ISSN: 3107-3883 (Online)

Global E-Journal of Social Scientific Research
Vol. 2| Issue 9| September 2026 | pp 1-26

PREDICTING DISEASE OR REPRODUCING INEQUALITY? ARTIFICIAL INTELLIGENCE, SOCIAL POWER AND THE FUTURE OF PREVENTIVE HEALTHCARE: A CRITICAL SOCIOLOGICAL PERSPECTIVE

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ABSTRACT

Artificial Intelligence (AI) is increasingly transforming healthcare through predictive analytics, automated screening, medical image interpretation, personalised risk assessment and digital health monitoring. These developments offer significant opportunities for preventive healthcare, particularly in the early identification and management of non-communicable diseases. However, the growing dependence on algorithmic systems also raises critical questions concerning social inequality, digital exclusion, data ownership, institutional accountability and the distribution of healthcare resources. This article critically examines whether AI-enabled preventive healthcare will contribute to more equitable health outcomes or reproduce existing forms of social disadvantage.

Adopting an interdisciplinary approach, the study integrates medical science, public health, sociology and digital technology through a critical analysis of secondary sources, including international health reports, peer-reviewed research and policy frameworks. It examines the relationship between AI-based health prediction and social determinants such as income, education, gender, age, occupation, geographical location, disability, digital literacy and access to healthcare. Particular attention is given to algorithmic bias, unequal representation in health datasets, commercialisation of personal health information and the digital divide.

The article argues that technological accuracy alone cannot guarantee equitable healthcare. An algorithm may perform effectively within a particular dataset while producing unequal outcomes for populations whose health conditions, social circumstances and healthcare access are inadequately represented. The study proposes an Integrated Sociotechnical Framework for Equitable AI-Enabled Preventive Healthcare, in which clinical validation, social vulnerability assessment, digital accessibility, community participation and ethical governance are treated as interconnected requirements. It concludes that AI should strengthen, rather than replace, human judgement and public healthcare responsibility. The future of preventive healthcare must therefore be evaluated not only by technological efficiency but also by its contribution to social justice, accessibility and population wellbeing.

DOI: https://doi.org/10.64706/4f8jye72

ISSN: 3107-3883 (Online)
Global E-Journal of Social Scientific Research
Vol. 2| Issue 9| September 2026 | pp 1-26

Keywords: Artificial Intelligence; Preventive Healthcare; Medical Sociology; Social Inequality; Algorithmic Bias; Digital Health; Social Determinants of Health; Health Equity; Public Health; Digital Divide.

1. INTRODUCTION

Healthcare systems across the world are experiencing a significant transformation through the adoption of Artificial Intelligence (AI), machine learning, predictive analytics, digital monitoring and automated decision-support technologies. These developments are changing how health risks are identified, how medical information is interpreted and how preventive interventions are planned. Traditionally, healthcare has largely depended on clinical consultations, diagnostic investigations and the treatment of identified diseases. Increasingly, technological systems are making it possible to identify patterns in health data before symptoms become clinically apparent.

Preventive healthcare is particularly important in addressing non-communicable diseases (NCDs), including cardiovascular diseases, cancer, diabetes and chronic respiratory diseases. According to the World Health Organization (WHO), NCDs caused at least 43 million deaths in 2021, representing approximately 75% of non-pandemic-related deaths globally. Of these deaths, 18 million occurred before the age of 70, and 82% of premature NCD deaths occurred in low- and middle-income countries (WHO, 2025). These figures demonstrate the importance of early detection, risk reduction and accessible preventive services.

AI technologies may contribute to these objectives through the analysis of electronic health records, medical images, laboratory results, wearable-device information and population-level health indicators. Machine-learning models can identify patterns associated with diabetes, cardiovascular disease, cancer and other health conditions. AI-assisted screening can also support healthcare professionals in identifying individuals who may require further clinical examination.

However, the expansion of AI in healthcare should not be understood exclusively as a technological development. Healthcare is also a social institution, influenced by economic resources, education, gender relations, family structures, cultural practices, geographical inequalities and the distribution of public services. Individuals do not experience health risks or access healthcare under identical conditions. A person with stable income, reliable internet connectivity, digital literacy and access to a specialist may benefit differently from AI-based preventive services than someone living in a remote area with limited healthcare infrastructure.

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This raises a fundamental question: Can a technology designed to predict disease also reproduce the inequalities that influence who becomes ill, who receives healthcare and whose health needs are recognised?

The question becomes particularly important when predictive systems are developed using historical healthcare data. Such data may reflect unequal access to diagnosis, treatment and medical expenditure. If an algorithm interprets healthcare utilisation as an indicator of actual health needs, it may underestimate the needs of people who have historically received less healthcare.

Obermeyer et al. (2019) demonstrated this problem through an analysis of a widely used healthcare risk-prediction algorithm in the United States. The algorithm used healthcare expenditure as a proxy for health needs. Because expenditure differed between Black and White patients with comparable health requirements, the system underestimated the needs of Black patients. The study showed that apparently reasonable predictive variables can reproduce structural inequalities when their social context is ignored.

This example illustrates why AI-enabled healthcare requires more than technical accuracy. It requires an understanding of the social conditions in which health data are generated and healthcare services are delivered.

The present article therefore approaches AI-enabled preventive healthcare through three interconnected perspectives: medical and scientific innovation, sociological analysis of health inequalities, and ethical and institutional governance. It argues that the success of AI in preventive healthcare must be assessed by examining not only whether an algorithm can predict disease but also whether its benefits are accessible, reliable and equitable across different sections of society.

2. STATEMENT OF THE RESEARCH PROBLEM

The increasing use of AI in healthcare has generated considerable optimism regarding early diagnosis, disease prediction, personalised prevention and improved health-system efficiency. However, the expansion of algorithmic healthcare also creates questions about the distribution of technological benefits and risks.

Most discussions of AI-based healthcare focus on model performance, diagnostic accuracy, processing efficiency and technological innovation. These dimensions are important, but they do not fully explain the social consequences of introducing AI into healthcare systems.

An algorithm may demonstrate high predictive accuracy in a particular population while performing less effectively in another. A digital health application may be technically available but inaccessible to individuals who lack smartphones, reliable internet connectivity, digital

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literacy or the financial resources required to use it. Similarly, automated risk assessments may fail to recognise the healthcare needs of populations whose experiences are inadequately represented in training datasets.

The problem is therefore not limited to the possibility of technical errors. It concerns the relationship between technological systems and existing social structures.

Three major concerns emerge.

First, algorithmic bias may arise when training datasets, outcome variables or proxy indicators reflect historical inequalities. Second, digital exclusion may prevent disadvantaged populations from accessing the benefits of AI-enabled prevention. Third, the commercial use of health data may create conflicts between individual privacy, institutional interests and public health objectives.

In countries such as India, these concerns deserve particular attention because healthcare access is influenced by substantial differences in income, education, geographical location, infrastructure, language and availability of medical professionals.

The central research problem is therefore:

Whether the integration of Artificial Intelligence into preventive healthcare will reduce existing health inequalities or reproduce and potentially intensify them through algorithmic decision-making, unequal digital access and socially unrepresentative health data.

3. OBJECTIVES OF THE STUDY

The study has the following objectives:

1. To examine the role of Artificial Intelligence in preventive healthcare, disease prediction and early diagnosis.
2. To analyse the relationship between AI-based healthcare and social determinants of health.
3. To critically examine algorithmic bias and the possibility of discrimination in automated health-risk assessment.
4. To investigate how income, education, gender, age, disability, occupation and geographical location influence access to digital preventive healthcare.
5. To examine the ethical and sociological implications of health-data collection, surveillance, privacy and commercialisation.

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6. To assess the importance of human judgement, institutional accountability and community participation in AI-enabled healthcare.
7. To propose a sociotechnical framework for equitable and socially responsible preventive healthcare.

4. RESEARCH QUESTIONS

The study is guided by the following research questions:

RQ1: How is Artificial Intelligence transforming preventive healthcare through disease prediction, screening and early diagnosis?

RQ2: To what extent can existing social and economic inequalities influence the accessibility and effectiveness of AI-enabled preventive healthcare?

RQ3: How can algorithmic bias and socially unrepresentative datasets affect the identification of healthcare needs among disadvantaged populations?

RQ4: Does the increasing dependence on digital health technologies risk creating new forms of healthcare exclusion?

RQ5: What are the implications of AI-based health monitoring for individual privacy, autonomy, institutional trust and data ownership?

RQ6: What institutional, ethical and policy mechanisms are necessary to ensure equitable implementation of AI in preventive healthcare?

5. RESEARCH PROPOSITIONS

As this article is based on secondary sources and does not undertake primary statistical testing, the following propositions are presented for future empirical investigation rather than as statistically verified hypotheses.

- P1: The effectiveness of AI-enabled preventive healthcare is influenced by the quality and representativeness of the health data used to develop predictive systems.
- P2: Socioeconomic inequalities and differences in digital literacy may influence access to and utilisation of AI-based preventive healthcare.
- P3: Algorithmic decision-making may reproduce existing healthcare inequalities when historical patterns of unequal access are incorporated into predictive models.

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- P4: Human oversight, transparent governance and community participation may strengthen the social acceptability and accountability of AI-enabled healthcare.
- P5: AI-enabled preventive healthcare is more likely to contribute to equitable health outcomes when technological interventions are integrated with accessible public healthcare services.

6. REVIEW OF LITERATURE

6.1 Artificial Intelligence and Healthcare Transformation

Artificial Intelligence refers to computational systems capable of performing tasks associated with human cognitive processes, including pattern recognition, prediction, classification and decision support. In healthcare, AI applications include medical image analysis, clinical decision-support systems, predictive risk assessment, automated reporting and digital patient monitoring.

Machine-learning techniques can identify relationships within large datasets that may not be easily recognised through conventional analytical approaches. These capabilities have created opportunities for more systematic screening and early identification of health risks.

Nevertheless, the performance of an AI system depends on the quality of the data, the appropriateness of the variables, the population in which it is developed and the clinical context in which it is used. A technically advanced system cannot automatically compensate for inadequate data or weaknesses in healthcare infrastructure.

6.2 AI and Preventive Healthcare

Preventive healthcare seeks to reduce the occurrence, progression and consequences of disease. It includes health education, vaccination, screening, early diagnosis, lifestyle interventions and risk management.

AI can contribute to preventive healthcare through the identification of patterns associated with disease risk. Examples include:

- Predictive identification of individuals at increased risk of diabetes.
- Analysis of cardiovascular risk indicators.
- Automated interpretation of retinal images for diabetic retinopathy screening.
- Identification of suspicious patterns in medical imaging.
- Monitoring of physiological indicators through wearable devices.

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- Analysis of population-level health information for public health planning.

The WHO publication *Going Digital for Noncommunicable Diseases: The Case for Action* (2024) recognises the potential of digital health interventions, including telemedicine, mobile health and health chatbots, in supporting NCD prevention and management. It also emphasises the importance of access to appropriate digital tools and infrastructure.

The contribution of AI must nevertheless be assessed in relation to actual healthcare outcomes. Predictive identification does not itself constitute diagnosis, treatment or successful prevention. Effective implementation requires clinical assessment, referral systems and continuity of care.

6.3 Social Determinants of Health

The sociological understanding of health extends beyond biological and individual behavioural factors. Social determinants include the conditions in which people are born, grow, live, work and age, together with the wider distribution of power, money and resources.

Income, educational attainment, employment, housing, nutrition, gender relations, social support and geographical location influence exposure to health risks and the ability to access healthcare.

These factors also influence the availability and quality of health information. Individuals with higher educational and economic resources may be better positioned to interpret digital health recommendations, access specialist services and undertake preventive investigations.

Consequently, AI-based preventive healthcare should be examined within the broader social organisation of health and healthcare delivery.

6.4 Digital Health Equity

Richardson et al. (2022) developed a framework for digital health equity that identifies digital determinants of health as important influences on the distribution of digital health benefits. Their work highlights the possibility that healthcare digitisation may widen existing disparities if digital environments and population needs are not adequately considered.

Digital exclusion is not limited to the absence of internet access. It also includes inadequate digital skills, limited understanding of health information, language barriers, inaccessible interfaces, affordability constraints and lack of trust.

Therefore, digital health equity requires more than making an application available. It requires ensuring that individuals can access, understand, use and benefit from digital healthcare services.

6.5 Algorithmic Bias and Healthcare Inequality

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One of the most significant contributions to the debate on algorithmic bias in healthcare is the study by Obermeyer et al. (2019), published in *Science*.

The researchers examined a widely used healthcare algorithm that was intended to identify patients requiring additional care. The algorithm used predicted healthcare expenditure as a proxy for health needs. However, unequal patterns of healthcare spending resulted in Black patients being assigned lower risk scores than White patients with comparable health needs.

The researchers estimated that correcting the bias would increase the proportion of Black patients identified for additional care from 17.7% to 46.5% among the relevant high-risk group.

This finding demonstrates that algorithmic bias does not necessarily arise only from inaccurate coding or defective software. It may also result from the social meaning of the variables used to train a model.

The study is particularly relevant to medical sociology because it shows how structural inequality can become embedded in apparently objective technological systems.

6.6 Medical Sociology and the Doctor–Patient Relationship

Medical sociology examines healthcare as a social institution involving professional authority, institutional structures, patient experiences and unequal access to resources.

AI introduces new actors into this relationship: algorithms, digital platforms, technology companies and data-processing institutions. Their involvement raises questions about who interprets health information, who makes decisions and who remains accountable when an automated recommendation is incorrect.

AI may assist medical professionals by providing additional information, but it cannot independently understand every dimension of a patient's social circumstances, family responsibilities, cultural practices or lived experience.

The appropriate relationship is therefore one of technological assistance combined with professional responsibility and informed patient participation.

7. THEORETICAL FRAMEWORK

The study draws upon four complementary sociological perspectives.

7.1 Social Determinants of Health Perspective

The social determinants approach explains that health outcomes are shaped by the conditions in which individuals live and by the unequal distribution of resources and opportunities.

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Applied to AI-enabled healthcare, this perspective suggests that predictive technologies must be examined alongside income, education, occupation, housing, nutrition, healthcare infrastructure and geographical access.

A disease prediction model may identify risk, but its preventive value depends partly on whether the individual has the resources and services required to respond to that prediction.

7.2 Social Gradient in Health

The social gradient perspective recognises that health inequalities are not restricted to a simple distinction between rich and poor. Health outcomes often vary across the entire socioeconomic hierarchy.

In digital healthcare, this may be reflected in differences in device ownership, internet quality, health literacy, affordability, access to specialists and ability to follow medical recommendations.

An AI service may therefore be equally available in formal terms while producing unequal practical benefits.

7.3 Intersectionality Perspective

Intersectionality provides a framework for understanding how different dimensions of social disadvantage interact.

For example, an older woman living in a rural area with limited income, disability or low digital literacy may experience multiple barriers to accessing AI-enabled healthcare.

These factors should not be examined in isolation. Their combined influence may create circumstances that cannot be adequately explained through a single category such as gender or income.

This perspective supports the need for disaggregated health data and inclusive service design.

7.4 Social Capital and Community Participation

Social capital refers broadly to relationships, networks, trust and forms of cooperation that enable individuals and communities to access support and resources.

Community health workers, family networks, local organisations and trusted healthcare institutions may play an important role in helping individuals understand digital health information and complete referrals.

AI-enabled preventive healthcare should therefore strengthen community-level health systems rather than assume that every individual can independently navigate digital services.

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8. RESEARCH METHODOLOGY

8.1 Research Design

The study adopts a descriptive, analytical and critical review design based on secondary data. It uses an interdisciplinary approach combining medical science, public health, sociology and digital health governance.

The research is not presented as a clinical trial, systematic review or primary population survey. It does not generate new patient-level observations or claim statistically tested relationships between social variables and AI performance.

8.2 Sources of Data

The study draws upon the following categories of secondary information:

1. World Health Organization publications on NCDs, digital health, health equity and AI ethics.
2. Peer-reviewed research on AI applications in medical diagnosis and preventive healthcare.
3. Research on algorithmic bias and digital health inequalities.
4. Published sociological and public health literature on social determinants of health.
5. International policy documents concerning data protection, privacy, accountability and responsible AI.
6. Published studies examining the relationship between digital access and healthcare utilisation.

8.3 Method of Analysis

The study uses thematic analysis of published literature and policy documents. The material is organised into five analytical themes:

- Clinical applications and predictive capabilities of AI.
- Social determinants and unequal healthcare access.
- Algorithmic bias and representation in health datasets.
- Digital exclusion, privacy and institutional accountability.
- Policy approaches to equitable AI-enabled preventive healthcare.

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The analysis compares the potential benefits of AI with the social and institutional conditions that may influence its implementation.

8.4 Sociological Variables for Future Empirical Research

The following variables are proposed for future field-based studies.

Sociological dimension	Possible indicators
Economic position	Income, employment and financial security
Education	Educational attainment and health literacy
Gender	Access to devices, decision-making and healthcare autonomy
Age	Digital familiarity and health-service requirements
Geography	Rural, urban and remote residence
Occupation	Working conditions and time available for screening
Disability	Accessibility of digital interfaces and services
Family structure	Household support and caregiving responsibilities
Digital access	Smartphone ownership, internet access and affordability
Language and culture	Language preference, health beliefs and communication barriers

These indicators form a proposed research framework. They are not presented as variables measured in the current article.

8.5 Analytical Framework

The study conceptualises preventive healthcare outcomes as a function of technological capability, clinical validation and social conditions:

Preventive Healthcare Outcomes = f (AI Capability, Clinical Validation, Social Determinants, Digital Accessibility, Healthcare Infrastructure, Community Participation and Ethical Governance).

This is a conceptual relationship rather than an estimated statistical equation.

9. FINDINGS AND CRITICAL ANALYSIS OF SECONDARY EVIDENCE

9.1 The Global Burden of Non-Communicable Diseases

The global burden of NCDs demonstrates the importance of preventive healthcare. WHO reported at least 43 million NCD deaths in 2021, including approximately 18 million premature deaths among people below the age of 70. A substantial proportion of premature NCD mortality occurs in low- and middle-income countries (WHO, 2025).

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These figures establish the public health relevance of early screening, risk identification and disease prevention.

AI may support the analysis of health indicators and the identification of individuals requiring further assessment. However, the existence of a predictive system does not guarantee that the individuals identified will receive timely medical attention.

In settings where diagnostic facilities, trained professionals or referral services are limited, prediction may not translate into prevention. The availability of follow-up services is therefore as important as the predictive capability of the technology.

9.2 Algorithmic Bias: Evidence of Social Inequality in Health Prediction

The study by Obermeyer et al. (2019) provides a documented example of how a healthcare algorithm can produce unequal results through the selection of an inappropriate proxy variable.

The algorithm predicted healthcare costs rather than directly assessing health needs. Because expenditure was influenced by unequal patterns of healthcare access, the model underestimated the health needs of a disadvantaged population.

The study has three important implications.

First, predictive accuracy must be assessed in relation to the actual objective of a model. Second, variables that appear statistically convenient may contain social assumptions. Third, historical healthcare data should not automatically be treated as neutral representations of population health.

This example does not establish that every AI healthcare system is discriminatory. It demonstrates that bias can arise through model design and through the social conditions reflected in the data.

9.3 Digital Access and the Unequal Distribution of Benefits

Digital health technologies may reduce geographical barriers by supporting remote consultations, electronic monitoring and access to health information. Nevertheless, the benefits depend on the availability of devices, connectivity, digital skills and accessible healthcare services.

Richardson et al. (2022) argue that digital determinants must be included in health equity frameworks. Their analysis supports the view that digital healthcare can widen disparities when the digital environment is not considered during the design and implementation of services.

The sociological implication is that digital availability should not be confused with social accessibility.

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For instance, a preventive health application may be technically available to all citizens, but its practical use may be limited by language, literacy, disability, affordability or lack of confidence in digital platforms.

9.4 Commercialisation and Ownership of Health Data

AI-based healthcare depends on the collection and analysis of information about individuals and populations. Such information may include medical history, diagnostic reports, biometric measurements, lifestyle patterns, location-related information and behavioural indicators.

The increasing involvement of private technology companies raises questions concerning the collection, processing, storage and secondary use of health data.

Health information is not merely a commercial resource. It relates to personal autonomy, confidentiality and the dignity of individuals.

A responsible preventive healthcare system must clarify:

- What information is collected and why.
- Whether individuals have given meaningful and informed consent.
- Who can access the information.
- Whether data are shared with commercial entities.
- How long information is retained.
- How individuals can exercise their rights.
- Who is accountable in the event of misuse or a data breach.

The social value of AI should not be achieved by weakening the privacy and autonomy of patients.

9.5 The Risk of Shifting Responsibility from Institutions to Individuals

AI-based health applications frequently encourage individuals to monitor their diet, physical activity, sleep, weight and other health indicators.

Such monitoring may support healthier behaviour. However, an exclusively individualised approach can overlook structural influences on health.

For example, unhealthy dietary patterns may be influenced by food affordability and availability. Physical inactivity may be related to occupational conditions, unsafe neighbourhoods or inadequate public spaces. Access to preventive screening may be

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constrained by employment responsibilities, transport costs or the availability of local health services.

It would therefore be inadequate to interpret every failure to follow a digital health recommendation as an individual failure of motivation.

Preventive healthcare requires both individual support and institutional action on the social conditions that influence health.

9.6 Human Judgement and Professional Accountability

AI can assist with pattern recognition and decision support, but clinical decisions involve more than statistical predictions.

A healthcare professional must consider symptoms, medical history, clinical examination, patient preferences and contextual information. An algorithmic recommendation may provide useful evidence, but it should not automatically replace professional judgement.

There must also be clear accountability when an automated recommendation contributes to an incorrect or harmful decision.

A system in which healthcare professionals, software developers and institutions can each deny responsibility would undermine public trust.

10. A CRITICAL SOCIOLOGICAL PERSPECTIVE: FIVE CENTRAL CONTROVERSIES

10.1 Is AI Creating a Two-Tier Healthcare System?

The first controversy concerns the possibility that AI-enabled healthcare may create different levels of access.

Individuals with greater financial resources may be able to use premium applications, wearable devices, private telemedicine and advanced diagnostic services. Individuals dependent on under-resourced public facilities may have fewer opportunities to benefit from such technologies.

This possibility requires empirical investigation. It should not be assumed that all private services are superior or that all public services are technologically inadequate. Nevertheless, unequal purchasing power and infrastructure can influence who receives the benefits of innovation.

The policy challenge is to prevent technological progress from becoming an additional source of healthcare stratification.

10.2 Can an Algorithm Recognise Socially Invisible Health Needs?

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Algorithms operate on the information made available to them. If a person's medical history is incomplete because they have never received regular medical care, their health needs may be poorly represented.

Similarly, populations with limited access to healthcare may generate fewer digital records than populations with regular access to medical services.

The absence of data should not be interpreted as the absence of disease or healthcare need.

This raises an important question for public health institutions: how can health systems ensure that individuals who are least visible in digital records are not also least visible in algorithmic decision-making?

10.3 Is Predictive Healthcare Becoming a Form of Digital Surveillance?

Continuous health monitoring may support early intervention, but it can also create concerns about excessive data collection and surveillance.

Wearable devices and digital applications may record sensitive information about daily activities, sleep, movement and physiological indicators.

When such information is collected without meaningful understanding or control by individuals, preventive healthcare risks becoming intrusive.

The distinction between supportive health monitoring and excessive surveillance must be established through transparent consent, proportional data collection and enforceable privacy protections.

10.4 Can AI Reproduce Gender and Cultural Inequalities?

Health data may inadequately represent the experiences of particular groups. Gender-related differences in healthcare access, occupational responsibilities, caregiving roles and decision-making can influence the availability and interpretation of health information.

Cultural and linguistic differences may also affect how individuals understand medical recommendations and interact with digital systems.

A standardised application developed for one population may not adequately address the needs of another.

Gender-responsive, culturally appropriate and multilingual design should therefore be considered essential components of equitable digital healthcare.

10.5 Can Technology Replace the Social Relationship Between Patients and Healthcare Professionals?

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Healthcare is not simply an exchange of information between a patient and a diagnostic system. It involves communication, professional responsibility, emotional support, trust and informed decision-making.

AI may improve access to information, but it cannot independently reproduce the full social and ethical dimensions of a professional healthcare relationship.

The most appropriate approach is to use AI as a supportive instrument while maintaining human oversight and patient participation.

11. AI AND PREVENTIVE HEALTHCARE IN THE INDIAN CONTEXT

India presents an important context for examining the relationship between AI, health equity and social development.

The country's healthcare environment includes advanced medical institutions, public health programmes, private healthcare providers, primary health facilities and community-level health services. However, access to healthcare and digital services is not uniform across geographical and socioeconomic groups.

The application of AI in Indian preventive healthcare should therefore be examined in relation to the following dimensions.

11.1 Rural–Urban Differences

People living in remote and rural areas may face difficulties in accessing specialist consultations, diagnostic facilities and reliable internet connectivity.

AI-assisted screening and telemedicine may help address certain geographical barriers. However, these services must be connected to local health facilities and referral mechanisms.

An application that identifies a possible health risk without providing a pathway to clinical assessment may have limited preventive value.

11.2 Income and Affordability

The affordability of smartphones, data services, diagnostic investigations and wearable devices can influence access to digital health interventions.

Publicly supported digital healthcare services should not assume that all households can independently purchase the technology required to participate.

Low-cost, accessible and publicly supported preventive services are important for ensuring that digital innovation does not become dependent on household purchasing power.

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11.3 Language and Health Literacy

India's linguistic diversity creates an important design consideration.

Health recommendations should be understandable to people with different levels of education and literacy. Digital interfaces should support relevant regional languages and accessible communication formats.

Simple language, audio instructions, assisted access and community-based health education may improve the usability of digital preventive services.

11.4 Gender and Family-Level Access

Access to digital devices and healthcare decisions may be influenced by household relationships and gender roles.

Preventive health interventions should therefore examine whether women and other disadvantaged groups can independently access information, make healthcare decisions and obtain follow-up services.

11.5 Community Health Systems

Community health workers and local healthcare institutions can provide an important link between AI-based screening and actual preventive intervention.

Their role may include explaining digital recommendations, facilitating screening, supporting referrals and helping individuals navigate healthcare services.

AI should strengthen the capacity of frontline health workers rather than displace their social and professional contribution.

12. PROPOSED INTEGRATED SOCIOTECHNICAL FRAMEWORK FOR EQUITABLE AI-ENABLED PREVENTIVE HEALTHCARE

Based on the literature and critical analysis, the study proposes an Integrated Sociotechnical Framework for Equitable AI-Enabled Preventive Healthcare.

The framework consists of five interconnected dimensions.

12.1 Clinical and Biological Dimension

This dimension includes medical history, symptoms, diagnostic indicators, laboratory results, physiological measurements and established clinical risk factors.

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Its purpose is to support evidence-based risk assessment and early identification of possible health conditions.

12.2 Sociological Dimension

This dimension examines the social conditions influencing health and access to preventive services, including:

- Income and economic security.
- Education and health literacy.
- Gender and age.
- Occupation and working conditions.
- Disability and accessibility.
- Family structure and social support.
- Rural–urban location.
- Cultural and linguistic context.

The purpose is to ensure that health risk is not interpreted solely through biological or behavioural indicators.

12.3 Technological Dimension

This dimension includes:

- AI and machine-learning models.
- Predictive analytics.
- Digital health applications.
- Wearable monitoring devices.
- Electronic health records.
- Medical image analysis.
- Secure data systems.

All technological components require appropriate validation, monitoring and protection against bias.

12.4 Institutional and Community Dimension

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This dimension connects technological prediction with actual healthcare services through:

- Primary healthcare institutions.
- Medical professionals.
- Community health workers.
- Public health programmes.
- Referral and follow-up services.
- Community organisations.

The objective is to ensure that identifying a potential health risk leads to an appropriate opportunity for professional assessment and preventive action.

12.5 Ethical and Governance Dimension

This cross-cutting dimension includes:

- Informed consent.
- Privacy and data protection.
- Transparency and explainability.
- Fairness and bias assessment.
- Human oversight.
- Professional accountability.
- Public participation.
- Independent evaluation.

The framework proposes that equitable preventive healthcare emerges from the interaction of these dimensions rather than from technological capability alone.

13. PROPOSED SOCIAL DETERMINANTS AND DIGITAL PREVENTIVE HEALTHCARE ASSESSMENT MATRIX

Social condition	Possible barrier
Low income	Device and service affordability
Limited education	Difficulty interpreting health information
Rural residence	Limited connectivity and specialist services
Gender inequality	Unequal access to devices and decisions

DOI: https://doi.org/10.64706/4f8jye72

ISSN: 3107-3883 (Online)
Global E-Journal of Social Scientific Research
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Older age	Difficulties using digital interfaces
Disability	Inaccessible applications
Occupational constraints	Limited time for screening
Language differences	Difficulty understanding recommendations
Social condition	Possible barrier
Low income	Device and service affordability
Limited education	Difficulty interpreting health information
Rural residence	Limited connectivity and specialist services
Weak community support	Incomplete follow-up
Institutional mistrust	Reluctance to share personal data

14. POLICY AND INSTITUTIONAL RECOMMENDATIONS

The analysis suggests that the implementation of AI in preventive healthcare requires coordinated action at technological, clinical, social and institutional levels.AI systems used for health-risk assessment should be evaluated across relevant population groups. Assessment should consider differences in age, gender, socioeconomic position, geographical location and other relevant characteristics.

Developers and healthcare institutions should examine false-positive and false-negative rates across groups rather than relying exclusively on overall accuracy. Health datasets should reflect the diversity of populations in which an AI system will be used. Models developed in one geographical or demographic context should not automatically be assumed to perform equally well in another. Local validation should be undertaken before large-scale implementation.AI recommendations should support, not replace, qualified healthcare professionals. Patients should have access to human assessment, an explanation of significant decisions and an appropriate mechanism for raising concerns. Digital health strategies should include affordable access, accessible interfaces, regional languages, digital literacy and assisted services. People who cannot use digital platforms should not be excluded from essential preventive healthcare. Institutions should establish transparent procedures for consent, collection, storage, access, sharing and retention of health information. The use of personal health data for commercial or secondary purposes should be subject to appropriate legal and ethical safeguards. Communities should be involved in the design, implementation and evaluation of AI-enabled preventive health services Participation can help identify local needs, language barriers, cultural concerns and practical obstacles that may not be visible to technology developers.AI healthcare policy should involve medical professionals, public health experts, sociologists, data scientists, legal experts, ethicists and community representatives. Sociological expertise is especially important for examining the distribution of benefits, the impact of social inequalities and the relationship between technology and institutional power.

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AI healthcare systems should be evaluated through a wider set of indicators:

1. Clinical validity and safety.
2. Diagnostic and predictive performance.
3. Accessibility and affordability.
4. Population-level coverage.
5. Referral completion and continuity of care.
6. User understanding and institutional trust.
7. Differences in performance across social groups.
8. Privacy and accountability.

This broader approach would make social outcomes an integral part of technological evaluation.

15. DISCUSSION

The findings from the secondary literature indicate that AI has considerable potential to support preventive healthcare. Predictive analytics, automated screening and digital monitoring may improve the identification of health risks and support more timely clinical intervention.

However, the analysis also demonstrates that the relationship between technological innovation and health outcomes is mediated by social conditions.

The example presented by Obermeyer et al. (2019) shows that algorithmic systems can reproduce inequalities when their design relies on proxy variables that reflect unequal healthcare utilisation. The digital health equity framework developed by Richardson et al. (2022) further demonstrates the importance of digital environments in determining who can benefit from technological interventions.

These findings support a broader sociological interpretation of AI. Technology is not introduced into a socially neutral environment. It operates within institutions and populations characterised by differences in resources, power, opportunities and access. A central contribution of this article is the distinction between predictive accuracy and social effectiveness. Predictive accuracy concerns how well a model identifies a particular outcome within a defined population and context. Social effectiveness concerns whether the system contributes to meaningful improvements in health across different sections of society. A system may perform well in a controlled technical evaluation but remain ineffective for people who

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cannot access the service, understand its recommendations or obtain follow-up treatment. Consequently, the evaluation of preventive AI should include both clinical and social outcomes.

Another important issue concerns the distribution of responsibility. Digital health applications often encourage individuals to monitor their own health. Such practices can support prevention, but they should not transfer the responsibility for public health entirely to individuals. Governments and healthcare institutions remain responsible for providing accessible services, reliable information, appropriate screening and referral pathways. AI should improve the ability of institutions to identify and address health needs, rather than become a substitute for public healthcare investment.

Medical sociology offers a necessary perspective for understanding the wider implications of AI-enabled healthcare. It examines how social structures influence exposure to disease, access to healthcare, professional authority, patient experiences and institutional trust. By integrating medical sociology with AI research, the present article expands the discussion from the technical question of whether an algorithm can predict disease to the broader question of whose health needs are recognised and whose interests are served.

The debate should not be reduced to a choice between technological progress and social protection. AI can contribute to more effective healthcare when its development is guided by clinical evidence, ethical standards and an understanding of social inequalities. The challenge is to create systems in which technological innovation and social justice reinforce one another.

16. LIMITATIONS OF THE STUDY

The present article is based on secondary sources and critical analysis. It does not include primary patient data, clinical trials, interviews, focus-group discussions or a population-level survey. The proposed sociological variables and analytical framework have not been empirically tested in the present study. They should therefore be interpreted as conceptual and research propositions rather than established statistical relationships.

The article also draws upon international evidence, including research conducted in the United States. Such findings cannot be directly generalised to India without appropriate contextual and empirical validation. Future research should examine the performance and social implications of AI-enabled preventive healthcare within specific Indian populations, healthcare institutions and regional contexts.

17. FUTURE RESEARCH DIRECTIONS

The study identifies several areas for future investigation.

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First, a population-based study could examine how income, education, gender, age and geographical location influence access to AI-enabled preventive healthcare.

Second, a comparative study could assess differences in the use of digital preventive services between rural and urban populations.

Third, an algorithmic fairness study could investigate whether predictive models produce different error rates across relevant social and demographic groups.

Fourth, a medical sociology study could explore patient trust, professional authority and perceptions of AI-assisted health decisions through interviews with patients and healthcare professionals.

Fifth, an institutional study could examine the readiness of public healthcare facilities to adopt AI-based screening and referral systems.

Sixth, a community-based study could assess whether the involvement of community health workers improves access, understanding and follow-up in AI-enabled preventive health programmes.

Such research would help establish a stronger empirical foundation for the relationship between technological innovation and health equity.

18. CONCLUSION

Artificial Intelligence has the potential to transform preventive healthcare through early disease prediction, automated screening, risk assessment and digital health monitoring. Its contribution to medical science and public health may be particularly important in addressing the growing burden of non-communicable diseases.

However, technological progress should not be treated as an automatic guarantee of better or more equitable healthcare.

The critical analysis presented in this article demonstrates that algorithmic systems operate within existing social and institutional structures. Their outcomes may be influenced by the quality and representativeness of health data, unequal access to medical services, digital literacy, affordability, gender relations, geographical inequalities and institutional accountability. The evidence of algorithmic bias reported by Obermeyer et al. (2019) demonstrates how social inequality can become embedded in health-prediction systems through seemingly neutral technical choices. Research on digital health equity similarly highlights the importance of ensuring that technological interventions are accessible and usable across different population groups.

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The central argument of this study is that the future of preventive healthcare must be determined not only by what Artificial Intelligence can predict, but also by whose health it can protect, whose needs it can recognise and who can access its benefits. AI should therefore be understood as a sociotechnical instrument rather than an independent solution to public health challenges. Its implementation must combine scientific validation with social inclusion, professional judgement, community participation and ethical governance.

For India and other developing societies, the priority should be to integrate AI with accessible primary healthcare, affordable digital infrastructure, multilingual health information and community-based preventive services. Ultimately, the success of AI-enabled healthcare should not be measured solely by processing speed, predictive accuracy or technological sophistication. It should also be measured by its ability to reduce avoidable health inequalities, strengthen public institutions and improve the wellbeing of individuals and communities.

The question is no longer simply whether Artificial Intelligence can predict disease. The more important question is whether society can ensure that this predictive power serves everyone fairly.

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