The Future of Preventive Healthcare: Can AI Make Early Disease Detection Accessible and Affordable in Developing Countries?

ABSTRACT:

However, preventive medicine requires early identification of disease, which remains a challenge for many low- and middle-income countries due to a shortage of trained health workers, insufficient distribution of diagnostic equipment, high out-of-pocket costs, and ineffective health information systems. One possible method of extending diagnostic services could be the application of artificial intelligence to medical image interpretation, risk prediction, laboratory decision support, and screening tests. The current paper explores the possibility of using AI to achieve early detection of diseases in developing countries with regard to conditions for doing business and implementing health system interventions.

The research design of the paper is a qualitative secondary analysis of peer-reviewed literature and institutional sources. The focus is on the application of AI to medical image interpretation, diabetic retinopathy screening, tuberculosis and lung radiography, laboratory medicine, risk prediction and point-of-care technologies.

From the literature, it appears that AI can help overcome some of the barriers through its ability to help health workers, increase the capacity of diagnostic services, and facilitate early referral. This statement is particularly true of the use of AI in diabetic retinopathy screening since there are some studies that demonstrate the economic efficiency of AI-based screening services in LMICs. But the affordability of such an intervention cannot rely only on software solutions. Other aspects like hardware, connectivity, maintenance, validation, training, data governance, regulations, and follow-up care will affect the actual costs of the AI service. AI seems to be the most useful as a complementary technology in the context of primary healthcare rather than a substitute for medical professionals or health systems.

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Keywords: artificial intelligence, preventive healthcare, early disease detection, low- and middle-income countries, digital health, health economics, medical diagnostics

CHAPTER 1: INTRODUCTION

1.1 Background of the Study

Preventive healthcare is based on the fundamental idea that diagnosing any health issue earlier increases intervention options compared to waiting for the disease to become more complicated. Early diagnosis through screening, risk assessment, regular monitoring, and intervention helps to avoid avoidable complications and allows for interventions at an early stage when treatments are still less complicated. However, providing such interventions can be difficult due to constraints in offering these services in LMICs. In addition to having fewer doctors and nurses, LMICs often lack diagnostic equipment, laboratories, specialist services, databases, and finances.

The financial aspect of the matter is crucial as well. According to WHO, 4.5 billion people in the world were unable to access basic health services, whereas 2 billion people were facing problems regarding fulfilling their health expenses in the latest global expenditures analysis. In many low- and lower-middle-income countries, people continue to incur out-of-pocket expenses for health care services (World Health Organisation [WHO], 2024). Therefore, preventive measures become viable only if no additional costs appear in using them.

The introduction of artificial intelligence into the conversation is due to algorithms being able to work with a great deal of medical data and see patterns in the data that might not always be possible to detect manually. There has been research carried out regarding the interpretation of retinal photographs, radiological images, lab data, and electronic health records. In a systematic review carried out by Liu et al. (2019), it was shown that in selected medical imaging studies that were externally validated, deep learning algorithms achieved diagnostic accuracy levels on par with those of healthcare professionals.

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It is not a question of whether AI can diagnose diseases in developing countries. The question is whether AI can economically improve the capacity for disease diagnosis. It is necessary to bring together health sciences, technology, economics, management, and public policy to do so. Although an AI algorithm can work perfectly in a research setting, it will fail to contribute to population health if it needs costly hardware, continuous high-speed connection, specialised technologists, or inaccessible data.

This paper will look into this broader issue. It views AI as an intervention in the health system.

1.2 Problem Statement

The ability to identify diseases early in developing countries is constrained by many interlinked factors. The availability of diagnostic services could be limited to urban centres, a shortage of specialists could make diagnosis take a long time, and patients might delay seeking help because of the cost or distance involved. There could also be a lack of standardisation of digital information in healthcare facilities or a lack of enough local data for training and validation of the algorithms. Ciecierski-Holmes et al. (2022) pointed out that the use of AI in LMICs still faced constraints such as availability and reliability of data, usability, and cost-effectiveness, among other factors.

At the same time, the existing literature on applications of AI in health care is generally driven by research carried out in rich countries. The success of an algorithm in one population does not guarantee success in another population, due to the different prevalence rates of diseases, types of equipment, languages, health-care practices, etc. Therefore, a crucial challenge in implementing an AI application consists of the following: even if the algorithm itself is cheap because of its low software cost, there may be large expenses for cameras, medical equipment, servers, internet, training of the personnel, maintenance, etc., for the health care system.

Thus, the problem we will review here is as follows.

1.3 Research Aim and Objectives

The objective of this secondary study is to analyse whether AI technology has the potential to increase access and lower costs of early disease detection in developing countries, with a special emphasis on health impact, health system capacity, cost-effectiveness, business models, and

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challenges for implementation.

The objectives are to:

• analyse current applications of AI in preventive healthcare and early disease detection;
• review the literature on AI-enabled diagnostic capability for screening and decision support;
• analyse economic and organisational factors influencing affordability;
• explore infrastructure, data, human capital, trust, privacy, and regulatory challenges;
• analyse the potential role of AI-enabled preventive care within a sustainable business model for healthcare; and
• review emerging trends and research priorities.

1.4 Research Questions

- What might be the use of AI in the early detection of disease in the developing world?
- How would AI-aided screenings help in simplifying the process of diagnosis?
- Can the early detection process via AI technology be economically more feasible than the existing process of screenings and diagnosis?
- What might be the challenges that can arise due to the application of AI technology in preventive care?
- What should be the model of doing business/healthcare economically feasible?

1.5 Significance of the Study

It is interdisciplinary in nature. In health science, it looks at the role that AI can play in screening and early detection of diseases. In business and management, it looks at cost, scalability, funding, deployment and adoption. It emphasises the need for decision-makers to measure the effectiveness of new technologies based on their benefits to the population, rather than just on their technical feasibility.

1.6 Scope and Delimitations

The review will focus mainly on AI applications that could help with early detection/screening/triage/risk stratification for LMICs. This includes medical imaging, diabetic retinopathy, respiratory and TB imaging, lab medicine, point-of-care testing, and predictive

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analytics. This article will not aim to cover the entire range of clinical applications of AI or even provide data on patients. It is not aimed at proving that AI can independently diagnose diseases. On the contrary, it will analyse AI as a decision support technology within the healthcare process.

CHAPTER 2: LITERATURE REVIEW

2.1 AI and the Expansion of Diagnostic Capacity

Although the literature broadly suggests that AI can increase diagnostic capacity, there seems to be variation in terms of the quality of the evidence available in different contexts. For example, Liu et al. (2019) conducted a review of 82 studies and concluded that, out of the studies that could be included in the meta-analysis, deep learning algorithms performed on par with healthcare professionals. In another systematic review by Aggarwal et al. (2021), there were 503 studies on deep learning in medical imaging, and the results indicated high diagnostic performance in ophthalmology, respiratory imaging and breast imaging. There was also considerable heterogeneity and issues related to methodology.

These results are important for LMICs, where a scarcity of specialists often restricts diagnostic capacity. With an AI technology performing the initial screening process in the primary-care setting, the health care system would use the resources of a specialist only when additional assessment is required.

2.2 AI in Low- and Middle-Income Countries

Ciecierski-Holmes et al. (2022) conducted one of the most comprehensive overviews of AI applications in LMICs' healthcare. This systematic scoping review included searches through several databases and found no more than ten studies with real-world applications of the technologies described. Applications include clinical decision support, treatment planning, triage assistants, and health chatbots. Even this small number of studies is interesting, as it shows that more progress has been made on development than on implementation.

There are many barriers to the successful implementation of AI, including limitations of datasets,

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reliability, workflow integration, usability, localisation, trustworthiness, and cost-effectiveness. All of those constraints do not apply exclusively to AI. They belong to the realm of health systems that require technologies to work with limited infrastructure. AI can alleviate some constraints related to the availability of the workforce but cannot replace electricity, connectivity, skilled personnel, medications, referral hospitals, and finance.

2.3 AI-Based Diabetic Retinopathy Screening

Diabetic retinopathy is an appropriate example for discussing AI and preventive healthcare, as retinal photographs can be analysed outside specialised eye care facilities using computer vision. Rizvi et al. (2023) have assessed the health economics of implementing AI for diabetic retinopathy screening in LMICs. In their systematic review, the authors have identified five economic evaluations, of which three demonstrated higher cost-effectiveness of AI screening compared to the standard one.

More up-to-date studies continue to provide evidence regarding the feasibility of such an application of AI technology. Namely, Onyeze et al. (2025) reviewed the existing AI applications for the diagnosis of diabetic retinopathy in LMICs, noting high accuracy and promising implementation feasibility but a lack of information regarding infrastructure, regulations, and sustainability of this process. The last point is quite characteristic of the literature on AI.

2.4 AI in Respiratory and Tuberculosis Screening

The use of AI for earlier diagnosis of respiratory diseases using chest radiography and related imaging methods is another application in which AI may have a positive impact. Medical imaging literature suggests that deep learning can detect abnormalities in chest X-rays and CT scans, although the accuracy is somewhat variable and needs to be externally validated (Aggarwal et al., 2021; Liu et al., 2019).

The use of AI for assisting radiography in LMICs will depend on the lack of radiologists and the burden of respiratory diseases. However, the economics of the solution will hinge on the presence or absence of imaging devices. If AI relies on the acquisition of a new digital X-ray

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device, then the cost framework is entirely different compared to the scenario when the model uses currently available infrastructure.

2.5 AI and Laboratory Medicine

Laboratory medicine is yet another relevant field, as the initial detection of diseases may be based on test results that need to be interpreted correctly and analysed under high-quality laboratory conditions. Oduoye et al. (2024) have reviewed the effect of artificial intelligence on laboratory medicine in LMICs and pointed out some possible uses of AI in the analysis, diagnostics, and management of patients. They also cited infrastructure, workforce, data and implementation challenges.

Artificial intelligence can assist laboratory medicine by flagging anomalies, identifying patterns across multiple parameters, supporting quality control, and prioritising specimens. Nevertheless, algorithmic analysis will not make up for poorly collected samples, poor reagents, inappropriate equipment, or lack of clinical information. The optimal model, therefore, would be one in which AI enhances the use of reliable laboratory facilities.

2.6 Point-of-Care and Portable Technologies

Such diagnostic technologies may be especially useful in the case of rural and underprivileged areas. A 2024 scoping review on AI applications for point-of-care ultrasound in resource-limited environments showed that the trend in the area includes growing interest in integrating portable ultrasound with AI-assisted interpretation of images.

However, such an approach is highly significant from a business perspective. While a portable technology may decrease the necessity for a patient to go to the hospital, an AI service could be used for image interpretation. However, this idea comes with additional costs associated with device purchasing, training, connection, cybersecurity, and maintenance. Thus, the key question is not whether the technology is cheaper than a hospital ultrasound machine, but whether it reduces overall expenses.

2.7 Data Sharing and Local Context

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However, AI relies on data, which is typically scattered in LMIC healthcare settings. Kaushik et al. (2025) identified barriers to data sharing as connectivity, hardware, motivation, resource allocation, ethics, policies and cybersecurity. Other barriers in their Thai case study include inconsistent data management systems, staff time shortages, poor health-data literacy, and lack of policies.

Data deficiency may lead to a vicious circle. For instance, AI developers require representative Health systems in such countries; standardised electronic records may be lacking, which hinders their ability to develop and test models using data from local settings. Internationally available data sets may not be representative of the local population. This makes a strong case for regional collaboration, data standards, secure data sharing, and validation of AI tools.

2.8 Equity and Bias

AI technology could also unintentionally increase inequity due to the fact that it is more available in wealthy urban hospitals than in rural settings. The problem may arise from the bias that occurs during data collection for training an AI system. Even if the system shows good performance overall, there may still be differences in how well it works for different ages, sexes, ethnic groups, stages of disease, or imaging machines.

Ethics guidelines by WHO stipulate that the use of AI technologies in healthcare has to respect people's autonomy, benefit humans, and ensure transparency and equity (WHO, 2021). Thus, to ensure equity in LMICs, one must consider who will be screened, who will pay, who is connected, and who will receive treatment.

2.9 Research Gap

There is an apparent bias in the literature concerning technical evidence versus implementation evidence. Many studies have been conducted regarding the assessment of algorithms; however, few have looked at the tracking of AI systems from implementation through to routine delivery of healthcare services and cost, patient outcomes, maintenance, workforce implications, and equity effects over the long term. Economic evaluation has focused on narrow applications such as diabetic retinopathy.

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Another gap relates to the business model. Health systems need to deal with procurement, financing, maintenance, training, software provision, and accountability. These are management issues as well as medical and technical issues. More work needs to be done on the public-private partnership model, pay-for-screening, subscription, public procurement, cross-subsidisation, and incorporation into national screening programmes.

CHAPTER 3: THEORETICAL FRAMEWORK AND CONCEPTUAL BACKGROUND

3.1 Preventive Healthcare and Early Detection

Preventive medicine encompasses interventions that aim to lower the chances or impact of a particular disease. In the field of preventive medicine, early detection and screening are particularly pertinent to AI since they rely on the recognition of patterns before the development of the disease itself. Early detection is effective only when there is proper follow-through with confirmatory tests or treatment after a positive result. There is a possibility that a screening programme could cause stress without any positive outcome.

The distinction is even more crucial for LMIC countries. As far as the economic value of early detection programmes is concerned, it is necessary to take into account all the costs of detection, treatment, transportation and follow-up. Yeong et al. (2023) conducted a systematic review of the cost-effectiveness of breast cancer early detection programmes in LMICs, which were influenced by the screening approach and context.

3.2 AI in Healthcare AI is concerned with computational technologies that are capable of performing jobs that involve learning, pattern recognition, prediction, classification and decision-making. In medicine, machine learning techniques can find statistical correlations in clinical data sets, while deep learning is more generally used for image and signal processing. Hence, AI may be applied at various stages of the preventive care process: patient identification, screening, imaging interpretation, case prioritisation, laboratory testing support, referrals, and population monitoring.

The WHO understands the opportunities and challenges of AI in health systems. The agency's guidelines state that "AI must be harnessed to contribute to people-centred and more equitable

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health systems, where governance, regulation, data protection, oversight by humans, and trust are paramount" (WHO, 2021, 2023). It offers an excellent theoretical framework for evaluating AI based not just on its accuracy but also on its equity, safety, accountability, and sustainability.

3.3 Technology Acceptance and Human-in-the-Loop Care

Institutions and individuals employ health care technologies, not just the technology itself. An important consideration that will inform this literature review is that the value of AI is likely maximised when clinicians or health practitioners can make sense of, have faith in, and properly use its results. This conclusion is because of the human-in-the-loop concept that sees AI as an assistant and not a replacement for clinicians' decision-making process.

This aspect is particularly important where the stakes of either a false negative or false positive could be very high. An AI system that mistakenly assures a clinician may delay treatment, while the technology's creation of false positives could overload diagnostic services. Implementation is hence likely to demand referral guidelines, quality assurance, training, and processes of challenging and overriding algorithmic recommendations.

3.4 Health Economics and the Value of AI

The economic benefit of artificial intelligence can be looked at from various perspectives: cost of the technology, cost of each episode of screening, time savings on personnel, differences in referral rate, diagnostic effectiveness, treatment promptness, avoiding complications, and patients' cost of transport or waiting time. A technology can be cost-saving, cost-effective, or just beneficial without being less costly.

Rizvi et al. (2023) performed a review of health-economic assessments of AI technologies for DR screening in LMICs. Their review revealed only five eligible economic studies, out of which three found AI-based screening to be more cost-effective than standard screening methods. It is the low number of economic studies that makes the finding rather encouraging than conclusive.

3.5 Conceptual Framework

The conceptual framework developed for this review links five stages:

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Health need → accessible data collection → AI-assisted risk or image interpretation → human verification and referral → earlier intervention and health-system value.

This framework also consists of two other criteria that cut across all stages: affordability and governance. Affordability encompasses hardware, software, training, maintenance, connectivity, and patient costs. Governance encompasses privacy, accountability, bias evaluation, regulation, transparency, and human involvement. It follows, therefore, that according to the model, AI will be able to generate value for preventive healthcare only by translating performance into affordability.

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CHAPTER 5: AI-ENABLED PREVENTIVE HEALTHCARE AND BUSINESS MODELS

5.1 AI as a Screening and Triage Tool

One of the most practical near-future uses of artificial intelligence in preventive care could be screening and triaging. Rather than expecting an algorithm to do all of the work involved in making a full diagnosis, artificial intelligence can simply be used to classify images or data such as low-risk, high-risk, or needing specialist review.

This solution is especially applicable in situations where specialists concentrate in urban areas. One clinic could take a picture of someone's retina or a chest X-ray, and artificial intelligence could pick out those people who require more analysis. In this way, artificial intelligence would serve as a capacity multiplier, as one specialist would be able to oversee a higher number of screening sites due to AI doing the first round of diagnostics.

5.2 Cost Components

Costs of the AI screening programme comprise at least six elements: hardware costs, software costs, connectivity costs, human resource costs, maintenance costs, and subsequent care costs. Hardware might include such devices as cameras, ultrasound machines, digital X-ray machines, server units, or even smartphones. Software costs may include licence fees, cloud computing services, machine learning upgrades, and cybersecurity costs.

It is a mistake to compare the purchase price of an AI product against the cost of a specialist. The better economic comparison would be cost per person who was correctly screened and treated.

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Key Cost Distribution in AI Implementation

Cost Component	Nature of Expense	Key Elements & Considerations
Hardware Infrastructure	Capital Expense (CapEx)	Retinal cameras, digital X-ray machines, handheld ultrasound probes, smartphones, edge servers.
Software & AI Licensing	Operating Expense (OpEx)	Algorithm per-use licenses, cloud hosting, periodic model re-validation, cybersecurity protocols.
Connectivity & Data	Operating Expense (OpEx)	Cellular/broadband data pipelines, local edge synchronisation, secure cloud backup.
Human Capital & Training	CapEx & OpEx	Upskilling health practitioners, continuous clinical workflow adaptation, IT management.
Maintenance & Support	Operating Expense (OpEx)	Device calibration, equipment repair, system uptime guarantees, software patches.
Follow-up Care & Referrals	Health System Expense	Confirmatory testing, treatment for true positives, referral tracking, patient navigation.

5.3 Business and Financing Models

There are different ways in which AI-powered preventive healthcare can be provided through an organisation. For instance, governments may acquire technology as part of their screening programmes. Alternatively, hospitals may purchase AI technology directly. There are other organisations offering screening services to customers, and tech companies may have different commercial arrangements. One option is using the subscription model; another one is pay-per-use.

It might be more sensible to opt for flexible financing models in developing countries. This way, for instance, a pay-per-use approach can lower the financial hurdle for small clinics. At the same time, ongoing expenses can become quite costly. This is why governments and private organisations need to assess the total cost of ownership before selecting a particular commercial model.

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The task of management is about making sure that the incentives of all the parties involved align. While there are certain benefits to selling as many tests as possible for a business, a public health programme might focus on minimising unnecessary tests and maximising population-level outcomes.

5.4 Workforce and Organisational Change

The use of AI in practice will transform work rather than remove it. Health professionals will have more time for quality assurance, communication, referral, and follow-up rather than spending time on interpretation. New positions will focus on data management, digital health processes, model performance monitoring, and support.

Therefore, the costs of training are included in the price of technology. In line with WHO recommendations on digital health, digital interventions are meant to complement health systems functionalities, while the performance of those interventions depends on training, governance, infrastructure, and implementation capacities (WHO, 2019). Even a technically advanced AI tool may fail if health care professionals cannot interpret its performance correctly.

5.5 Scalability

Scalability is among the best advantages of AI. After testing the algorithm, deploying the software in new sites may be simpler than training many specialists. However, it is important not to mistake software scalability for health system scalability. The addition of each site will mean the necessity of providing devices, electricity, connections, technical assistance, specialists and quality assurance.

The design of the scalable solution requires modularity. It means that screening could be done at community or primary-care levels, whereas specialist analysis and intervention should be carried out out, out, out, out centrally. Cloud or edge computing technologies could be used for various connectivity settings. User-friendly interface in the local language and clear workflow are among such design considerations.

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5.6 Comparative Application Areas

Application	Potential Preventive Value	Main Cost Issue	Key Implementation Risk
Diabetic Retinopathy	Earlier identification of retinal disease	Imaging device + screening workflow	False results and referral capacity
Chest Imaging	Earlier detection/triage of respiratory disease	Digital imaging infrastructure	Dataset and device variation
Laboratory Medicine	Flagging abnormal or high-risk results	Lab digitisation and integration	Poor-quality or incomplete data
Point-of-Care Ultrasound	Earlier assessment in underserved areas	Portable equipment + training	Operator skill and connectivity
Risk Prediction	Identifying patients needing follow-up	Data infrastructure	Bias and generalisability

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CHAPTER 6: FINDINGS AND DISCUSSION

6.1 Key Findings from the Literature

Firstly, AI appears to have valid prospects in extending early detection capability, though most of the evidence is available for well-defined tasks and not full-fledged autonomous diagnoses. The studies related to medical imaging have shown that deep learning models are capable of performing well in diagnostic procedures under certain conditions (Aggarwal et al., 2021; Liu et al., 2019). The LMIC-specific evidence, on the other hand, has shown applications in decision-making, triage, imaging, laboratory medicine, and other fields (Ciecierski-Holmes et al., 2022).

Secondly, affordability depends on the application. While there is some positive economic evidence that diabetic retinopathy is cost-effective in LMICs, it is incorrect to assume the same for all diseases. Cost-effectiveness varies depending on the equipment needed, prevalence of the disease, availability of specialists, and further treatment facilities.

The third finding is that infrastructure plays a decisive role. AI tools need infrastructure such as connectivity, power supply, digital record-keeping, data standards, technology, and technical support to operate outside the research lab. As Kaushik et al. (2025) mentioned, there are technical, organisational, legal, ethical and economic barriers to data sharing.

The fourth finding is that the AI tools must be used alongside human care. This point is emphasised by WHO guidance, which stresses that the importance of human involvement lies in oversight, safety, equity, and responsible governance.

6.2 Benefits of AI for Preventive Healthcare

- Increased scope for screening services in areas where specialists are not readily available.
- Quick identification and prioritisation of abnormal cases.
- Improved consistency in first-tier interpretation for selected screening services.
- Decreased travel and waiting times in cases where screening can be conducted in the vicinity.
- Increased efficiency for health personnel via decision support and triage.
- Increased cost-effectiveness of selected screening services.

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• Optimal utilisation of specialists' time is achieved by focusing on high-risk cases.
• Increased scope for integration of screening services within digital health and primary care networks.

6.3 Emerging Trends

Various other trends are expected to influence the future of preventive healthcare powered by AI. Edge AI can enable models to work closer to the point of care without relying on the availability of a constant connection to the internet. The techniques of privacy-preserving and federated learning will enable organisations to collaborate and share data even without having the whole database at once. The use of explainable AI will let doctors understand why the algorithm made that decision. Multimodal AI will enable combining all of these variables into a single model. The development of portable technologies is another trend that needs to be highlighted here. The WHO 2026 Target Product Profile for In-Vitro Diagnostics focuses on designing the diagnostic product with LMIC settings in mind, rather than modifying a product originally developed for high-income countries. The same rule applies to AI-based products.

6.4 Challenges and Limitations

Accuracy alone is insufficient. The algorithm could have low performance when imaging tools, demographics, disease distribution, and workflow conditions are different from those in the learning process. Drift can also arise due to changes in disease trends and practices. Cybersecurity and privacy are significant issues because medical information is highly confidential.

Organisational risks can also be present. An excess number of alarms from an algorithm increases workload instead of decreasing it. Lack of trust on the part of employees results in insufficient use of AI. Over-reliance on the system creates automation bias.

6.5 Can AI Really Make Early Detection Affordable?

From the evidence above, an answer can be offered subject to certain conditions: AI is capable of lowering the cost of certain early detections, but it is not inevitable. In this regard, the task should be replaced or augmented by AI; existing equipment should be used; there should be

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enough disease burden for screening; and finally, early detection and treatment should be ensured.

When AI is implemented as a stand-alone technology without proper infrastructure and follow-up, it does not provide a significant advantage over the current situation. An example is a low-cost algorithm that performs tests in a clinic that lacks a system for confirming the test results and offering treatment. In this scenario, the introduction of AI does not improve the health of the population in question.

From this analysis, it is safe to conclude that AI lowers the cost of marginal screening tasks, but the overall cost of the programme must be assessed at the level of the health-care system.

6.6 Discussion of the Research Questions

RQ1: AI can facilitate early diagnosis through image classification, risk prediction, decision-making, lab analysis, and triage.

RQ2: AI can contribute to increased access because first-level testing can take place closer to primary care, where the number of specialists is lacking.

RQ3: Cost-effectiveness has been demonstrated for certain applications, specifically diabetic retinopathy screening, although insufficient data prevents us from claiming general cost-effectiveness.

RQ4: The major obstacles to deployment are infrastructure, quality of data, local validation, cybersecurity, regulation, education of the workforce, workflow, bias, and patient trust.

RQ5: A sustainable model should involve collaboration between public health services, private technology vendors, local healthcare organisations, and funding options. Deployment will be determined not only by the algorithm itself but also by procurement and governance.

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CHAPTER 7: FUTURE DIRECTIONS, ETHICAL AND REGULATORY CONSIDERATIONS

7.1 Future Directions

Future research should shift focus from algorithm-based research to implementation and health outcome research. Research should include total costs, maintenance needs, staffing time, patient outcomes, follow-up referrals, and demographic group performance. Longitudinal research would also be very important, as the benefits of preventive healthcare are seen over time.

In addition, future research should consider other delivery systems. For example, a government-owned website may have different costs and different equity impacts than a private subscription system. Rural and urban settings are not equivalent, and language, access to equipment, electricity, and health-seeking behaviour may all play a role.

7.2 Ethical Considerations

Preventive healthcare using artificial intelligence (AI) also gives rise to various ethical issues related to privacy, consent, fairness, transparency, accountability, and the autonomy of people. According to the guidelines published by WHO on AI ethics, "humans should maintain control over the use of AI, and appropriate oversight is required to avoid harm and ensure autonomy" (WHO, 2021).

The issue of bias is especially critical in this case because if there is no representative data used in the process of training AI, the latter will generate different outcomes for certain populations. Therefore, developers and healthcare organisations should assess the performance of AI-based technologies across specific demographic and clinical populations. Additionally, patients must be aware of the presence of AI in treatment and who is responsible for particular decisions.

7.3 Regulatory Considerations

The regulatory regimes should take into account that AI systems can be reprogrammed, retrained, and modified post-deployment. The WHO guidelines from 2023 emphasise the aspects of risk-benefit analysis, performance evaluations, monitoring, and the consideration of various

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stakeholders' perspectives. There are also principles of Good Machine Learning Practice, developed by the FDA and the International Medical Device Regulators Forum, that cover the whole lifecycle of AI/ML medical devices (FDA, 2025).

In the case of developing countries, they can have underdeveloped regulatory regimes. Regional collaboration, standardisation, international technical assistance, and risk-based regulation can help avoid duplication and ensure safety. Regulation should not be just about approvals but also about post-deployment monitoring, reporting on adverse effects, cybersecurity, privacy, and model modifications.

7.4 Practical Recommendations

- Start with the valuable screening functions where AI has a good rationale from clinical and business standpoints.
- Conduct validation on local populations, local devices, and local clinical practices before widespread adoption.
- Consider the cost of ownership instead of merely the price of software itself.
- Deploy AI as decision support with specific human intervention and referrals.
- Implement interoperable electronic health records and standardise the collection of health data.
- Provide training and technical support through procurement agreements.
- Ensure systematic monitoring of bias, model drift, cybersecurity, and clinical performance.
- Financial instruments can help reduce the initial hurdles without creating high recurring costs.
- Measure patient outcomes and equity in addition to the accuracy of the algorithm.
- Establish governance systems for AI at the national and regional levels.

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CHAPTER 8: CONCLUSION

8.1 Summary of the Study

This secondary study assessed the potential of artificial intelligence to increase access and affordability of early disease detection in developing nations. It included information obtained from the areas of AI diagnostics, medical imaging, diabetic retinopathy screening, laboratory medicine, point-of-care diagnostics, digital health, health economics, and AI governance.

8.2 Major Conclusions

There is support in the literature on the ability of AI to improve preventive healthcare services, especially in settings where there are not enough specialists. AI could assist in interpreting screening images, identifying high-risk patients, referring them for further evaluation and helping health care workers. Some applications show that AI-assisted screening can be economically efficient.

However, the application of AI technology is not an alternative to an effective health system. According to WHO guidelines, it is impossible to substitute digital solutions with health workers, finances, governance, drugs, and infrastructure. The same rule applies to AI. It is necessary to have a full chain in order to establish an efficient preventive health programme, including screening, diagnosis, treatment, and follow-up.

Thus, the solution to the research question will depend on some factors. With AI, one can make some forms of diseases easier and cheaper to detect, but one should do this locally, evaluate it economically, and clinically validate it. The best use of AI would not involve substituting doctors with software but extending their capacities through the technology.

8.3 Practical Implications

For healthcare managers, the results indicate that they should align technology acquisition with health outcome metrics and total cost of ownership. For companies, sustainable product design should take into account local infrastructure and transparent pricing models since it would be

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wrong to assume that what works in a HIC would work in an LMIC without changes. For policymakers, funding not only AI but also data infrastructure, standards, education, and regulation is equally important. For health practitioners, AI literacy will be ever more important, as doctors will have to explain algorithms' results.

8.4 Limitations of the Study

The present study depends on secondary sources, and thus its results hinge on the quality and volume of the existing body of evidence. While the literature base for LMIC is still less extensive than that for HICs, applications are different as well, and thus the comparison becomes problematic. Economic studies would employ various cost, time horizon, and healthcare system assumptions. This paper provides a narrative review and thus does not include any calculation of effect size.

8.5 Recommendations for Future Research

Future research would benefit from conducting prospective implementation research in both rural and urban LMICs, comparing the performance of AI screening with that of conventional practices, and reporting patient outcomes, as well as technological performance. Economic studies need to incorporate the cost of equipment, training, maintenance, connectivity, referrals, and treatment. In addition, economic models need to be conducted, as economic viability is critical for the sustenance of such an intervention in the long run. Future research must also explicitly consider equity.

8.6 Final Perspective

Ultimately, preventive healthcare aims to contact individuals while there is still time to address any disease. AI could transform the health care sector, but its effectiveness would depend on how it is introduced. An ideal situation in the future would see AI working within a bigger system where screening is cheaply available where it is required, data exists locally, trained health workers are present, reliable referral systems exist, businesses act responsibly, and regulation takes place.

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