[50]

With various interactions occurring between different stakeholders, the marginalization of RUAs is often portrayed in stark terms. However, while exclusion and injustice are indeed recurring patterns, it is important to acknowledge as well the micro-encounters of hospitality and assistance that arise within these settings.[51] Research in various RUAs has identified individuals who actively welcome and support newcomers within their communities. These individuals work to expand the boundaries of inclusion and address persistent injustices.[52]

Due to this intricate interplay, technological progress, including the emergence of AI, presents a dual challenge for RUA communities. Without a proactive approach, technological advancements may adversely impact growth prospects in RUAs and widen the urban-rural income gap.[53] Rural and underdeveloped areas are particularly vulnerable to job displacement due to automation, especially in economies heavily reliant on repetitive tasks.[54] Additionally, digitalization brings adverse consequences such as the marginalization of individuals unable to keep pace with technological advancements and the erosion of traditional practices, as digital tools increasingly mediate interactions between workers and their work environment.[55] Furthermore, the proliferation of distance learning may lead to the closure of local schools, while the adoption of digital automation in agriculture may erode farmers' experiential knowledge and instincts, fostering greater dependence on data-driven analysis and decision-making systems.[56]

The AI revolution holds significant promise for addressing numerous public health challenges through the development of globally interoperable surveillance systems[57] and comprehensive repositories of electronic medical records.[58] This transformation aims to facilitate consensus among data platform developers, supporting institutions, agencies, decision-makers, and policy experts regarding the standards for collecting, storing, evaluating, and sharing data.[59] However, this perspective warrants careful reconsideration, because at its core, AI implementation carries an inherent limitation: the accuracy of the model's effectiveness is highly dependent on both the quantity and representativeness of data.[60] This implies that assumptions about global readiness for an AI-based transformation relies on the premise that official health statistics at national and community levels

46 Daniel T. Lichter and Kenneth M. Johnson, "Emerging Rural Settlement Patterns and the Geographic Redistribution of America's New Immigrants*," Rural Sociology 71, no. 1 (2006).
47 Tom van Heuvelen, "Recovering the Missing Middle: A Mesocomparative Analysis of within-Group Inequa
48 Ruth McAreavey and David L. Brown, "Comparative Analysis of Rural Poverty and Inequality in the Uk and the Us," Palgrave Communications 5, no. 1 (2019).
49 Ruth McAreavey, "Migrant Identities in a New Immigration Destination: Revealing the Limitations of the 'Hard Working' Migrant Identity," Population, Space and Place 23, no. 6 (2017).
50 Bettina Bock, Katalin Kovács, and Mark Shucksmith, "Changing Social Characteristics, Patterns of Inequality and Exclusion," (2014).
51 Sarah Kyambi et al., "Choices Ahead: Approaches to Lower Skilled Labour Migration after Brexit," (Edinburgh: The University of Edinburgh, 2018).
52 Monica W. Varsanyi, "Neoliberalism and Nativism: Local Anti-Immigrant Policy Activism and an Emerging Politics of Scale," International Journal of Urban and Regional Research 35, no. 2 (2011).
53 Milla Sarja, Tiina Onkila, and Marileena Mäkelä, "A Systematic Literature Review of the Transition to the Circular Economy in Business Organizations: Obstacles, Catalysts and Ambivalences," Journal of Cleaner Production 286 (2021).
54 OECD, "Rural Well-Being: Geography of Opportunities," in *OECD Rural Studies* (Paris2020).
55 Nelly Condori-Fernandez and Patricia Lago, "Characterizing the Contribution of Quality Requirements to Software Sustainability," Journal of Systems and Software 137 (2018).
56 Alessio Ferrari et al., "Drivers, Barriers and Impacts of Digitalisation in Rural Areas from the Viewpoint of Experts," Information and Software Technology 145 (2022).
57 E. D. Carter et al., "Surveillance System Integration: Reporting the Results of a Global Multicountry Survey," *Public Health* 231 (2024).
58 Donnelly et al., "A Systematic Review of Electronic Medical Record Driven Quality Measurement and Feedback Systems."
59 Amisha et al., "Overview of Artificial Intelligence in Medicine," Journal of Family Medicine and Primary Care 8, no. 7 (2019).
60 Olawade et al., "Using Artificial Intelligence to Improve Public Health: A Narrative Review."

accurately capture populations with high fidelity, granularity, and representativeness.[61]

3.2.2 The Exclusivity of AI

Existing global assessments demonstrate the uneven readiness for AI adoption across sectors and regions. The 2023 Government AI Readiness Index, for instance, reported average scores of 84.8 for high-income countries but below 40 for many low-income settings, with the largest gaps observed in data and infrastructure capacity.[62] In another example, surveys in the United States found an AI adoption rate of 43.9% in metropolitan hospital compared to only 17.7% in non-metropolitan facilities.[63] These figures illustrate that the probability of successful AI implementation is closely tied to measurable readiness factors, which remain disproportionately limited in RUAs.

As inequalities continue to widen in areas with low AI-readiness factors, such as RUAs, the accompanying information gap also deepens. Researchers have often struggled to highlight inequalities within a particular community because detailed and useful insights are frequently obscured by broad generalization and aggregated data.[64] On an individual level, such conditions may result in stigmatization. On a national level, the presentation of such data (health status summaries, disease prevalence rates, and participation in global surveillance) reveals glaring disparities between countries.[65]

At the individual level, it is crucial that AI initiatives do not perpetuate the existing inequities faced by vulnerable populations.[66] For example, an AI application designed to predict the likelihood of an individual reoffending was found to be significantly biased against Black individuals, consistently predicting a higher risk of recidivism compared to White individuals. In contrast, statistics indicate that Black individuals were only half as likely to reoffend as their White counterparts.[67] As the majority of RUAs residents, particularly in underdeveloped urban areas, comprise people of color and/or immigrants,[68] this demographic distribution therefore exacerbates the unfairness in AI-based data generation.[69]

Unfairness towards vulnerable groups has also been documented in algorithms employed for public health, hospital management, and federal compensation programs.[70] These biases are particularly pernicious because they can stem from seemingly mundane decisions, as the health data used to train these AI is often collected predominantly from White populations and frequently omits ethno-racial information altogether. Conversely, when ethno-racial data has historically been included, it has often been incorporated inappropriately.[71]

For example, the continued use of pulmonary function and pain scores adjusted for race within healthcare systems has contributed to adverse health outcomes for people of color.[72] Another population health AI in the United States predicted that Black patients had 48,772 more active chronic conditions than White patients, solely due to one measure of predictive bias in their dataset.[73] In summary, the key takeaway from this dystopic condition is that "those with privilege (i.e., White people, men, higher socioeconomic status, and English speakers) tend to have better outcomes with the use of these algorithms, where as those less privilege (i.e. women, non-binary individuals, and non-English speakers) experience worse outcomes".[74]

61 Naumova, "Public Health Inequalities, Structural Missingness, and Digital Revolution: Time to Question Assumptions."
62 Emma Hankins et al., "Government Ai Readiness Index," ed. Oxford Insights (Oxford Insights, 2023).
63 Nicole Summers-Gabr, "The Use of Ai in the Health Care Workplace: The U.S. Experience," Federal Reserve Bank of St. Louis, https://www.stlouisfed.org/on-the-economy/2025/jul/use-ai-health-care-workplace-us-experience?utm_source=chatgpt.com.
64 J. Hudson et al., "Adverse Cardiovascular Events and Mortality in Men during Testosterone Treatment: An Individual Patient and Aggregate Data Meta-Analysis," *Lancet Healthy Longev* 3, no. 6 (2022).
65 Ryan B. Simpson et al., "Completeness of Open Access Flunet Influenza Surveillance Data for Pan-America in 2005-2019," *Scientific reports* 11, no. 1 (2021).
66 Smith et al., "Four Equity Considerations for the Use of Artificial Intelligence in Public Health."; Nicole M. Thomasian, Carsten Eickhoff, and Eli Y. Adashi, "Advancing Health Equity with Artificial Intelligence," Journal of public health policy 42, no. 4 (2021).
67 Jonathan Xin Wang et al., "Health Equity in Artificial Intelligence and Primary Care Research: Protocol for a Scoping Review," *JMIR research protocols* 10, no. 9 (2021).
68 Bock, Kovács, and Shucksmith, "Changing Social Characteristics, Patterns of Inequality and Exclusion."; Larson et al., "State of the Health Workforce in Rural America: Profiles and Comparisons."
69 Obermeyer et al., "Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations."
70 Thomasian, Eickhoff, and Adashi, "Advancing Health Equity with Artificial Intelligence."
71 Backman, "Eliminating Racial Bias in Health Care Ai: Expert Panel Offers Guidelines".
72 Noorbakhsh-Sabet et al., "Artificial Intelligence Transforms the Future of Health Care."
73 Obermeyer et al., "Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations."
74 McAreavey and Brown, "Comparative Analysis of Rural Poverty and Inequality in the Uk and the Us."

Reflecting on the COVID-19 chatbot discussed in Section 3.1, it becomes evident that AI is "exclusive by design" for individuals with technological literacy.[75] Typically, these tech-savvy individuals reside in urban areas, leaving those in RUAs without the guidance or support to use this novel and often perplexing technology. Additionally, the interpretation and explanation of AI results pose significant challenges. The validation of AI systems is often questionable, necessitating specialized skills and specific training, which are accessible only to a limited group of people.[76]

Another issue pertains to the impact of AI's opacity on the effectiveness of public information access rights, particularly the right to algorithmic transparency and explainability.[77] As previously mentioned by Ghassemi et al., a key objective of AI explainability is to enhance the trustworthiness and legitimacy of AI systems[78] by making at least some aspects of AI decision-making understandable to stakeholders.[79] If AI is to be implemented in RUAs where the stakeholders lack sufficient understanding, then a crucial question that arises is who should be empowered to demand that a particular AI application be made explainable.

The exclusivity surrounding AI development and operation can both influence and be shaped by national level technological advancements. It is often claimed that spatial distance has become negligible in this era of high mobility, where digitalization provides significant opportunities for remote areas to reconnect and revitalize.[80] While this might be theoretically true, the promise of connectivity remains largely unfulfilled, as developing AI and promoting digital rurality entails substantial material expenses.[81] In practice, RUAs lag in high-speed internet access, as building a fiber network in rural areas is costly, with higher per-user expenses compared to urban areas due to the lack of economies of scale. Without supporting infrastructures, it is unsurprising that implementing AI in these areas is challenging, compelling communities to rely on collective and voluntary initiatives.[82] For instance, some Dutch communities have overcome these obstacles by establishing broadband internet cooperatives, where citizens, governments, and local businesses collaborate. These cooperatives aim to aggregate user interest, negotiate costs and network types with suppliers, and, in some cases, create open network to support people living in RUAs.[83]

The future development of AI must focus on utilizing contextually relevant data sources; otherwise, we risk jumping from a post-factual age directly into a non-factual one – since, AI tools have been found to "provide non-existing references in digital epidemiology".[84] Such undesirable biases further perpetuate existing health inequities, increasing the risk of poor health outcomes for vulnerable populations.[85]

3.3 Increasing Data Equity from RUAs

The concern that AI systems may perpetuate inequities in RUAs has led to the ideal that AI initiatives should accomplish two primary objectives: (1) they must be designed and deployed in ways that neither create nor sustain the health disparities currently affecting vulnerable populations, and (2) they must actively work to address and eliminate existing health inequities.[86] Achieving these objectives requires systemic changes, such as the development of local frameworks to oversee the equity dimension in the deployment of AI solutions.[87] Furthermore, these goals necessitate equal opportunities for the collection and analysis of population health data,

75 Hamilton Mann, "Artificial Intelligence Is Exclusive-by-Design," The European Business Review, https://www.europeanbusinessreview.com/artificial-intelligence-is-exclusive-by-design/.
76 Ghassemi, Oakden-Rayner, and Beam, "The False Hope of Current Approaches to Explainable Artificial Intelligence in Health Care."
77 Perry Keller and Archie Drake, "Exclusivity and Paternalism in the Public Governance of Explainable Ai," Computer Law & Security Review 40 (2020).
78 Ghassemi, Oakden-Rayner, and Beam, "The False Hope of Current Approaches to Explainable Artificial Intelligence in Health Care."
79 Lilian Edwards and Michael Veale, Slave to the Algorithm? Why a 'Right to an Explanation' Is Probably Not the Remedy You Are Looking For (2017).
80 Koen Salemink, Dirk Strijker, and Gary Bosworth, "Rural Development in the Digital Age: A Systematic Literature Review on Unequal Ict Availability, Adoption, and Use in Rural Areas," Journal of Rural Studies 54 (2017).; Ida J. Terluin, "Differences in Economic Development in Rural Regions of Advanced Countries: An Overview and Critical Analysis of Theories," ibid.19, no. 3 (2003).
81 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."
82 Anna Sofia Lundgren and Anna Johansson, "Digital Rurality: Producing the Countryside in Online Struggles for Rural Survival," Journal of Rural Studies 51 (2017).
83 Leanne Townsend et al., "Building Virtual Bridges: How Rural Micro-Enterprises Develop Social Capital in Online and Face-to-Face Settings," Sociologia Ruralis 56, no. 1 (2014).
84 A. Bothra et al., "The Epidemiology of Infectious Diseases Meets Ai: A Match Made in Heaven," Pathogens 12, no. 2 (2023).
85 Wang et al., "Health Equity in Artificial Intelligence and Primary Care Research: Protocol for a Scoping Review."
86 Smith et al., "Four Equity Considerations for the Use of Artificial Intelligence in Public Health."
87 Thomasian, Eickhoff, and Adashi, "Advancing Health Equity with Artificial Intelligence."

including the comprehensive encompassing the extensive data from residents of RUAs.

Incorporating an equity dimension at various stages of AI development will require an assessment of data representativeness and continuous post-deployment monitoring.[88] Additionally, it is essential to acknowledge and report limitations related to the training dataset, such as ethno-racial biases.[89] Implementing continuous evaluation practices for AI systems ensures that they perform as intended and help eliminate systemic inequalities within the healthcare system.[90] In this context, we outline strategies to enhance data equity for RUAs populations through the utilization of AI, by promoting social innovation supported by active community participation and human capital development.

3.3.1 Developing AI-based Social Innovation

Satalkina and Streiner define social innovation as an intervention aimed at inducing structural changes within a social context, focusing on systemic enhancements of society through various functional domains such as technology, business, and organization.[91] This approach has been shown to be effective in addressing the marginalization of RUAs.[92] According to Bock, social innovation is characterized by several distinct traits[93] – this section explores how AI can integrate with these traits and impact RUA communities.

Firstly, social innovation originates from civic action and aims to meet residents' needs by providing services that are previously unavailable or alternatives to services that are no longer available.[94] This concept can also be viewed as a response to the dismantling of the welfare state, reverting to traditional models of mutual assistance but in a more formalized manner.[95] Instead of relying on private networks, these efforts are realized through functional networks specifically established for this purpose. For instance, in Australia, where flooding and forest fires are frequent, ongoing projects employ AI to enhance disaster risk management in remote communities.[96] The provision of disaster prediction services is crucial for advancing health outcomes within these communities.[97]

Another hallmark of social innovation is a call for cooperatives and collective action with individual autonomy at the core of its philosophy.[98] Although social innovations themselves are not profit-oriented, this approach does not preclude economic success or professional, business-like operations and organization.[99] The development of AI can facilitate this process by establishing effective communication networks within different communities, including RUAs.[100] An example from Australia is the High Resolves initiative, which leverages AI to support social innovation by empowering students and teachers to become AI developers and create solutions for local challenges. This grassroots approach not only addresses specific community issues but also enhances AI literacy and fosters a sense of agency toward the collective well-being of the community.[101]

The reorganization of public services through the development and implementation of social innovation enterprises[102] can create new opportunities for RUAs residents. This reorganization accelerates the development of new business and delivery models that operate on fundamentally different principles compared to traditional private or public services. These models are distinguished by their combination of salaried and voluntary labor, collaboration between local and external partners, and the return of decision-making power to producers and

88 T. Davenport and R. Kalakota, "The Potential for Artificial Intelligence in Healthcare," Future Healthc J 6, no. 2 (2019).
89 IHA, "Ai Can Threaten Health Equity for Marginalised Populations: The Eu Must Act Now."
90 Pandey, Chakraborty, and Kumar, "Role of Artificial Intelligence in Health Communication."; Yogesh K. Dwivedi et al., "Artificial Intelligence (Ai): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy," *International Journal of Information Management* 57 (2021).
91 Liliya Satalkina and Gerald Steiner, "Social Innovation: A Retrospective Perspective," Minerva 60, no. 4 (2022).
92 Markus Schermer and Sigrid Kroismayr, "Social Innovation in Rural Areas," Österreichische Zeitschrift für Soziologie 45, no. 1 (2020).
93 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."
94 Ibid.
95 Satalkina and Steiner, "Social Innovation: A Retrospective Perspective."
96 Bilal Abu-Salih et al., "The Development of a Road Network Flood Risk Detection Model Using Optimised Ensemble Learning," Engineering Applications of Artificial Intelligence 122 (2023).
97 Benjamin Plackett, "The Rural Areas Missing out on Ai Opportunities," Nature 610, no. 7931 (2022).
98 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."
99 K. Radford and Sally Shortall, "Socially Enterprising Communities: Their Dynamics and Readiness for Service Innovation," Community Co-Production: Social Enterprise in Remote and Rural Communities (2012).
100 Pandey, Chakraborty, and Kumar, "Role of Artificial Intelligence in Health Communication."
101 L. Loble and A. Hawcroft, "Shaping Ai and Edtech to Tackle Australia?S Learning Divide," (Sydney, NSW Australia: University of Technology Sydney, 2022).
102 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."

consumers — groups typically marginalized by large public and private corporations.[103]

An illustrative example of this is RECODE, an AI-based social innovation partnership in Brazil with more than 1,050 digital empowerment centers in 12 countries and 1.8 million trainees.[104] RECODE is dedicated to inclusive digital education, particularly in equipping low-income individuals with full-stack development skills. Their recent initiative in Brazil aims to democratize generative AI education by leveraging community engagement insights from Rio de Janeiro's favelas to develop a curriculum that provides vulnerable youths with AI skills.[105]

In the implementation of social innovations, the necessity to reorganize and reinvent local service provision creates novel forms of collaboration among residents, businesses, third-sector organizations, and the government,[106] thereby enhancing the connectivity of RUAs. LifeBank, a healthcare supply chain company in Nigeria, exemplifies the transformative potential of AI in improving healthcare delivery in underdeveloped regions4.[107] The company's proprietary technology stack manages operations from supply chains to payment processing and employs blockchain technology to ensure transparency in blood supply chains.[108]

Many social innovations strive to reclaim a stronger voice within their communities, seeking to function independently from government control,[109] which is often perceived as insufficient or hindering genuine progress. Dissatisfaction with the existing quality of services, these combinations resulted in a desire for more localized, sustainable, and affordable high-quality products and services[110] serves as another key driver of social innovation.

New social innovation technologies can also empower residents of RUAs to take action at reduced costs.[111] Research by Wang et al. has demonstrated that AI-based medical screening offers significant cost-effectiveness across various scenarios and populations.[112] Supporting this, Hu et al. found that implementing AI-based diabetic retinopathy screening in primary care settings is both highly effective and cost-saving for both indigenous and non-indigenous populations.[113]

Finally, a significant caveat of social innovation lies in the uncertainty regarding the accessibility and affordability of new delivery models for all citizens.[114] When these initiatives are organized through local cooperative networks, there is a potential risk of excluding non-members who fall outside the specific target community.[115] Several constraints hinder the development of social innovation, such as a lack of financial resources, human resources, and knowledge.[116] While legal constraints and insufficient policy support are generally not the central focus, in-depth case studies reveal that these factors are critical for the development and institutionalization of social innovations.[117]

3.3.2 Encouraging Active Community Participation and Human Capital Development

Generally, existing literature has identified two primary challenges in implementing AI in RUAs: difficulties in accessing and utilizing data to monitor and mitigate health disparities, and the necessity for training in data utilization to tackle healthcare inequities.[118] Residents often encounter barriers related to data access

103 Taco Brandsen et al., "The Good, the Bad and the Ugly in Social Innovation," in Social Innovations in the Urban Context, ed. Taco Brandsen, et al. (Cham: Springer International Publishing, 2016).
104 WEF, "Ai for Impact: Strengthening Ai Ecosystems for Social Innovation," in Insight Report (World Economic Forum, 2024).
105 RECODE, «About Recode,» RECODE, https://recode.org.br/en/sobre-a-recode/.
106 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."
107 Yomi Kazeem, "Investors Are Backing a Startup Tackling Nigeria's Blood Delivery Challenge," Quartz, https://qz.com/africa/1192712/nigerian-blood-delivery-startup-lifebank-funded-by-echo-vc-co-creation-hubs-growth-capital.
108 Marlene Okoth, "Leap Years: Digitising Blood Delivery Saves Lives in Nigeria," Decisive Agents, https://decisiveagents.com/leap-years-digitising-blood-delivery-saves-lives-in-nigeria/.
109 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."
110 Ibid.
111 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."
112 Yueye Wang et al., "Economic Evaluation for Medical Artificial Intelligence: Accuracy Vs. Cost-Effectiveness in a Diabetic Retinopathy Screening Case," NPJ digital medicine 7, no. 1 (2024).
113 W. Hu et al., "Population Impact and Cost-Effectiveness of Artificial Intelligence-Based Diabetic Retinopathy Screening in People Living with Diabetes in Australia: A Cost Effectiveness Analysis," *EClinicalMedicine* 67 (2024).
114 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."
115 Schermer and Kroismayr, "Social Innovation in Rural Areas."
116 Bock, "Rural Marginalisation and the Role of Social Innovation: A Turn Towards Nexogenous Development and Rural Reconnection."
117 Brandsen et al., "The Good, the Bad and the Ugly in Social Innovation."
118 B. Bekemeier et al., "Data, Capacity-Building, and Training Needs to Address Rural Health Inequities in the Northwest United States: A Qualitative Study," *J Am Med Inform Assoc* 26, no. 8-9 (2019).; Guo and Li, "The Application of Medical Artificial Intelligence Technology in Rural Areas of Developing Countries."; Liu et al., "Can Rural Health Insurance Improve Equity in Health Care

and usage, which stem from factors such as limited data availability, concerns regarding data quality, a shortage of personnel with the required analytical expertise and resources, and the diverse nature of rural jurisdictions. However, interviews with RUAs residents have highlighted opportunities to enhance their capacity by focusing on targeted training initiatives − particularly in the effective visualization and communication of data to drive informed decision-making.[119]

Training initiatives represent a form of active community participation, defined as a group of activities in which the community engages under the following conditions: (1) involvement in decision-making processes, including the allocation of local resources and budgets, traditionally managed by the central government;[120] (2) voluntary participation in program implementation activities, where community members actively contribute their efforts to development projects;[121] (3) engagement in monitoring, assessment, and evaluation of development programs; and (4) application of development outcomes to ensure equitable distribution and enhance the quality of life.[122]

The motivation for active community participation is shaped by various factors. Gedeona identified several internal factors, such as gender, education, age, income levels, and occupation that influence the desire to contribute to community development.[123] Meanwhile, active community participation is also externally influenced by governmental efforts in disseminating information to the public and the involvement of the private sector. Mustanir et al. further highlight several determinants that impact community involvement in development, including values and beliefs, marital status, societal symbols, and cultural knowledge.[124]

Human capital plays a pivotal role in fostering active community participation in RUAs,[125] as it generates a knowledge-driven society capable of both absorbing and generating knowledge, promoting innovation, and enabling local adaptation to evolving technological advancements.[126] Therefore, equipping workers with the necessary skill set to access high-wage roles is crucial for adapting to AI automation. Individuals who possess skills that complement technology and can perform non-routine tasks are the best positioned to seize opportunities in this digital era.[127] Conversely, lower levels of education and skills among rural populations hinder the adoption and utilization of AI.[128] Investing in training programs for rural workers to acquire new skills is essential for preparing them for emerging job roles. Research indicates that success in technology-rich workplaces requires more than just digital proficiency; workers also need a blend of cognitive abilities including literacy, numeracy, problem-solving, as well as analytical intuition, critical thinking, and behavioral skills.[129]

Focusing on skill-based career pathways rather than specific jobs can facilitate occupational transitions and enhance the lifelong productivity of RUA labor force.[130] Not all workers need to acquire entirely new skills during career changes; rather, education and experience can prepare them for less automatable occupations. To minimize the costs associated with education and training, governance can play a role by reducing regulatory barriers to occupations (such as quotas and certification costs) and promoting forward-thinking, skills-based educational policies.[131] These measures can facilitate smoother transitions between occupations and harness the productive

Utilization? A Comparison between China and Vietnam."; Putri et al., "A Critical Review of Definitions of Rural Areas in Indonesia and Implications for Health Workforce Policy and Research."

119 Bekemeier et al., "Data, Capacity-Building, and Training Needs to Address Rural Health Inequities in the Northwest United States: A Qualitative Study."

120 Arif Arfianto and Ahmad Balahmar, "Pemberdayaan Masyarakat Dalam Pembangunan Ekonomi Desa," JKMP (Jurnal Kebijakan dan Manajemen Publik) 2 (2016).

121 Lichter and Johnson, "Emerging Rural Settlement Patterns and the Geographic Redistribution of America's New Immigrants*."

122 Kuswanto and Irzal Anderson, "Structural Model of Community Participation in Rural Development in Jambi Province, Indonesia," Population and Economics 7, no. 2 (2023).

123 Hendrikus Triwibawanto Gedeona, "Tata Kelola Perencanaan Dan Pelaksanaan Pembangunan Kesehatan (Studi Mengenai Partisipasi Masyarakat Dan Kompleksitasnya Di Kota Cimahi)," Jurnal Ilmu Administrasi 12, no. 1 (2019).

124 Ahmad Mustanir et al., "Peranan Aparatur Pemerintah Desa Dan Partisipasi Masyarakat Dalam Musyawarah Perencanaan Pembangunan Di Desa Tonrongnge Kecamatan Baranti Kabupaten Sidenreng Rappang," Jurnal Ilmiah Clean Government 2, no. 1 (2018).

125 Abhisek Mishra et al., "Understanding Community Participation in Rural Health Care: A Participatory Learning and Action Approach," *Frontiers in public health* 10 (2022).

126 OECD, "Oecd Territorial Reviews: Hidalgo, Mexico," in OECD Terrirotial Reviews (Paris2019).

127 "Rural Well-Being: Geography of Opportunities."

128 Salemink, Strijker, and Bosworth, "Rural Development in the Digital Age: A Systematic Literature Review on Unequal Ict Availability, Adoption, and Use in Rural Areas."

129 Strasser, Kam, and Regalado, "Rural Health Care Access and Policy in Developing Countries."

130 OECD, "Oecd Territorial Reviews: Hidalgo, Mexico."

131 A. D. Foster, "Creating Good Employment Opportunities for the Rural Sector," ADB Econ Work Pap Ser 271 (2011).

potential of the labor force in RUAs.[132]

A combination of public and private training initiatives can effectively equip RUAs workers with the skills and career pathways they need.[133] Improved coordination among education and training providers, employers, and labor unions is crucial to offering training options that meet workers' needs for career advancement and transitions.[134] This coordination should be supported by fiscal incentives and conducive regulatory frameworks aimed at aligning the workforce's skills with the present and future requirements of the private sector.[135] Only then can stakeholders better anticipate and meet the evolving demands of the labor market, thereby enhancing the RUAs human capital in adapting to AI implementation, particularly in the health sector.[136]

3.4 The Ideal: A Just, Inclusive, and Humane AI Framework

In the context of current healthcare development, several critical measures should be undertaken by relevant stakeholders to achieve a just, inclusive, and humane AI framework that can mitigate the health inequities experienced by residents of RUAs.[137] This approach should establish and enforce rules that guarantee the robust protection of personal health data and confidentiality.[138] By ensuring transparency in the development process of its algorithms, an ideal AI system should be capable of assessing potential biases and abuses resulting from its predictions or calculations.[139] Furthermore, the level of explainability is crucial, as it provides a meaningful way for AI to support informed decision-making.[140] Ultimately, this ideal AI framework should excel in three key pillars: fairness, sustainability, and ethics.

3.4.1 Ensuring Fairness and Inclusivity

Systematic fairness is the prevention of discrimination by ensuring that outcomes of a system are administered equitably to all individuals. In healthcare, fairness encompasses the equitable allocation of resources, opportunities, and outcomes across diverse demographics.[141] Within AI development, fairness is assessed by comparing model performance across both protected and unprotected characteristics in accordance with relevant equal rights legislation in domestic jurisdictions.[142] To foster equity in AI-driven healthcare and ensure fair and accurate treatment for all, it is crucial to formulate a holistic strategy that addresses biases on multiple fronts, along with their ethical, legal, and practical considerations.[143]

Regular audits and validation of AI systems are pivotal in detecting and rectifying potential biases, ensuring their inclusivity and effectiveness across diverse healthcare contexts.[144] External audits performed by independent experts or organizations can assess the fairness and overall performance of AI models.[145] As the use of public health AI continues to expand, healthcare professionals must remain vigilant, scrutinizing critical metrics throughout both the algorithm development and deployment phases.[146]

In terms of fairness and inclusivity, one common observation across the reviewed literature is the inconsistency between the terminology used in healthcare and that employed in human rights discourse.[147] Academic and policy discussions in the healthcare and AI-related fields often refer to "fairness" and "equity" as terms describing non-biased learning algorithms.[148] Yet, international human rights frameworks, including treaties,

132 OECD, "Oecd Territorial Reviews: Hidalgo, Mexico."
133 Mustanir et al., "Peranan Aparatur Pemerintah Desa Dan Partisipasi Masyarakat Dalam Musyawarah Perencanaan Pembangunan Di Desa Tonrongnge Kecamatan Baranti Kabupaten Sidenreng Rappang."
134 Kyambi et al., "Choices Ahead: Approaches to Lower Skilled Labour Migration after Brexit."
135 OECD, "Oecd Territorial Reviews: Hidalgo, Mexico."
136 Mishra et al., "Understanding Community Participation in Rural Health Care: A Participatory Learning and Action Approach."
137 Mittermaier, Raza, and Kvedar, "Bias in Ai-Based Models for Medical Applications: Challenges and Mitigation Strategies."
138 IHA, "Ai Can Threaten Health Equity for Marginalised Populations: The Eu Must Act Now."
139 Obermeyer et al., "Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations."
140 Ghassemi, Oakden-Rayner, and Beam, "The False Hope of Current Approaches to Explainable Artificial Intelligence in Health Care."
141 Marmot and Bell, "Fair Society, Healthy Lives."
142 Emilio Ferrara, "Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies," Sci 6, no. 1 (2024).
143 Daiju Ueda et al., "Fairness of Artificial Intelligence in Healthcare: Review and Recommendations," *Japanese journal of radiology* 42, no. 1 (2024).
144 Shah et al., "Artificial Intelligence and Machine Learning in Clinical Development: A Translational Perspective."
145 Fisher and Rosella, "Priorities for Successful Use of Artificial Intelligence by Public Health Organizations: A Literature Review."
146 Ueda et al., "Fairness of Artificial Intelligence in Healthcare: Review and Recommendations."
147 We are grateful to Elizabeth Rhoads, whose thoughtful suggestions helped shape the conceptual alignment presented here.
148 Bekemeier et al., "Data, Capacity-Building, and Training Needs to Address Rural Health Inequities in the Northwest United States: A Qualitative Study."; Ferrara, "Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation

statutes, and conventions, do not adopt these terms explicitly.[149] Instead, they prioritize the legal terminology of non-discrimination, emphasizing equal — not equitable — access for all individuals, regardless of social, genetic, or economic factors. This distinction is fundamental, as fairness (in the colloquial or distributive sense) is not equivalent to the legally recognized principle of non-discrimination[150].

This terminological divergence creates a conceptual gap between researchers in healthcare AI and those in human rights who focus on the right to health. To bridge this divide and ensure clarity on how AI in healthcare intersects with human rights protections, it is imperative to harmonize language. Aligning semantics across disciplines can prevent misunderstanding and help shift the focus toward shared, actionable objectives.[151] For instance, the Toronto Declaration on Machine Learning explicitly calls for the adoption of universal human rights terminology, especially non-discrimination, when designing AI systems in health to safeguard rights effectively.[152]

3.4.2 Designing Sustainability

As outlined in Section 3.2, RUAs face challenges stemming from limited resources which hinder the adoption of innovative technologies like AI-based healthcare; therefore, it is important to integrate sustainability and manageability into AI development.[153] It is necessary to produce empirical evidence to comprehensively understand the impacts, implications, risks, and opportunities associated with AI-driven healthcare technologies in resourced-limited contexts.[154] Designing AI for such environments requires overcoming significant obstacles, particularly in optimizing complex models to operate effectively under resource constraints. This calls for novel strategies in model compression and efficient algorithmic design.[155]

To create a solid foundation for AI manageability, evaluating the social impact of current AI applications is crucial for prompting policymakers and AI developers to gather public perceptions regarding where, how, and to what extent the technology is deployed.[156] This approach aims to promote sustainability by aligning government priorities with end-user preferences.[157] Another important consideration is ensuring stakeholder acceptance across diverse AI application domains, particularly within the public sector, where budget forecasting could be hindered by corrupt practices.[158] Conversely, expanding technology may not always be the optimal solution, and clear guidelines on AI procurement within the public sector could be useful in discerning where its implementation may be unnecessary.[159] Lastly, policymakers should adopt a sector-specific use of AI, as this approach allows them and the RUAs community to assess which AI models may present higher risks in certain sectors while posing minimal harm in others.[160,]

Strategies".; Thomasian, Eickhoff, and Adashi, "Advancing Health Equity with Artificial Intelligence."; Ueda et al., "Fairness of Artificial Intelligence in Healthcare: Review and Recommendations."; Wang et al., "Health Equity in Artificial Intelligence and Primary Care Research: Protocol for a Scoping Review."

149 Assembly, "Universal Declaration of Human Rights."; "Digital Innovation, Technologies, and the Right to Health: Report of the Special Rappoteur on the Right of Everyone to the Enjoyment of the Highest Attainable Standard of Physical and Mental Health."

150 Department of Foreign Affairs and Trade, "International Covenant on Civil and Political Rights," in *Australian Treaty Series* (New York1966).

151 Naumova, "Public Health Inequalities, Structural Missingness, and Digital Revolution: Time to Question Assumptions."; Mohammad Amir Khusru Akhtar, Mohit Kumar, and Anand Nayyar, "Ensuring Fairness and Non-Discrimination in Explainable Ai," in Towards Ethical and Socially Responsible Explainable Ai: Challenges and Opportunities, ed. Mohammad Amir Khusru Akhtar, Mohit Kumar, and Anand Nayyar (Cham: Springer Nature Switzerland, 2024).

152 Amnesty International and Access Now, "The Toronto Declaration," (Toronto: Amnesty International, 2018).

153 Olawade et al., "Using Artificial Intelligence to Improve Public Health: A Narrative Review."

154 Ayantola Alayande, "Generative Ai in Low-Resourced Contexts: Considerations for Innovators and Policymakers," Bennett Institute for Public Policy, https://www.bennettinstitute.cam.ac.uk/blog/ai-in-low-resourced-contexts/.

155 Sai Krishna Revanth Vuruma et al., "From Cloud to Edge: Rethinking Generative Ai for Low-Resource Design Challenges," arXiv, https://arxiv.org/abs/2402.12702v1.

156 Zahra Hoodbhoy, Babar Hasan, and Khan Siddiqui, "Does Artificial Intelligence Have Any Role in Healthcare in Low Resource Settings?," Journal of Medical Artificial Intelligence 2 (2019).

157 Condori-Fernandez and Lago, "Characterizing the Contribution of Quality Requirements to Software Sustainability."

158 Sarja, Onkila, and Mäkelä, "A Systematic Literature Review of the Transition to the Circular Economy in Business Organizations: Obstacles, Catalysts and Ambivalences."

159 Alayande, "Generative Ai in Low-Resourced Contexts: Considerations for Innovators and Policymakers".

160 Dwivedi et al., "Artificial Intelligence (Ai): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy."; OECD, "Rural Well-Being: Geography of Opportunities."

3.4.3 Ethical Considerations

Preserving data privacy is a critical ethical and legal concern that profoundly impacts the autonomy of AI-users.[161] A pivotal issue in this involves obtaining informed consent for data usage, ensuring that member of RUAs community fully understand how the AI systems collect, use, share, and store their data. Delivering this requires transparent communication about the purposes, risks, and benefits of data sharing to empower patients to make informed decisions about their participation in AI-driven healthcare initiative.[162] Safeguarding data storage and transmission through robust encryption and anonymization techniques is also crucial to protect against unauthorized access, data breaches, and other cybersecurity threats.[163]

To prevent potential liability issues, all roles and obligations of various stakeholders − including AI developers, community members, and healthcare institutions − should be meticulously considered when implementing an AI.[164] The intended use and limitations of AI should be explicitly communicated to enable every involved party to make informed decisions regarding their application within these technological interventions.[165] Healthcare institutions play a pivotal role in supervising the integration of AI into healthcare systems by ensuring adequate infrastructure, training, and support for the safe and effective utilization of AI.[166] This encompasses the establishment of comprehensive policies and procedures for managing risks and adverse outcomes, alongside continuous monitoring and assessment of AI performance to foster ongoing quality improvement. A robust framework for accountability and responsibility is essential to ensure that AI stakeholders can effectively address emerging ethical and legal challenges.[167]

Transparency and accountability are integral components of ethical AI in healthcare,[168] as both can mitigate confirmation bias that may arise from human interpretation of AI-generated.[169] Confirmation bias refers to the human tendency to favor information that aligns with their pre-existing beliefs or hypotheses.[170] In the context of AI, this bias can lead individuals to interpret AI-generated explanations positively, even when the system's accuracy or reliability is questionable. Recognizing the limitation of explainable AI is crucial for maintaining a realistic understanding of both its potential benefits and shortcomings, particularly within the high-stakes domain of healthcare.[171]

4. Conclusion

In conclusion, this comprehensive review highlights the profound impact of AI development on residents in RUAs. As the frontier of innovation continues to expand, it becomes increasingly crucial to recognize and mitigate the potential health disparities and injustices that may arise from the application of AI in healthcare. AI deployment in healthcare must be guided by three key pillars identified in this review: fairness and inclusivity, sustainability, and ethical governance. Fairness requires the use of representative data, active community participation, and deliberate efforts to close digital and skill gaps. Sustainability demands adequate infrastructure, long-term financing, and investment in human capital through training initiatives and coordinated support from education providers, employers, and labor unions. Ethical governance calls for regular audits, transparent processes, accountability mechanisms, and adherence to international human rights principles, including the right to health.

Additionally, active community participation and human capital development are pivotal in facilitating the adoption and adaptation of AI technologies in RUAs. Training initiatives, along with improved coordination among education and training providers, employers, and labor unions, can equip workers with the necessary skill

161 Effy Vayena, Alessandro Blasimme, and I. Glenn Cohen, "Machine Learning in Medicine: Addressing Ethical Challenges," PLoS medicine 15, no. 11 (2018).
162 Ueda et al., "Fairness of Artificial Intelligence in Healthcare: Review and Recommendations."
163 Karim Abouelmehdi, Abderrahim Beni-Hessane, and Hayat Khaloufi, "Big Healthcare Data: Preserving Security and Privacy," Journal of Big Data 5, no. 1 (2018).
164 Emanuele Neri et al., "Artificial Intelligence: Who Is Responsible for the Diagnosis?," *La radiologia medica* 125, no. 6 (2020).no. 6 (2020
165 Ferrara, "Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies".
166 Vayena, Blasimme, and Cohen, "Machine Learning in Medicine: Addressing Ethical Challenges."
167 Wang et al., "Health Equity in Artificial Intelligence and Primary Care Research: Protocol for a Scoping Review."
168 Ueda et al., "Fairness of Artificial Intelligence in Healthcare: Review and Recommendations."
169 Ghassemi, Oakden-Rayner, and Beam, "The False Hope of Current Approaches to Explainable Artificial Intelligence in Health Care."
170 Masaki Suzuki and Yusuke Yamamoto, "Characterizing the Influence of Confirmation Bias on Web Search Behavior," Frontiers in psychology 12 (2021).
171 Mittermaier, Raza, and Kvedar, "Bias in Ai-Based Models for Medical Applications: Challenges and Mitigation Strategies."

set to meet evolving AI-driven workforce demands. By embedding these pillars into the design and implementation of AI systems, policymakers and stakeholders can ensure that AI contributes to healthcare excellence while safeguarding equality, inclusion, and the fulfilment of human rights for all members of society.

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Statement of Originality

We, the authors, affirm that the present manuscript is an original work that has not been published previously, in whole or in part, nor is it currently under consideration for publication elsewhere. To the best of our knowledge, this work does not infringe upon any existing copyrights, proprietary rights, or intellectual property, and it is entirely free from plagiarism or unauthorized use of others' ideas. All sources of information and data, whether publicly available or privately obtained, have been appropriately acknowledged and cited in accordance with established scientific and ethical standards.