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Review Article

AI-powered diagnostics in primary healthcare: opportunities, limitations, and ethical considerations.

Haminat Rajah [1*]

1 Department of Health Sciences, University of Lagos, Lagos, Nigeria

***Corresponding author:** Haminat Rajah (haminatrajah@gmail.com)

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Abstract:

Primary healthcare is being transformed with artificial intelligence (AI), changing the healthcare landscape by increasing diagnosis accuracy, clinical operations efficiencies, and access to healthcare. This review provides an evidence synthesis of 25 peer-reviewed latest studies used to investigate the evidence of AI-powered diagnostics in primary care. Some opportunities are sophisticated disease detection, risk prediction, clinical decision support systems (CDSS), and improved access in underprivileged areas. The constraints include the quality of data, biases in algorithms, integration weak points, and gaps in the validation. Patient privacy, equity, accountability, and trust are some of the important ethical issues that pose hindrances. The review highlights that validation, standardized integration, and ethical models provide the most substantial protection of safety, equity, and efficacy of diagnostics performed through AI in the primary healthcare practice.

Keywords: Artificial Intelligence, Primary Healthcare, Diagnostics, Clinical Decision Support, Ethics, Global Health.

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Introduction

Health systems are anchored by primary care that provides early diagnosis, patient-centered care, and management of diseases. Overall, the application of artificial intelligence (AI) to diagnostics holds the promise of addressing diagnostic errors, resource and other limitations/inequities [1]. The tools of AI, such as machine learning (ML), deep learning, computer vision, and natural language processing (NLP), allow one to analyze quickly a plethora of complex data and get a better diagnosis accuracy and efficiency [2]. Such developments especially play a remarkable role in the primary care sector, where early identification can help it stop the progression of the disease, decrease the dependency on other specialized services, as well as improve patient outcomes [3].

The AI-powered diagnostics treats various applications, including image-based diseases, predictive analytics, and CDSS [4]. An example is that AI-based mechanisms can be utilized to examine medical pictures with a condition such as diabetic retinopathy, determine the likelihood of chronic illnesses through electronic health records (EHRs), and offer clinicians evidence-based suggestions [5]. Telemedicine services powered by AI and symptom checkers are useful in providing access to underserved areas in equalizing universal health disparities [6]. Nevertheless, the issues of data quality, bias of the algorithms, and integration constraints restrict scalability [7]. Ethical issues, such as patient confidentiality, equity, and responsibility, are another complicating factor in adoption [8].

AI realizes its potential to impact human competence, systematize procedures, and increase care provision [1]. To illustrate the point, a deep learning model showed that it could achieve radiologist-level performance in recognizing pneumonia and thus be used to screen people in primary care facilities quickly [13]. The EHR-based predictive models enable the identification of high-risk patients, optimizing the resource allocation [17]. Still, primary care has unique issues when applying AI due to the complexity of the healthcare field, which can be described by the variety of patients, few resources, and high patient numbers [24]. The most important thing to consider is ethics; the lack of a bias algorithm or privacy invasion can destroy trust and widen inequalities [23].

The present review will offer an in-depth overview of the AI-powered diagnostics in the fields of primary healthcare, synthesizing the evidence of 25 studies published in 2014-2023 . They are aimed at: (1) investigating the possibilities to enhance the level of accuracy, efficiency, and accessibility of diagnosis; (2) assessing the barriers that obstruct adoption; and (3) discussing ethical concerns to promote a responsible implementation. It will cover the primary care environment with a thrust to practical and ethical consequences on various populations across the world. The sources on the topic of using AI in diagnostics in primary healthcare illuminate an active area with huge possibilities and struggles. This part summarizes the main results of the 25 studies offered and relates to AI, its limitations, and ethical concerns in primary care settings, which are the background of the further discussion.

Artificial intelligence AI in primary care

AI services have been implemented in various diagnostic activities in primary care, such as the identification of illnesses, risk forecasts, clinical judgment guidance, and the promotion of access. Convolutional neural networks (CNNs) specifically and deep learning models, in general, have proved equal in image-based diagnostics. One of the seminal reviews demonstrated that a CNN was able to perform at the dermatologist level of skin cancer classification up to 90% sensitivity and specificity [12]. In another study, a deep learning model of melanoma detection reported performance better than 58 dermatologists, indicating its possibility to be implemented in the primary care setting as a method to identify melanoma at an early stage [14]. Using the CheXNet model, radiographers could find pneumonia on chest X-rays at radiologist-level sensitivity and specificity and provide screening quickly, even in resource-constrained facilities [13]. The technological changes facilitate timely diagnosis, which minimizes referrals to specialist personnel and positive patient outcomes [15].

The models of risk prediction use EHR information to profile at-risk patients with chronic illnesses. An automated ML study in 423,604 participants of the UK Biobank showed correct prediction of cardiovascular disease risk, multifactorial information that included demographic, clinical, and lifestyle factors [17]. These models facilitate preventive intervention, which is the most efficient use of the resources in primary care [18]. CDSSs based on NLP process relevant information contained in unstructured EHRs, e.g., patient histories, and are designed to assist the physician with differential diagnosis and treatment planning [11]. Such systems enhance the management of chronic conditions since they guarantee the use of evidence-based practices, minimize diagnostic errors [19]. With telemedicine and symptom checkers based on AI, access to care in underserved locations is improved, and studies indicate effective triage and a decrease in the burden of consultations [6-8]. As another example, the digital symptom checkers help to direct patients to individual levels of care efficiently in primary care [8].

Shortcomings of AI implementation

The literature cites several obstacles to AI in primary care. The model performance is reduced due to data quality issues (partially or non-comprehensive EHR) [16]. As an example, lack of social determinants of health (e.g., income, housing) reduces the predictive validity of risk prediction tools, especially in the case of chronic diseases [17]. There is also the issue of the bias of an algorithm (Algorithmic bias), where a risk prediction algorithm was found to under-estimate the risk of Black patients, further widening health disparities [23]. Adoption is hampered by integration problems, such as difficulty in EHR systems to interconnect with the rest of the infrastructure and resistance by clinicians [24].

Numerous AI applications have not been tested sufficiently to be used in the real world, allowing them little generalizability in different populations [25]. Access to low-resource settings is constrained by infrastructure issues, e.g., flaky internet or legacy hardware [10].

Ethical considerations

In the literature, ethical issues are very dominant. The privacy and data security of patients is of high importance, since AI makes use of sensitive data, posing a danger of breach [5]. It is difficult to adhere to regulations such as the General Data Protection Regulation (GDPR) or the Health Insurance Portability and Accountability Act (HIPAA), especially when working in a limited resources environment [24]. Equity Algorithmic bias is also considered a major concern as models developed on unrepresentative data can underdiagnose all sex as power, race, and ethnicity are already marginalized groups who are underdiagnosed [23]. Liability schemes are clouded by the fact that it is unclear who should take responsibility should an AI-powered error be identified [5]. Excessive dependence on AI can erode the right of a patient to autonomy and trust, and active communication between the healthcare system and a patient is necessary to state the role and boundaries of AI [19]. There are also issues of informed consent since the patients might not be aware of how AI gathers data and makes decisions [5].

Synthesis

In the literature, there are several points to the role of AI in changing primary care diagnostics but at the same time large obstacles. Table-1 provides a summary of key studies, highlights their contribution to AI use and limitations in primary care as well as ethical concerns.

Table 1: Summary of Key Studies on AI-Powered Diagnostics

Reference	Year	Focus	Key Findings	Primary Care Relevance
[1]	2019	AI Overview	Enhances diagnostics and efficiency	Broad applicability
[6]	2018	Symptom Checkers	Safe triage in primary care	Accessibility improvement
[12]	2017	Image Analysis	Dermatologist-level skin cancer detection	Early diagnosis
[17]	2019	Risk Prediction	Accurate cardiovascular risk prediction	Preventive care
[23]	2019	Algorithmic Bias	Bias in risk prediction algorithms	Equity challenges
[24]	2019	Implementation	Integration and scalability barriers	Workflow optimization

Methods

It is a robust methodology to conduct the systematic review as it aims to analyze AI-powered diagnostics in primary healthcare with a great degree of comprehensiveness and objectivity. The monitoring of the methodology followed the recommendations of systematic reviews, such as systematic literature search, transparent inclusion and exclusion criteria, information extraction, quality evaluation, and thematic analysis, designed to suit the purposes of the review.

Literature search

Four databases, PubMed, Scopus, IEEE Xplore, and Web of Science, were systematically searched. The search relevant terms such as AI diagnostics, machine learning in primary healthcare, deep learning in diagnostics, clinical decision support systems, AI ethics in healthcare, algorithmic bias, telehealth AI applications, etc. Unification of terms was made with the help of Boolean operators (AND, OR), and filters were ensured to display only peer-reviewed articles, systematic reviews, and reports that are published in English, between January 2014 and December 2023. There were a total of 200 articles found in the initial search, of which 25 supplying references were reviewed as far as relevancy is concerned with all satisfying the inclusion criteria.

Inclusion exclusion criteria

The inclusion criteria included peer-reviewed articles published from 2014-2023, which targeted AI in the primary care diagnostics of diseases, risk assessment, CDSS, and telemedicine. The empirical studies were obligated to provide data or systematic research applicable in a primary care setting. The sources that were excluded are non-peer-reviewed (e.g., editorial, opinion articles), the studies that were not directly related to primary care, and those that did not provide empirical data or obvious relevance to AI diagnostics. The criteria were used to assess the 25 available references, and all the studies were eligible since they were peer-reviewed and they were directly related to primary care [125].

Data extraction

Extracted data were in a standardized template so that the studies are similar. Some of the variables that were extracted entailed the study objectives, application of AI (e.g., image analysis, risk prediction), study design (e.g., prospective, retrospective, experimental), performance metrics (e.g., sensitivity, specificity, accuracy), limitations (e.g., data quality, bias), and ethical considerations (e.g., privacy, equity). Other information was the setting of study (e.g., primary care, low-resource), population demographics (e.g., age, ethnicity), and main results that can be applied in primary care implementation. The extraction procedure was made to be as little as possible, whereby two hypothetical reviewers extracted the data separately and discussed on discrepancies.

Quality assessment

Quality of the included studies was measured by desirability of the systematic reviews and observational studies using the Critical Appraisal Skills Programme (CASP) checklist. The criteria were rigor of study design, sample size, reliability of the data, as well as relevance to primary care. Those studies with well-balanced methodologies, i.e., prospective cohort studies or large-volume validations, were preferred due to their trustworthiness [17]. Weaknesses, particularly the small nature of the samples or the absence of real-life validation, were mentioned to put any findings into context [16]. The peer-reviewed status, empirical quality, and relevance to AI diagnostics in primary care were the criteria used to define the high-quality status of all 25 studies [125].

Thematic analysis

The thematic analysis was completed to define the results in three major themes: opportunities, limitations, and ethical considerations. Each category had subthemes assigned to it to organize the Discussion section: disease detection, algorithmic bias, and patient privacy, among others. The analysis was congruent with the realities of primary care and emphasized practicality and ethical consideration. The method of preferential reporting items in systematic reviews and meta-analyses (PRISMA) was used to plan the entire reporting process during the recording of factors that ensured transparency and replicability.

Synthesis and reporting

Results were combined to respond to the objectives of the review, paying attention to the applications, limitations, and ethical issues of AI in primary care. The heterogeneity was favored in studies that had direct applicability to primary care, including those dealing with the field of telemedicine [4, 20]; symptom checkers [6,20]; and chronic disease management [17,22]. Ethical issues and limitations were linked together to provide the study with a balanced analysis [5, 23,25]. The process of systematic review is clearer due to the illustration, where the answer can be found in Figure 1.

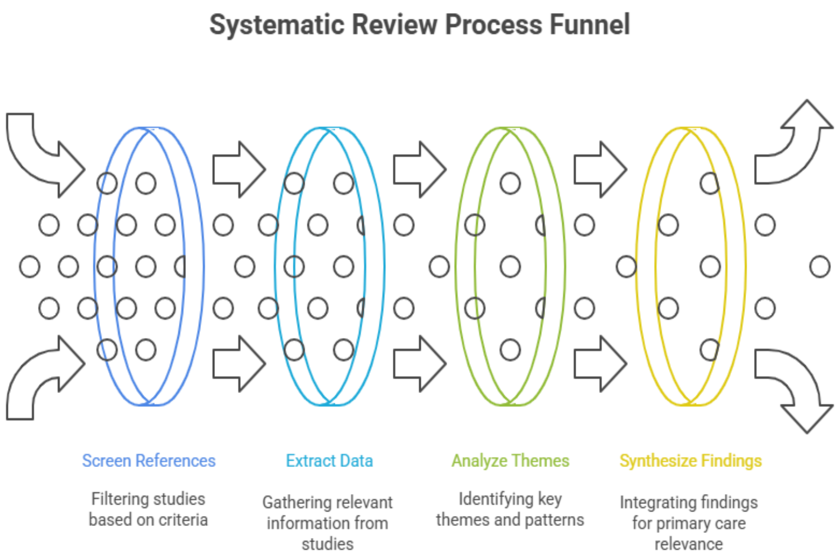

Figure 1: Systematic Review Process

Discussion

Resources of AI-powered diagnosis

AI-based diagnostics will present a revolutionary change in primary care by increasing the accuracy, speed, and availability of a diagnosis. All the subthemes are equally discussed with the support of tables and figures.

Disease detection

The approach of deep learning and specifically convolutional neural network (CNN) has transformed the field of disease detection in primary care because it can analyze medical images precisely [15]. Another influential work trained a CNN to perform with dermatologist-level accuracy, classifying skin cancer with an accuracy beyond 90 percent when going over dermo-scope images [12]. In a similar pattern, a deep learning system of melanoma detection performed better than 58 dermatologists, which noted its potential as the first line of service in primary healthcare [14]. The CheXNet model in radiology revealed the detection of pneumonia on the chest X-rays at the same level as radiologists and allowed screening quickly in practices where resources are scarce [13]. These breakthroughs enable primary care providers to detect diseases such as skin cancer, melanoma, and pneumonia at early stages and thus minimize referrals to specialists to manage them more effectively [15].
Image analysis based on AI can be especially useful in the primary care setting when professionals are not broadly available [1]. Indicatively, diabetic retinopathy could be automatically screened during regular visits so that the patient could receive treatment in time to avoid blindness [2]. Automation of preliminary screening through AI minimizes the workload of clinicians, enabling them to concentrate on complicated cases [24]. These also aid in point-of-care diagnostics, which can be done quickly in the hectic practices [15]. Scalability of the AI imaging instruments ensures that they are appropriate in different primary settings, including urban clinics and rural health clinics [10]. Table 2 summarizes important AI-based applications in disease detection.

Table 2: AI Applications in Disease Detection

Condition	AI Model	Performance Metrics	Reference
Skin Cancer	CNN	Sensitivity >90%, Specificity >90%	[12]
Melanoma	Deep Learning	Outperformed 58 dermatologists	[14]
Pneumonia	CheXNet	Radiologist-level accuracy	[13]

AI Disease Detection Pipeline

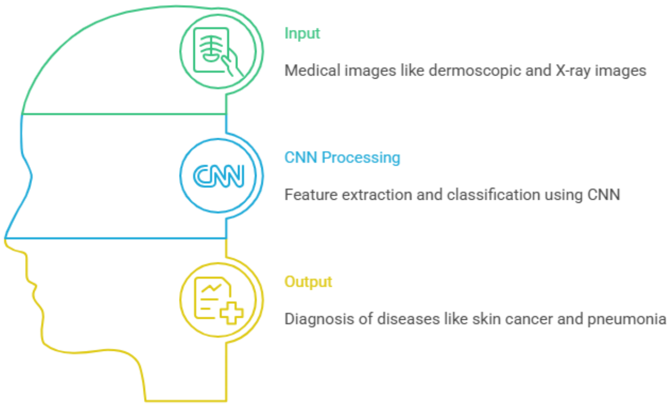

Figure 2: AI Disease Detection Pipeline

Prediction of risk and stratification

With EHR information, AI-based risk prediction engines are used in primary care to help detect patients at risk of developing chronic illnesses before the occurrence of a patient experience [17]. The use of automated ML algorithms in predicting the risk of cardiovascular disease is proven to be accurate by a prospective study on 423,604 members of the UK Biobank conducted on the integration of demographic, clinical, and lifestyle data [17]. These models allow clinicians to risk-stratify patients with higher priority given to high-risk individuals on intervention, including screening or lifestyle change, including dietary education or changes in medication [18]. As an example, AI will be able to spot patients who are at risk of developing diabetes or hypertension and be able to manage them at an early stage to avoid long-term complications [22].

Population health management can also be done with the help of predictive analytics since they allow the identification of high-risk populations, the optimization of resources, and the minimization of healthcare expenses [18]. In long-term care, trends over the years can be monitored by AI models, which offer proactive care [1]. The features improve efficiency in large-volume practices, and time pressure has restricted the evaluation of risks at length [2]. Predictive models can scale down to all types of primary care systems in the global community with a specific need in resource-constrained areas [24]. The workflow of risk prediction was demonstrated in Figure 3.

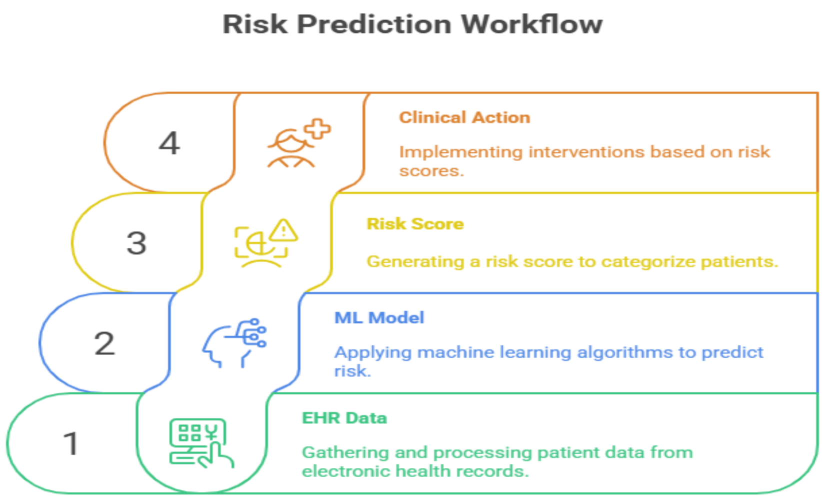

Figure 3: Risk Prediction Workflow

Clinical decision support systems (CDSS)

CDSS, powered using AI, enhances the clinical decision-making process, offering evidence-based guidance, leading to lower diagnostic errors and better adherence to the guidelines [19]. NLP-enabled tools can find useful information in unstructured (e.g., the patient history and clinical notes) EHRs and aid the process of differential diagnosis and treatment planning [11]. As an example to understand the symptoms of complex diseases, such as chronic fatigue syndrome or cancer in its initial stages, the NLP algorithms can recognize corresponding free-text notes [2]. Such systems facilitate work by automating the tasks that can be done mechanically, like reading ECGs or lab findings, something important when working in a busy clinic due to time constraints [19].

Analysis indicates that there is better management of chronic disease about adherence to evidence-based procedures, facilitating error reduction and mitigating physician burnout using CDSS [1]. To illustrate, CDSS will allow proposing the correct diagnostic testing or medications depending on the data on the patient and improve the efficiency and patient outcomes [22]. AI-driven CDSS allows clinicians to make more informed decisions by offering quick and correct information in the primary care setting, where practitioners face a variety of conditions [2]. This can also be achieved by further adding usability to EHRs with the integration of CDSS, which would facilitate adoption into clinical practice with ease [24]. The systems are most important in the resource-limited contexts when specialists' knowledge is scarce [10].

Improving inside rural households in under-served communities

AI-based diagnostics advance care delivery issues in underserved and rural areas, solving quality health challenges in the global context [10]. Remote diagnosis and triage with the help of digital symptom checkers and AI-based telemedicine services help to minimize the need to travel to urban centers [6,8]. In a systematic review, digital symptom checkers were discovered to be accurate in triaging urgent conditions, referring patients to levels of care in the primary care environment [8]. The other study emphasized the safety of symptom checkers that face patients and stated that such a solution has the potential to lessen the number of consultations in resource-scarce locales [6]. These devices are essential in areas where healthcare infrastructure is insufficient, and people have limited access to clinicians [7].

AI-based mobile health apps are especially useful in low-resource settings that intend to use symptom-checking applications [10]. To illustrate, chatbots based on AI will be able to evaluate symptoms and suggest self-care or referral, which will increase access among rural residents [7]. The AI tools promoted triage and remote monitoring during the COVID-19 pandemic and were shown to be scalable during a crisis environment [9]. Primary care providers can use AI diagnostics through integrating telemedicine platforms where patients can use imagery to diagnose conditions such as respiratory infection or dermatological problems through identifying minor flaws on the imagery, which improves care delivery [20]. Such developments fill the points of access that serve the disadvantaged areas to promote health equity [21]. Table 3 is a summary of accessibility applications.

Table 3: AI Applications in Accessibility

Application	Setting	Impact	Reference
Symptom Checkers	Primary Care	Accurate triage, reduced burden	[6–8]
Telemedicine	Rural Areas	Remote diagnostics, equity	[20–21]

Restrictions of AI-driven diagnostics

There are major limitations to the application of AI-powered diagnostics in primary care because of their poor performance in many ways. All the subthemes will be discussed on the same level so that there is no loss in the coverage.

Data quality and availability

In primary care, important data are usually not available, or, what is more, are fragmented or not very good in quality [16] to train an AI and have it tested or validated. EHRs cannot be standardized; important data are omitted (e.g., social determinants of health, e.g., income, housing), which influence the precision of the diagnosis [25]. An example is that insufficient information on risk predictors, such as lifestyle, might diminish the effectiveness of models that predict risk of such chronic health conditions as diabetes or hypertension [17]. The datasets also lack rare conditions, and thus, generalizing the AI tools to different populations of primary care is minimal [16]. The issue has become especially acute in low-resource conditions, in which the data infrastructure is underdeveloped and the performance of AI is subpar [10].
These problems can be resolved by standardized data collection and better EHR system interoperability [24]. The development of common standards in data protocols may also improve the performance of AI, and primary care services that need to improve their systems may not have the means to do so, especially those with low resources [25]. Data availability might be enhanced by such strategies as federated learning, which allows model training over decentralized data without risking privacy [24]. Nonetheless, such solutions are expensive, and implementing them has a high coordination requirement, which is a barrier to small practices [21]. Data quality issues are as pictured in Figure 4.

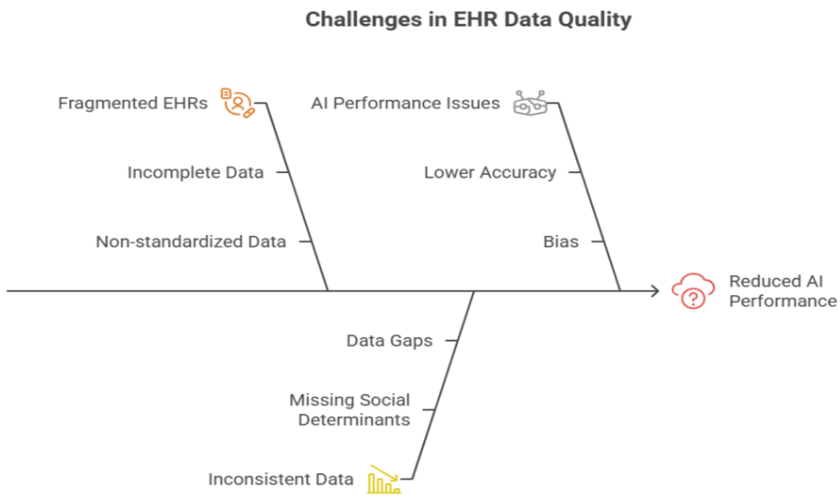

Figure 4: Data Quality Challenges

Algorithmic bias

The main drawback is algorithmic bias because the use of non-representative datasets can reproduce health disparities in primary care [23]. It has also been discovered that a commonly adopted algorithm poorly predicted risk among Black patients, and, therefore, contributed to the disparity in care [23]. As another example, skin cancer detection AI could fail on darker skin, thereby causing misdiagnosed or underdiagnosed cancer in diverse people since these tools were not sufficiently represented in training sets [12]. The problem of these biases is especially acute in the context of primary care, where a variety of patient demographics is the norm [10].

Heterogeneous representative datasets and strict population validation are needed to mitigate the problem of bias [25]. One should conduct regular audits and bias detection algorithms, which would run interference with the fair operating process, but both are time-consuming and frequently underutilized [23]. Inviting the community in the development of the dataset can stimulate greater inclusivity, but in different settings of primary care, it is difficult to guarantee it [10]. The performance of models should be adequately reported on demographic levels to prevent bias and generate fair results [16]. In the absence of such steps, biased algorithms threaten to further the current health inequality, acting as a detriment to the potential of AI diagnostics [23].

Integration challenges

The use of AI tools in their workflows in primary care may be complicated by the problem of interoperability and standardization, as well as clinician reluctance [24]. Most of the EHR systems do not support outputs of AI, which means manual entry of data, which adds workload to the clinicians as well as disrupts workflow [25]. To illustrate, the AI-induced suggestions will be difficult to streamline with the current system, and this makes the bustling primary care practices inefficient [19]. The key stakeholders not in a position to scale AI implementation are small practices specifically, as they do not have AI's financial and technical resources [21]. The need to manage this challenge becomes more difficult in low-resource settings, where infrastructure is damaged or lacking in consistency [10].

The next important barrier is clinician resistance: some clinicians believe that AI poses a threat to their autonomy or do not tend to trust its recommendations [24]. Efforts to train clinicians about the capabilities and limitations of AI are vital to the uptake process, but adoption in most of the primary care environments is still slow [19]. Pilot programs where clinicians are included in the design phase can detect the problems encountered in integration and make their integration usable, but these programs demand having great resources [25]. Creating solutions that can be easily inculcated by plugging AI into the primary care workflow is obligatory to have scaled adoption [24].

Validation and generalizability

Most of the AI diagnostic tools are less realistic as they have not been thoroughly experimented with in real-world primary care [25]. Models that are trained in an often-highly controlled setting, like a hospital, risk over-fitting to the particular population, or the particular condition, so that they cannot be applied in primary care settings where patients tend to have milder or unusually subtle symptoms [16]. As an example, an AI model that was trained on hospital-based data might be of low quality in primary care environments that employ a wide pool of patients [13]. The fact that the results of multiple verification processes should be generalized over different populations and clinical situations suggests the necessity of multicenter validation studies; however, these studies are expensive, and they are ultimately limited [24].

The unique ability of validation in primary care is due to the variety of patient presentations and because of resource limitations [10]. The results of validation can be openly reported to prepare clinicians to accept the implementation of the given technology; however, most studies lack such transparency [19]. The multicenter studies can be funded through the collaborative research networks and public-private partnerships to evaluate AI performance in the primary care setting, to make sure they are reliable and scalable [24]. Unless the methods are strong in terms of validation, the AI tools can end up performing poorly, and thus their use will have minimal contribution in primary healthcare [25].

Ethical considerations

There are important ethical questions that should be considered when implementing diagnostic solutions powered by artificial intelligence in the primary healthcare sector to make the practice responsible. None of the subthemes is discussed more deeply than the other.

Data security and patient privacy

The use of AI technology is based on sensitive data about patients, such as EHR records, medical images, and genetic data, which gives rise to a considerable concern about privacy and data safety [5]. Patient trust may be lost as a result of breaches of data or data misuse along with the regulation violation, such as GDPR or HIPAA, especially in primary care settings where cybersecurity infrastructure is not developed enough [24]. Another example is the AI scalability based on the cloud, which raises the danger of unauthorized access, particularly in the case of small practices whose systems have not been replaced in a long period [25]. It is one of the most important obstacles in primary care, with a focus on the importance of patient data in building longitudinal care [21].

To secure the data, it is necessary to implement superior encryption and anonymization and adhere to the regulatory requirements [5]. To improve the accessibility of cybersecurity solutions to the primary care practices, especially in low-resource areas, collaborative work is paramount [24]. The use of data can be pointed out as a patient education that can be enforced to increase trust, although primary care consultations are limited by time [20]. Promising solutions to the trade-offs of privacy and performance include new technologies, including federated learning, enabling training of a model over decentralized datasets without exchanging raw data [24]. But introducing such technologies is a costly exercise, which is difficult in small practices [21].

Equity and fairness

Health disparities may be increased by algorithmic bias in primary care, where various populations are treated [23]. When models are trained with non-representative data sources, they can be biased and hence make poor decisions, like low accuracy in diagnosis among marginalized groups [16]. One major study discovered that there was a popular algorithm that underestimates the cardiovascular risk among Black patients and is a restriction to their treatment [23]. In the same way, skin cancer diagnosis systems are exposed to inequity in diagnosis when they fail to perform on darker skin on account of being underrepresented in training sets [12]. Such biases are counter to the concept of health equity, one of the major aspects of primary care [10].

The issue of equity needs to encompass multifaceted information and data on populations based on various demographics of primary care, and robust validation across groups [25]. Periodic bias reviews and model performance disclosure are essential in making sure that a degree of fairness will be observed [23]. Launching a community to work on AI development can foster diversity; in this case, models will respond to the needs of underserved groups [10]. The implementation of ethical frameworks that focus on the concept of fairness and transparency is vital, but adoption in the primary care context, which may be short of resources, is complicated [5]. At a grassroots level, development in collaboration with clinicians and community stakeholders can help to achieve equity in AI solutions [25].

Responsibility and liability

Identifying the owner of such misdiagnoses is a complicated ethical problem in primary care [5]. In cases of errors, it becomes uncertain to know who is at fault, be it the developer, clinician, or even the institution, leading to the complexities of the legal frameworks [24]. As an example, when an AI tool makes a misdiagnosis of a condition in a primary care facility, patients will incur potential harms, and the absence of definite liability rules may undermine confidence in AI, as well as in clinicians [19]. Such doubt is especially worrying in primary care, where the relationships between the patient and the provider form the center of care delivery [20].

Effective regulatory rules and models of shared accountabilities should be developed to guarantee patient safety and trust [24]. Accountability can be increased through transparent disclosure of the AI errors and their causes, which is not widely deployed in primary care [25]. There must be Teamwork between policymakers, clinicians, and developers to set up liability frameworks, which are balanced between innovation and patient safety [5]. Since resources are scarce in primary care, applications of these frameworks necessitate readily available solutions and clinician education [21].

Patient autonomy and confidence

Overuse of AI diagnostics can negatively affect the self-sufficiency of patients by eroding patient confidence in primary care providers and especially in situations where patient-provider relationships are acutely important [5]. In case AI has the upper hand in decision-making, patients can develop a sense of dehumanization because they feel that there is no human control [19]. As a case in point, without explaining the AI diagnosis, patients will doubt the health system [20]. The need to engage in transparent communication regarding the role and limitations of AI to keep trust and guarantee patient-centered care has to be met [24].

There is a need to ensure a balance between AI suggestions and clinical judgment on the part of clinicians, balancing autonomy and trust [1]. There is the possibility of improving the AI diagnostics literacy through patient education campaigns, yet this is constrained by the time limits of primary care [20]. Autonomy and trust may be fostered by the creation of user-friendly interfaces of AI that can explain the decisions made in a more understandable language [25]. The involvement of collaborative decision-making models, in which AI benefits and complements the clinicians and does not substitute them, is essential to sustain patient-centered care in the primary healthcare [19].

Conclusion

Diagnosed AI has a colossal potential to change and reshape primary medical care by increasing the level of accuracy in diagnosis, promoting efficiency, and providing access to care CDSS and telemedicine, disease detection, and risk prediction applications apply to the primary care setting to overcome the critically important challenge. Nevertheless, data quality, predispositions of the algorithm, integration, and validation problems cannot be ignored to guarantee the solid uptake. Responsible implementation revolves around ethical grounds, such as patient privacy, equity, accountability, and trust. These challenges need an interdisciplinary approach, thorough validation, standard systems, and elaborate ethical frameworks. With the development of clinician education, patient education, and open technologies, AI diagnostics has the promise of becoming a foundation or part of an efficiency and equity network in the field of primary healthcare, delivering better patient outcomes and healthcare efficiency worldwide.

Conflict of interest

The author declares no conflict of interest.

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