AI in E-Healthcare Delivery Application: Evaluating Challenges for LMICs

ABSTRACT:

Objective: Artificial Intelligence (AI) is transforming global healthcare; however, Low- and Middle-Income Countries (LMICs) face limited access to AI-driven eHealth solutions. This study evaluates the challenges of AI in eHealth in LMICs, addresses implementation hurdles, and proposes solutions to fill research gaps. It examines the current state and explores social, ethical, and legal implications. This research aims to comprehensively review and integrate the existing knowledge on AI challenges in eHealth for LMICs.

Materials and Methods: We used the SLR technique to review the existing literature. We searched proprietary healthcare databases, including PubMed, Cochrane, Medline, IBECS, LILACS, Scopus, Science Direct, and Google Scholar. After searching relevant medical and technology databases for pertinent papers, the eligibility requirements were established based on the idea (AI adoption in e-health) and context (e-health settings in LMICs).

Results: Big data analysis, project leadership ownership, commitment to AI, and AI talent cause more delays in adoption, job security, and Machine-Human interactions, trying to reduce high implementation cost, lack of interoperability, try to minimize resistance to change, try to find short- and long-term funding, users probably have a multitude of social contexts (local context accounted for) that influence their decision to use AI data-gathering devices, level and exercise style influence users' decision to use data-gathering devices.

Discussion and Conclusions: Strategies such as capacity building, partnerships (between similar countries and developed countries, as exemplified by best practices), and ethical regulations can pave the way for AI's transformative role in enhancing healthcare outcomes. LMICs should analyze the effects of technological lenses, such as different generations of TAM and UTAUT, on application adoption in their context.

Keywords: eHealth, Artificial Intelligence (AI), Low- and Middle-Income Countries (LMICs), Application

1. Introduction and background

In recent years, AI has experienced unprecedented growth, revolutionizing industries and sectors through its ability to process massive amounts of data, support informed decision-making, and derive meaningful insights. One domain that has undergone a remarkable transformation through the integration of AI is eHealth. "eHealth" refers to the use of digital technologies and electronic communication to enhance healthcare delivery, promote health literacy, and improve patient outcomes [1-192]. This paper examines the pivotal connection between AI and eHealth, investigating the reasons for integrating these two domains and the potential implications for healthcare systems worldwide. AI in healthcare is defined as the development of technology systems that preserve, analyze, and manage data [2], make informed decisions [3], and assist users in the healthcare industry by replicating human cognitive processes [4-5]. AI has several applications in the medical field and is successfully employed for patient data management, research, diagnosis [6], treatment, and clinical documentation [7]. Some view AI as

complementary to humans, for example, in decision support or augmentation scenarios where healthcare professionals supervise and work together. Other benefits include progressive error reduction in patient outcomes [8], optimization of the health system, cost reductions [9], and increased value. [10] states that healthcare professionals can utilize AI to address various subjects, such as human biology, robotics, and medical statistics. The term "e" terminology evolved in the 1990s [11]. The broad term "eHealth" encompasses Health Informatics (HI), Electronic Medical Records (EMRs), Electronic Health Records (EHRs), Health Information Systems (HIS), e-prescribing, Telemedicine, and Teleconsulting [12].

AI and eHealth synergize to significantly transform the healthcare industry. Integrating advanced AI algorithms and machine learning with eHealth technologies unlocks valuable insights from health data. Predictive analytics enables healthcare providers to predict health trends and identify high-risk patients for preventive measures. AI-driven systems forecast disease outbreaks, optimize resource allocation, and enhance public health initiatives, improving healthcare efficiency [13-15]. AI integration streamlines clinical workflows, automates administrative tasks, and empowers healthcare professionals to focus on patient care [16-17]. Precision medicine becomes feasible with AI's ability to identify subtle patterns in large datasets, enabling personalized medicine arrangements based on individual patient characteristics. AI-powered chatbots and virtual assistants on eHealth platforms enhance patient engagement by delivering customized health information and medication reminders. AI-driven eHealth tools improve health outcomes and well-being by fostering informed and proactive patient engagement. The potential of AI in eHealth is vast and promises a forthcoming personalized, competent, and patient-centric healthcare.

Implementing AI in eHealth delivery seems necessary but challenging, with relatively uncertain success [e.g., 18-19]. Despite several attempts to adopt AI to assist with medical information recording, only a few have been successfully implemented [20]. Some AI projects, however, have failed in healthcare [21].

Raising implementation success rates is essential to reducing AI disappointment and financial losses, especially in LMICs [22]. This can be achieved through continuous learning, careful understanding of necessity, investigation, thoughtfulness, and consideration of the underlying "success or failure" factors in AI completion for eHealth delivery [23]. Still, they have some limitations compared to other countries, so they need to improve their success rate.

Despite a rise in health spending worldwide, the distribution remains wildly unequal, with high-income nations receiving about 80% of the US$8.5 trillion spent on healthcare in 2020[1]. Government spending is less critical when financing health expenses for LMICs, which are mainly covered by foreign aid and personal savings. For instance, out-of-pocket costs account for 44% of health expenditures in low-income nations. In comparison, foreign help accounts for 29%[2]. Limited financial resources, technological infrastructure, and qualified personnel further impede the integration of eHealth and AI technologies in LMICs. Foreign aid has increased over the past 19 years (2000-2019). Still, it has mainly focused on infectious diseases, leaving a financial deficit

[1] https://www.who.int/publications/i/item/9789240017788
[2] https://www.who.int/publications/i/item/9789240017788

for noncommunicable diseases and more extensive improvements to the healthcare system[3]. Critical economic and health spending data for LMICs, compared with high-income nations, are shown in **Table 1**.

Table 1: Key economic and health expenditure statistics for LMICs compared to High-Income Countries

Metrics	Low-Income Countries	Lower-Middle-Income Countries (LMICs)	Upper-Middle-Income Countries	High-Income Countries
GNI per capita (US$).[4]	< $1,045	$1,046 - $4,095	$4,096 - $12,695	> $12,696
Health Spending (% of GDP) .[5]	~5%	~5%	~6%	~12%
Out-of-pocket spending (OOPS) .[6]	44%	Significant	Moderate	Low
External Aid Contribution .[7]	29%	Significant	Moderate	Low
Government Health Spending .[8]	27% (inferred)	Moderate	Increasing	70%
Priority in Health Spending.[9]	Declining/Stabilizing	Stagnating	Increasing	Increasing
Focus of External Aid .[10]	Infectious Diseases	Infectious Diseases	Infectious Diseases	Non-communicable Diseases

The disparity in GDP (Gross Domestic Product) and healthcare expenditures between LMICs and high-income countries underscores the need for enhanced financial strategies, technology integration, and international support to improve healthcare delivery and leverage eHealth and AI advancements in LMICs.

As we have already discussed, AI-driven eHealth interventions can enhance health outcomes in LMICs; however, their widespread implementation will require a careful balancing of ethical, legal, and practical issues. One significant challenge is the lack of robust digital infrastructure, which hampers the deployment and scalability of AI solutions [24]. Technological barriers include unreliable internet and electricity infrastructure, which are critical for AI systems to function effectively and can limit effective engagement and integration [25-26]. Financial constraints prevent the purchase of innovative technologies and medical equipment necessary to modernize healthcare services [27]. Significant barriers to achieving interoperability in LMICs include inadequate data sources, fragmented health information systems, varied health IT infrastructure, a lack of standardization, and concerns about data privacy [28-190]. LMICs' approach to collecting comprehensive, high-quality data may be limited by inadequate infrastructure, limited digitalization, and a fragmented healthcare system [29]. Due to a lack of open discussion about the suitable usage, hardware, and software programs introduced in hospitals, trusts, or nationwide, billions of dollars have been wasted, and these programs have quickly become outdated [27].

Despite its many benefits, the high costs of acquiring and maintaining AI technologies, as well as the need for regular updates, pose significant barriers to many healthcare providers' ability to use AI effectively [30]. Ethical and legal issues also arise, particularly concerning data privacy and the

[3] https://files.aho.afro.who.int/afahobckpcontainer/production/files/2_Global_expenditure_on_health_Public_spending_on_the_rise.pdf
[4] https://www.worldbank.org
[5] https://www.who.int/publications/i/item/9789240017788
[6] https://www.who.int/publications/i/item/9789240017788
[7] https://www.who.int/publications/i/item/9789240017788
[8] https://www.healthdata.org/research-analysis/library/financing-global-health-2019-tracking-health-spending-time-crisis
[9] https://www.healthdata.org/research-analysis/library/financing-global-health-2019-tracking-health-spending-time-crisis
[10] https://www.healthdata.org/research-analysis/library/financing-global-health-2019-tracking-health-spending-time-crisis

security of personal health information [31]. Data privacy and security, crucial for safeguarding the benefits of patients, healthcare workers, and scholars, are fundamental because AI applications require broad access to sensitive data; breaches can have severe repercussions for individuals and undermine public trust in healthcare systems [27].To improve the secure distribution and protection of electronic health data, it is crucial to prioritize maintaining the privacy, confidentiality, and integrity of medical records [32].

A well-trained workforce in LMICs is crucial for overcoming the severe shortage of AI capabilities, including machine learning skills and language proficiency [30]. Developing countries are most at risk of quality breaches due to a lack of standardized protocols and regulations, leading to significant variations in quality and safety. Additionally, a well-trained workforce is necessary to overcome the shortage of AI ability and the unfamiliarity with innovative technologies [33]. The effectiveness of eHealth interventions in improving demand is often limited by geographical access to digital technologies, digital literacy, and pre-existing socio-cultural norms at the community level [34]. Healthcare systems in LMICs face challenges such as underdeveloped infrastructure, limited funding, and a shortage of skilled professionals. However, they receive more support from a larger presence of naturopathic healthcare, and as a result, they have a lower need for hospice and chronic-care institutions [35]. Even with chatbots now in place, clinicians must still verify transcribed notes for accuracy and completeness, as patient care ultimately rests with them, not the technology. At the same time, AI tools can streamline medical history-taking, but they require careful clinician oversight to ensure accuracy and prioritize patient safety [36].

Overcoming these obstacles and ensuring that AI technologies are applied safely, morally, and ethically improves healthcare quality for everyone; legislators, healthcare professionals, and the public must work together [37]. Facilities that provide higher staff motivation, increased funding, and enhanced digital literacy achieve higher adoption rates of eHealth technology, thereby improving service coordination and patient satisfaction. Meanwhile, enhancing AI adoption in eHealth hinges on addressing issues related to data protection, digital literacy, and training [38]. Encouragements from multisectoral organizations and government agencies significantly enhance the effectiveness and success of digital health technologies in large-scale healthcare systems. It highlights the importance of conveying this conceptual perspective to healthcare providers to improve time efficiency and eliminate wasteful processes [39]. Effective implementation of AI in laboratory medicine in LMICs requires substantial funding for digital infrastructure, the establishment of data-sharing networks, and the development of supervisory guidelines, emphasizing cooperative efforts among participants, including governments, nongovernmental entities, and international organizations, to overcome obstacles responsibly [29]. By addressing the above issues and leveraging AI-based models in healthcare, researchers and healthcare professionals can move toward intelligent care and gain a more accurate understanding of the potential study requirements of AI in innovative care [40].

LMICs face daunting challenges due to ineffective access to affordable healthcare services, leaving millions vulnerable [234] and [43]. This is where the transformative potential of AI comes into play [235] and [40] to support healthcare systems such as eHealth. Despite the promise of AI, its implementation in healthcare settings within these countries is not without hurdles [236]. The WHO (World Health Organization) has recently outlined critical ethical and governance

challenges related to AI in health [237] and [39]. A key opportunity lies in digitizing medical and health records [238] and [30]. These records are vital inputs for practical AI applications, providing the demographic and clinical data needed for better decision-making. Moreover, incorporating decision-support systems into healthcare processes can significantly decrease the burden on healthcare workers, permitting them to focus on patient care. However, we must navigate significant ethical and regulatory concerns. By addressing these challenges, we can leverage AI's potential to transform healthcare in LMICs, ultimately saving lives and enhancing overall health outcomes.

Implementing AI in LMICs for healthcare faces a critical challenge stemming from the extensive development and deployment of AI systems in developed countries. When the data used to create these AI systems does not represent the local context, it leads to contextual bias. As highlighted in the source, contextual bias refers to predictive AI models trained on data that fails to accurately reflect the realities of their intended use. This presents a significant risk to the pledge that AI will democratize access to healthcare services in LMICs. Models based on unacceptable data cannot effectively aid primary healthcare practitioners and exacerbate the deficiency of specialized professionals. Additionally, the prevalence of machine learning model development in developed countries perpetuates inequality, concentrating wealth, resources, and decision-making authority within a narrow group of countries, companies, or individuals [241] and [40]. Addressing this challenge is crucial to ensuring that AI effectively transforms healthcare in LMICs, rather than exacerbating existing disparities.

To maximize the benefits of AI-based models, they must be developed and implemented within a robust legal and regulatory framework tailored to the unique public health challenges faced by LMICs [242] and [39]. Such a framework will encourage the responsible adoption of these technologies and enhance the effectiveness of healthcare systems by accommodating the biological and demographic diversity of the populations they serve [240] and [30]. Failing to consider these factors risks further entrenching existing health and socioeconomic disparities [239] and [43]. Therefore, we must recognize that managing AI is not merely about solving isolated health issues; it is an opportunity to transform and progress the health systems of LMICs. The most significant limitation is the lack of knowledge about eHealth and AI concepts, particularly in LMICs. Researchers should develop strategies to encourage users in LMICs to adopt eHealth solutions that incorporate AI applications. Thus, the literature review is the beginning of the game.

We have some literature reviews on the challenges and solutions for transforming health ecosystems in LMICs through AI [31], the impact of AI on global health and healthcare in developing nations [33], and AI for strengthening healthcare systems in LMICs [58]. However, their methodology (database, search string, and search queries) and results have some limitations. They do not analyze the state of AI applications in eHealth as an essential aspect from a user's perspective, through the lens of technology (as a knowledge gap), in LMICs. Ultimately, we need to better understand the barriers to user acceptance of AI applications in LMIC eHealth systems so we can address them in the future.

This research aims to comprehensively review and integrate the existing knowledge on AI challenges in eHealth and its implications for LMICs. Understanding the impact of AI and eHealth strategies on healthcare in LMICs is crucial. The study examines the potential advantages and challenges of implementing AI in eHealth within these countries. To accomplish this, the research

integrates multiple studies on AI in eHealth, establishes connections within the existing literature, identifies research gaps, and provides recommendations for future studies [41]. Despite growing interest in AI in eHealth among academic circles in LMICs, the subject remains fragmented and requires comprehensive qualitative and quantitative studies on its effectiveness [42]. Most existing research focuses on the benefits and challenges of AI in eHealth in developed nations [e.g., 43]. However, there is a concentration of AI-related material in eHealth in specific Asian and African countries, such as Kenya and India [44-45]. For LMICs to benefit fully, a thorough understanding of how AI in eHealth interacts with their healthcare systems is crucial [46]. The urgency of implementing technology-driven solutions for LMIC healthcare systems is underscored by the COVID-19 pandemic, which highlighted the strong link between eHealth, AI, and digital inequalities [47-49-191]. Healthcare costs are projected to rise significantly by 2040 due to lifestyle changes, reduced physical activity, demanding work schedules, and advances in medical monitoring equipment and remote devices [50-51]. However, more credible research grounded in clear empirical findings on AI in eHealth in LMICs [52-53] is needed. This review aims to identify gaps in the adoption and acceptance of AI applications in eHealth and to explore successful implementation strategies. The study provides an overview of AI in eHealth systems in LMICs, outlines the systematic method used in this review, presents a theory-driven research agenda, and concludes with observations. By analyzing AI challenges in the eHealth literature in LMICs against this backdrop and examining academic papers, the study identifies potential areas for future research and integration in this field [54-55]. Overall, the aim is to foster a deeper understanding of the challenges of AI in eHealth for LMICs, paving the way for more effective e-healthcare strategies in these regions.

The primary objective of this paper is to investigate the impact of AI and the need for improving eHealth quality systems in LMCIs, and to identify effective practices for adoption. By conducting a comprehensive literature review, establishing connections, identifying research gaps, and providing recommendations for further study, this paper aims to provide a thorough understanding of AI in e-Health in LMICs [e.g., 56-57-58-59]. Consequently, a pertinent question has been raised: "What are the architectural framework needs [60] and challenges for AI application developers in LMICs to deliver appropriate eHealth systems?

This question is the primary focus of this study. Despite the emphasis on related issues and the potential complementarity of initiatives, challenges for LMIC literature have received limited attention within the AI and eHealth communities. A review of existing research papers published in reputable journals reveals a need for more theoretical and analytical integration between the two domains. To bridge this gap and identify potential areas for research integration, this paper comprehensively evaluates the challenges of AI in the eHealth literature of LMICs.

Finally, this study makes a significant contribution to AI and eHealth research by combining fragmented methodological and conceptual research in LMICs [61]. Additionally, it expands our understanding by examining how gaps in the theoretical lens influence AI adoption practices in e-healthcare systems in LMICs. By analyzing adoption and acceptance barriers, this study provides guidance to policymakers, healthcare providers, and stakeholders on how to promote the use of AI in eHealth. It also considers the existing scope of work from the perspectives of governments, institutions, stakeholders, and program partners, while examining variables specific to developing-country settings [62].

This research addresses specific clinical needs, such as enhanced clinical decision support and treatment planning, where user-friendliness hinders the implementation of AI applications and data collection and technology acceptance in low- and middle-income countries (LMICs). Additionally, eHealth, which could mitigate barriers to surgical care, remains under-researched regarding its clinical assessment and skills effectiveness in LMICs and can be improved by, for example, virtual and augmented reality, digital, and system twins to have more user trust in AIs' applications, users, and the cost-effectiveness of their e-health system applications.

The research presented in this paper contributes to three key areas. Firstly, it provides a valuable resource for scholars in both AI and eHealth who seek to comprehend and utilize the comprehensive framework. Secondly, our thorough analysis enables us to evaluate the impact of AI in the eHealth literature across its various pillars, identify gaps, and highlight numerous opportunities for future research. Our findings demonstrate more complementarities between these two fields than previously acknowledged. Cross-fertilization of the AI and eHealth literature is advisable and often necessary in the 21st century. Finally, this study contributes to the AI in eHealth literature by presenting a systematic account of the evolution of critical ideas and encouraging the complementary development of literature in both domains. Such an approach can help LMICs overcome obstacles to achieving their national healthcare goals.

2. Methodology

Using the SLR (Systematic Literature Review) technique, this study examined the field of AI in eHealth in LMICs. According to [63], an SLR enables the investigation of the body of knowledge in a particular field of study, including the accuracy, dependability, and replicability of research procedures. Several academics argue that the method enables the identification of both qualitative and quantitative characteristics, highlighting the leading authors, journals, and keywords, while also facilitating a comprehensive literature review [64-65]. The authors believe the best approach is an SLR, since it systematically examines a broad range of available literature. This review aimed to comprehensively scope and assess the existing literature on AI in eHealth in LMICs. The SLR approach ensures a rigorous, organized process for comprehensively identifying, selecting, and analyzing relevant sources to understand the research landscape related to our chosen topic. We conducted our study using the five steps listed [66-41], which were also often used by other systematic studies: 1) Question formulation; 2) Databases and search strategies; 3) Research collection and assessment; 4) Analysis and synthesis; and 5) Summary. We describe each stage in detail below.

2. 1. Question formulation

It is essential to develop coherent research questions to define the parameters of a study plan and provide it with a more precise direction [67-68]. After analyzing critical discussions in related studies to gain a robust understanding of the subject area, a study question was identified, and the need for evaluation research was emphasized. A review proposal was then developed. The objective of the research question is to define the qualitative and quantitative components of the knowledge flow being studied. It aims to assess the state of the science and applications of AI in eHealth in LMICs.

2.2. Databases and search strategies

It is suggested [67, p. 214] that "an iterative process of definition, clarification, and refinement" be used during the first stages of a systematic review. Two research team members showed relevant keywords and phrases for the examination procedure [41]. This method minimized researchers' bias and ensured that the search procedure had relevant variations of the search keywords. Our examination of relations was divided into triplet themes: eHealth, AI, and LMICs. We also considered other variations of these important provisions to broaden the scope of exploration [41]. The researchers developed search strings or selection algorithms to identify relevant studies after determining the keywords and their corresponding categories. A thorough search string of the different terms was used to maximize the search range (**Table 2** and **Table 2-1**). To optimize the relevance of the studies retrieved, the look-for sequence confirmed that each associated paper included at least two, and often all, of the keywords from each of the three theme pillars (in this paper, we used PRISMA as a technique for our SLR [e.g., 69]).

We searched through various electronic healthcare databases, including PubMed, Cochrane, Medline, IBECS, LILACS, and Google Scholar, to include information from both public and healthcare-specific sources. Based on the context (eHealth settings in LMICs) and concept (AI adoption), we conducted an electronic database search for relevant papers and defined eligibility criteria. To illustrate and analyze the findings, we also incorporated qualitative studies published in peer-reviewed quantitative journals [55]. Furthermore, we employed snowball sampling [70] by manually examining the reference lists of review articles identified during the transmission process for potential relevant references, given the review topic [71]. This provided us with access to the best coverage of journal titles in this area.

Inclusion and exclusion criteria were used when selecting publications for evaluation to ensure the accuracy and reliability of the information gathered. The exploration was restricted to the article (document type), authors' summaries, delivered summaries, and academic journals (publication type). The following items were not included: book chapters, books, letters to the editor, editorials, conference materials, working papers, and reports. After conducting a pilot search, we discovered critical terminology in three main classifications to define our search strategies based on triplet thematic notions. We performed title and abstract screening, followed by full-text screening. A review examined substantial evidence on strategies to address specific AI concerns and improve e-health delivery in LMICs. For each category, we carried out a separate search. Then, we conducted a search that incorporated all three categories to safeguard the search technique and address the study questions.

Finally, a screening strategy was established. A screening strategy has two phases. Firstly, two reviewers independently assessed the title and abstract of each study and categorized them as "Rejection" if both reviewers agreed to exclude the study, "Perhaps" if there was ambiguity from one or both reviewers (in which case both reviewers would intervene to resolve the inconsistency), and "Sure" if both reviewers recommended the study for inclusion. Following this, the full texts of all studies were reviewed by two reviewers using the same criteria for final inclusion. They read in-depth articles to gather data on the challenges of implementing AI for e-health delivery in LMICs.

We meticulously designed an Excel file to extract thematic data and identify uniform, meaningful information [e.g., 72-73]. Thematic analysis is an essential tool in qualitative research, providing a robust method for in-depth and comprehensive explanations of studies [we have followed a six-

phase process; 74-75]. We grouped the extracted data into relevant themes using deductive and inductive reasoning [76-77-78-79-80]. The deductive method establishes the primary categories based on our research objectives, encompassing the e-health method, LMICs, and the method for integrating AI into application design.

Our analysis used the inductive method to investigate the potential challenges of implementing AI for e-health delivery in LMICs. By employing the combined reasoning method, we effectively categorized these challenges and identified emerging themes and requirements later.

Table 2: Search string conducted for AI in eHealth in LMICs

Step	Sub-step	Explanation
Planning the research	- Problem design and description of themes - Refinement of keywords and expansion of the collection process	Progress of the plan emphasizing the necessity to focus on the subsequent investigation issues: - Investigate the recent state, encounters, and possible applications of AI in the healthcare industry in LMICs. This research question incorporates three thematic concepts: AI, eHealth, and LMIC. AI Keywords: Artificial Intelligence*, AI in eHealth in LMICs*, Challenges in AI in eHealth*. eHealth Keywords: eHealth*, Healthcare in LMICs* Digital Health* LMICs Keywords: Low-and-middle income countries*
Supervising the exploration and location analyses	- Archive collection and citation seek out	Articles from PubMed, Cochrane, Medline, IBECS, LILACS, Scopus, Science Direct, and Google Scholar were selected. The latter strains were applied: (i) Keywords included in the title, abstract, and body; (ii) Publication period: 2018 – Dec 2023; (iii) Document type: article; (iv) Publication type: academic journal; (v) Language: English.
	Inclusion and exclusion criteria	Inclusion: We decided to include only journal articles on AI in LMIC eHealth. We acknowledge that this carefully selected approach might have involved excluding some papers, but we are confident that such a cautious approach offers stability advantages. Exclusion: To ensure a dependable investigation unit, we excluded book chapters, books, editorials, reviews, letters to the editor, conference proceedings, case studies, reports, working papers, and grey literature.
	- Repeat elimination	Possible critical analyses were incorporated into the Word document, and replicate investigations were excluded. The titles, abstracts, bodies, and conclusions of all potentially relevant studies were evaluated and compared against suitable-for-intent criteria. In numerous instances, study introductions and conclusions were also assessed to establish significance. Later, fit-for-objective standards were used to select investigations for further consideration, including inclusion criteria and papers focusing on AI in LMIC eHealth.
Taking and evaluating research	- Assessment and assortment	Segregation principles: (i) papers concentrate on AI and eHealth matters but do not cover LMICs; (ii) papers do not deliver at least two themes. Most papers focused on all three research themes (AI, eHealth, and LMICs); (iii) papers focused only on developed countries.
	- Study and fusion	The full texts of carefully chosen papers were thoroughly investigated. An expressive analysis of select articles was performed, and expressive data were removed. Thematic assessment is focused on identifying and analyzing emerging ideas.

Table 2-1: Search Queries (Jan 2018 - December 2023), Performed on databases (e.g., Cochrane, Google Scholar, and PubMed)

((“eHealth”) OR (“eHealth features/characteristics”) OR (“electronic diseases/illnesses/sicknesses care system/structure”) OR (“eHealth sector”) OR “eHealth care”)) AND ((“artificial intelligence”/ “artificial intelligence”) OR (“machine intelligence”) OR (“automated reasoning”/ “automated reasoning”) OR (“deep learning”/“deep learning”)

OR ("machine learning" OR "artificial intelligence-based innovations") OR ("artificial intelligence-based assessment")) AND ("LMIC") Cochrane

"AI," AND "LMIC" AND ("health medical records" OR "electronic medical records" OR "digital health" OR "mobile health" OR "health information structure/systems" OR "teleconsulting" OR "health informatics" OR "eHealth" OR "mHealth" OR "telemedicine" OR "telehealth") Google Scholar

((eHealth sector/area/part/division [Abstract/Title]) OR (electronic diseases/illnesses/sicknesses care system [Abstract/Title]) OR (eHealth features/characteristics [Terms]) OR (eHealth care sector/area/part/division [Abstract/Title]) OR (eHealth) OR (diseases/illnesses/sicknesses care system/structure [Text])) AND ((artificial intelligence [Terms]) OR (artificial intelligence [Title/ Abstract]) OR (AI [Abstract/Title])) AND ((mHealth) OR (telemedicine [Abstract/Title]) OR (digital health [Abstract/Title]) OR (mobile health [Abstract/Title]) OR (health information systems [Abstract/Title]) OR eHealth [Abstract/Title]) OR (health medical records [Abstract/Title]) OR (electronic medical records [Abstract/Title]) OR (teleconsulting) [Abstract/Title]) OR (telehealth [Abstract/Title]) OR (eHealth informatics system [Abstract/Title]) AND (LMIC [Title/Abstract]) OR (LMIC [Text]) PubMed

2.3. *Research collection and assessment*

Reading the titles, abstracts, and summaries was the next step in determining whether the papers aligned with the research questions. The two team members evaluated 854 papers. Researchers employed a method to categorize papers into three groups: those relevant to the study, those that might have been useful, and those that were not, as illustrated in Fig. 1. Cross-checking the evaluation results between researchers enhanced the objectivity of the selection process. Any questions or differences of opinion were clarified through debate and further understanding of the articles, particularly regarding findings in the relevant and potentially related categories. After the co-authors' iterative consultation and review of the abstracts, sixty-eight articles were selected for further evaluation. In this study, the reviewers thoroughly assessed the available data to ensure relevance and the prospective sources. The reviewers collaborated to identify issues and propose solutions. Because of the nature of our assessment, we grouped the data we collected by country. We presented the critical results in a narrative format, organized by correlations derived from the research data included in the review.

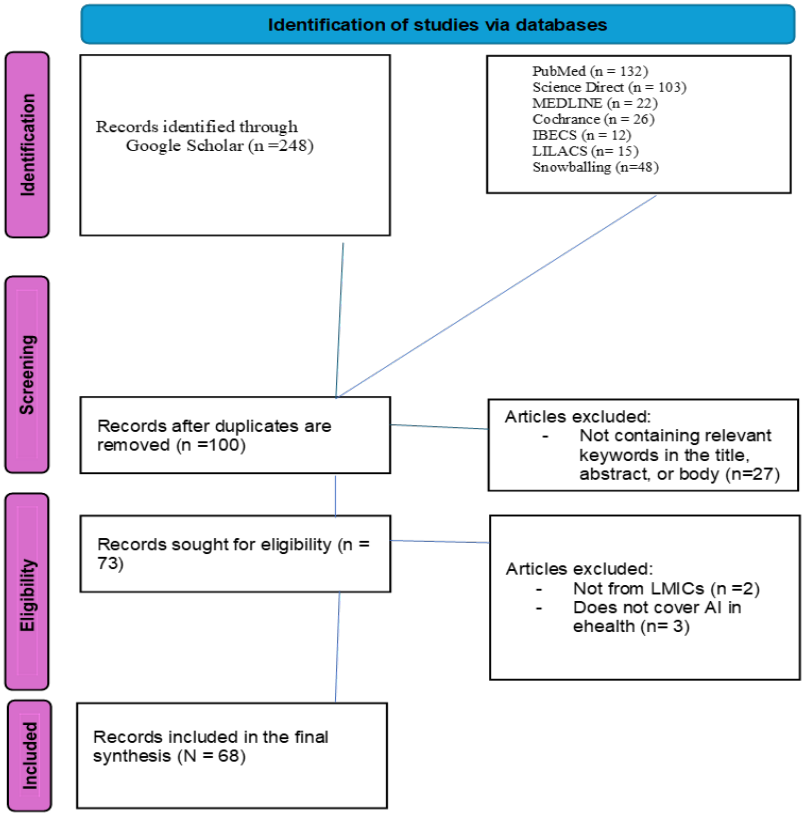


Figure 1: PRISMA flowchart of the systematic review[11]

2.4. Analysis and synthesis

In line with a recognized method, we initially conducted an informative review of the papers, followed by a thematic analysis of the papers in our experiment [67]. The thematic assessment focused on identifying and highlighting evolving themes, contradictions, differences, and conflicts among the various viewpoints within the triplet of thematic notions. We focused on extracting relevant data from each paper. The two research team members conducted the analysis and synthesis stage. They often examined their development and cross-examined their findings to confirm they used a related and reliable methodology when studying and combining the comfort of articles.

2.5 Findings

[11] PubMed: Public Medicin-Medline: Medcien line- Cochrance-LBECS- LILACS:Latin Aamercan and Caribbean Health sicners literature

The critical elements of each paper in our sample are highlighted in our descriptive analysis of the results. We then present a thematic argument that encapsulates and integrates the main conclusions from a detailed analysis of studies. To understand the main themes and movements in the focus form of narrative, we assessed journals by publication year, journal, method, region/country, and division of concentration. The study on this subject is fragmented and incorporates several disciplinary viewpoints. Journals across various disciplines have published papers on AI and its interaction with eHealth in LMICs. Our analysis of research papers on the use of AI solutions in eHealth in LMICs reveals a surge in publications. Of the sixty-eight papers in the sample, most were published in 2021. This may indicate the prominence of triplet thematic notions and suggest that conversations about these subjects are becoming increasingly common among academics, healthcare professionals, policymakers, and stakeholders. We discovered that most research on the use of AI systems is issued in developed, high-income countries [81], spans a wide range of clinical contexts and disciplines, and primarily focuses on healthcare professionals as users. Table 3 presents the review results on AI for eHealth in LMICs, and Table 4 shows that Asia and Africa have the highest number of published papers related to LMICs. All the papers focused on application development. Numerous studies have been conducted on the subject matter. Most primary data-based research uses data-driven AI-based/mixed-methods techniques to reach conclusions [Table 5]. The studies reveal that there is often a need for more data to measure the validity of the impact of AI solutions in eHealth in LMICs. This highlights the difficulty of evaluating AI in eHealth in its current state, given the complexity of these networks and the fuzziness of their boundaries. The primary themes throughout this research were the absence of digital infrastructure, the availability of low-quality data, social and ethical considerations, and legal frameworks, as highlighted in Table 5. AI-based eHealth technologies have made it easier for LMICs to manage their healthcare systems. They can aid in automation, disease surveillance, and forecasting, thereby improving patient outcomes and reducing the high cost of care.

Table 3: Review results in AI for eHealth in LMICs

No	Ref	Year	Subject matter	Method	Position	Industry Concentrate	Crucial Results
1	[82]	2018	Acceptability and feasibility of text messaging to support healthcare	Randomized controlled trials	Iraq	App	The client recommends the eHealth program to other clients, personally rating the message as a whole and obtaining benefits from the messages.
2	[83]	2018	Internet-based behavioral activation with support versus online minimal support	Randomized controlled trials	Indonesia	App	Online behavioral activation reduced symptoms and could help to address the mental health gap in LMICs (by email or chat)
3	[84]	2018	mHealth use for non-communicable disease	Mixed methods	Leban	App	SMS-based interventions targeting individuals were adequate among those living in rural areas; a modified methodology was used for illiterate, unemployed, and elderly individuals.
4	[85]	2018	Identifying the most critical predictors of sputum conversion and deaths in patients	Machine Learning	Tanzania	App	Use an ensemble of AI algorithms to show the most important predictors of death in patients.
5	[86]	2018	A combination of a technology-based mental health selection	Mixed methods	Peru	App	The handle of an inspection app confirmed by preparation and guidance is reasonable and finds a high frequency of undisclosed psychological symptoms.

			program into the routine practices of health				
6	[87]	2018	Using mHealth to develop case recognition and medicine launch	Mixed methods	South Africa	App	Patient-level encounters are often associated with a lack of expertise, difficulty understanding the content, and issues with obtaining and responding to text messages, particularly when using their secret PIN.
7	[88]	2018	Using Mobile Health to Enhance Outcomes of Non-communicable Disorders	Mixed methods	Lebanon	App	mHealth could provide a practical and amplified effect on traditional non-communicable diseases
8	[89]	2018	A remote collaborative care program	Open-label (non-randomized) trial	Chile	App	Remote Collaborative Care: A specialist mental health team reviewed patient data and provided remote assistance once a week. The program operated telephone monitoring, shared electronic health records, and provided remote supervision.
9	[90]	2018	Pilot and Development testing of an internet-based self-help involvement	Pilot pre-post evaluation	Indian	App	Practice and Use Self-Help: A Guide
10	[91]	2020	Digital health interventions	Mixed method	Pakistan	App	Public and private organizations must actively mobilize, regulate, and expand the digital health sector.
11	[92]	2019	The impact of a mHealth clinical decision-making support system	Randomized controlled trials	Ghana	App	There is a need for careful and rigorous evaluation of the implementation and effects of mHealth interventions.
12	[93]	2019	Using Mobile Health to Support Clinical Decision-Making	Randomized controlled trials	Ghana	App	Describe the pattern of requests made to an SMS text messaging–based mobile clinical decision-making support system (mHealth) by helping verbal communication between frontline health workers.
13	[94]	2019	Using mHealth Tools to Develop Access and Coverage	Randomized controlled trials	Argentina	App	Using mHealth tools enables healthcare providers to monitor high-risk patients in their homes, increases the likelihood of participation in risk factor management, and facilitates referrals.
14	[95]	2019	Impressions of an online mindfulness involvement concentrating on concentration, observing, and approval	Randomized controlled trials	China	App	Online mindfulness intervention, delivered over WeChat.
15	[96]	2019	A clinical trial of mobile phone motivational	Randomized controlled trials	Kenya	App	Mobile phone motivation could improve health service care
16	[97]	2019	mHealth involvement to advance the provision of care services	Randomized controlled trials	India	App	The Innovative Mobile Phone Technology for Community Health Operations included a mobile phone and a web-based application, featuring various technology-based job aids to facilitate arranging home visits, providing counseling during home visits, screening for complications, and ensuring adequate supervision by Primary Health Center staff.
17	[98]	2019	SMART health	Randomized controlled trials	India	App	(1) growing patient commitment strategies through cost subsidies, mobile technology, and addressing unintentional adherence barriers (2) greater incorporation of the involvement keen on the succeeding system integrating influences such as human resource and supply chain

							management involvement for improving the quality of health service (3) Measuring the intermediation set in a diverse service distribution environment via private segment assignment. (4) Testing separate task-sharing models, which may incorporate an encouraged ordering role and assignment of other workers, such as pharmacists, nurses, and partnered health professionals
18	[99]	2019	The success of a mHealth-based electronic decision support system for integrated management	Randomized controlled trials	India	App	Sometimes, WellCare does not offer sufficient incremental benefit over enhanced usual care in managing certain chronic conditions.
19	[100]	2019	User assessment of a nurse-supported smartphone	Qualitative	Peru	App	Users reported encountering SMS messages and pop-ups on their phones at involvement establishments.
20	[101]	2019	Feelings and Appropriateness of Text Messaging for Primary Care	Qualitative	Argentina	App	Acceptability was considered adequate based on the texts' actual use, occurrence, and their role as reminders. Text messages could help the patient understand procedures. Additionally, exposure to the texts appeared to help change risk perceptions and care practices and function as psychosocial support. Another important outcome was the role of text messaging as a potential facilitator, with strong evidence of improved patient-physician communication among those who received it. Involvement in educational messages and notices via text messaging within a care program contributed positively to care. It was accepted by individuals with specific problems, characterized by low educational levels, who reside in low-resource settings.
21	[102]	2019	Strengthening health systems through informatics capacity development	Conceptual	Sri Lankan	App	Sustainable implementation of eHealth
22	[103]	2019	An intelligent and multifaceted mobile health system for delivering evidence-based	Cross-sectional	China	App	Fundamental differences in workplace expressions, main concerns, and work cultures may create barriers to effective partnerships. The mHealth system was practical for supporting newly trained healthcare workers. Still, there is a lack of awareness and knowledge, no prevailing electronic record system for handling patients' appointments, and boundless notice affecting mobile health technology in daily work; the system should be frank to acquire and usage, patient management, follow-up visits, online training, reminders, performance review and management, haphazard review and quality controller for settlement physicians, integrating with SMS and voice messaging system.
23	[104]	2019	Practicality study of programmed collaborative voice response telephone calls	Quasi-experimental	Thailand	App	A system of interactive voice response monitoring and nurse prompting is possible but not ideal for all; it is burdensome, needs more patient engagement, and is initially unpleasant.
24	[105]	2019	Enhancement in case management algorithms and value of care	Not specified	Tanzania	App	Select indicators for upgrading the features of eHealth

25	[106]	2019	Estimate of cholera outbreak using weather data	Conventional machine learning	Tanzania	App	Predict epidemic outbreaks based on seasonal weather fluctuations
26	[107]	2019	Detection of malaria parasites	Conventional machine learning	Tanzania	App	Develop a physically robust, low-cost system that requires minimal maintenance for predicting.
27	[108]	2019	A digital mental healthcare	Deep learning	India	App	A fully automated clinical decision support system with connected modules for management, follow-up, and diagnosis is practical for non-specialists after brief training and minimal supervision from psychiatrists, enabling them to deliver mental health care at remote sites.
28	[109]	2019	Use of a mobile phone app	Emotional Control/Pilot pre-post evaluation	Brazil and Peru	App	It was feasible, and access to an extensive database is necessary to generalize the result.
29	[110]	2019	Support the mental well-being	Quasi-experimental	Thailand	App	Web-based program
30	[111]	2019	The success and adequacy of mobile telephone adherence verification for Mental Health in Primary Care	A pilot randomized controlled trial	Lagos, Nigeria	App	Mobile telephone support, clinical recovery, and quality of life are associated with lower sadness scores and are suitable for clients in primary care. An extensive database is needed to generalize the result; cultural effects are not considered.
31	[112]	2020	Can machine learning be helpful as a screening tool for primary care?	Randomized controlled trials	Brazil	App	AI has enabled several rich applications in medicine, particularly in psychiatry.
32	[113]	2020	Applying a mHealth system to remind and suggest remaining clients	Mixed methods	South Africa	App	Using mHealth for callbacks and recommendations is possible and can progress interaction. Evaluating facility capacity in advance and integrating mHealth with existing health information systems are necessary. In addition, health facility staff respected the system's characteristics but faced challenges and requested adjustments, including the automatic contribution of customer-specific information from the health information system and the automatic recording of when remembered and referred clients and public members arrived.
33	[114]	2020	The performance of an integrated e-framework in managing programs at primary healthcare centers	Mixed methods	Indonesia	App	Text messages can be implemented in control programs at primary health care centers. Factors to consider during the implementation of a health information system include the digital divide, the staff workload of primary health care centers, and the level of commitment and leadership within the health office.
34	[115]	2020	mHealth adoption among primary care physicians	Cross-sectional	Malaysia	App	Performance expectations and ease of use were associated with the use of mHealth apps for medical reference. Family medicine trainees working in a government practice implemented the use of mHealth apps for medical calculations. Internet connectivity, performance expectancy, and collaborators' use were associated with the use of mHealth alongside electronic health records. Performance expectations accompany mHealth recommendations to patients, requiring them to follow health information and undergo patient education.
35	[116]	2020	Assessing the viability and acceptability of a mobile health	Cross-sectional	Nepal	App	Lack of awareness about health information and inadequate medication adherence were shown to be problematic. A digital health intervention that uses feature phones may be a conventional and

							pragmatic way to implement an evidence-based program.
36	[117]	2020	Assessment and Experience on the transition from paper to electronic medical records	Qualitative	Argentina	App	Electronic health records enable physicians to determine why patients seek medical consultation.
37	[118]	2020	Operability, effectiveness, and project technology adequate of mHealth for providing primary health care services by community health workers in underserved areas	Qualitative	Afghanistan and Pakistan	App	A mobile-based (m-health) system that supports electronic medical record entry and retrieval, along with video communication features for education and awareness, was found to be easy to use by most health workers. Clients also appreciated the video component. Also, the follow-ups improved.
38	[119]	2020	Process estimation of the systematic medical appraisal, referral, and treatment (SMART) for mental health	Quasi-experimental	India	App	Anti-stigma campaign, training health contributors to apply tablets to examine at-risk individuals, training doctors to make decision endorsements using tablets
39	[120]	2020	Internet Use and eHealth Literacy	Cross-sectional anonymous web-based survey	Pakistan	App	The aggregate eHealth scores showed high confidence in finding health-related information online.
40	[121]	2020	eRx – A technological advance to speed up diagnostics	Deep learning	Peru	Computer-Aided Diagnosis (CAD)	Electronic Mobile system (called 'eRx') development
41	[122]	2020	Realizing a socio-technical system for tuberculosis diagnosis	Quasi-experimental	Peru	App/ Computer Automated Diagnosis (CAD)	Accelerated diagnosis by using a mobile phone and the workload of health workers hinder the practical use.
42	[123]	2020	Smartphone self-test audiometry	Diagnostic accuracy	South Africa	App	Smartphone self-test audiometry provided reliable and accurate judgments of hearing levels for adults.
43	[124]	2020	See the coming COVID-19 incidence across an analysis of Google Trends data	Deep learning	Iran	App	The machine learning models demonstrated a higher net benefit in terms of their analytical capability.
44	[125]	2020	Prediction of perinatal death	Conventional Machine learning	Tanzania	App	The machine learning models demonstrated a higher net benefit in terms of their analytical capacity.
45	[126]	2020	Identification and medication of malaria	Deep learning	Tanzania	App	The study demonstrates the effectiveness of supervised learning models in identifying patients based on their warning signs and demographic characteristics.
46	[127]	2020	Forecasting the prevalence of the COVID-19 outbreak	Deep learning	Egypt	App	The machine learning models demonstrated a significant improvement in their analytical skills.
47	[128]	2020	Influence of trust and privacy concerns on technology	Structural equation model, conceptual model	India	App	Effect of trust and privacy concerns on acceptance of technology in healthcare

			acceptance in healthcare				
48	[129]	2020	Estimate and avoidance of preterm births across different cohorts.	Machine Learning	Tanzania	App	The machine learning models had a higher net value in their analytical capacity.
49	[130]	2020	Assessment of the correspondence condition of wild mosquitoes from near-infrared spectra	Conventional Machine Learning	Tanzania	App	Develop an autoencoder and artificial neural network-based approach to assess the natural case of specific disorders.
50	[131]	2020	Implementing technology-supported care	Randomized controlled trials	Colombia	App	This care model, designed to estimate the implementation of technology-supported viewing, identification, and care, is feasible and indicates significantly higher rates of diagnosis.
51	[132]	2020	Improving health facility delivery rates in a large-scale digital health	Conceptual	Zanzibar, Tanzania	App	Incorporating digital technology provided detailed documentation of the program implementation and enabled real-time innovations within the app.
52	[133]	2020	Maintenance of optimal vaccine stocks	Conventional Machine learning	Tanzania	App	The machine learning models showed a higher net gain in analytical ability.
53	[134]	2020	Impact and Design and evaluation of a digital reproductive health program by using a cluster randomized design	Human-centered/Hybrid Trial	Rwanda	App	Digital intervention successfully achieves the intended health outcomes, but which mechanisms are likely to drive this effectiveness?
54	[135]	2021	Predicting the use of labor induction intervention	Conventional Machine learning	Tanzania	App	The machine learning models had a greater net advantage in predictive performance.
55	[136]	2021	The employment of a primary care-based integrated mobile health intervention for stroke management	Mixed methods	China	App	A primary-care-based integrated mobile health intervention is successfully implemented, strengthening the loop involving the technology-enabled and human-delivered components.
56	[137]	2021	Leveraging data and AI to release the ability of digital health.	Conceptual road map based on expert discussion	Philippines, Chile, Estonia, Gabon, Ghana, Malawi, Nigeria, Pakistan, Rwanda, Brazil, India, Kenya, Malaysia, Mali, Mexico, Bangladesh, and South Africa	App	Insufficient funding and limited workforce capacity pose significant barriers to developing digital health systems. To overcome these challenges, countries can harness six critical building blocks: policy, regulatory framework, infrastructure, interoperability, partnerships, financing, and national strategy. Embracing these building blocks ensures that digital health systems operate seamlessly and remain interconnected.
57	[138]	2021	Potential effectiveness and acceptability of eHealth equipment for training primary health workers	Mixed methods	Nigeria	App	The study found that video training reports encouraged via digital technology are possible and appropriate for improving clinical knowledge, reported practices, and attitudes.
58	[139]	2021	Decrease of pregnant women	Regression as the base	Tanzania	App	The influence of a payment-for-performance arrangement on decreasing the prevalence of

			bypassing nearby delivery healthcare services through a performance-based financial scheme	of machine learning			avoiding near health accommodations for providing services in facilities with appropriate tools and more experienced staff.
59	[140]	2021	Developing a fuzzy expert system to establish the levels of eHealth literacy	Machine Learning	Iran	App	We describe the design, implementation, and evaluation of a fuzzy expert system for determining electronic health literacy levels.
60	[141]	2021	Demonstrating the feasibility of digital health to support pediatric patients	Mixed methods	South Africa	App	The mHealth technology captured essential information that provides an impression of the overall involvement; the performance cost has already been identified as a potential barrier, and older people must provide more support.
61	[142]	2021	Surveillance of medications for specific maladies	Conceptual	LMIC	App	The disjointed nature of available data and its lack of representativeness severely restrict their utility in advising health policymakers and allocating funds efficiently for eHealth programs. The formidable challenges in implementing eHealth stem from deficient health information systems, limited laboratory capacity, and inadequate health system governance, all of which demand urgent attention and increased resources.
62	[143]	2021	How can we improve access to medical imaging in low- and middle-income countries?	Conceptual	LMIC	Computer-Automated Diagnosis	The connection between professional and international organizations is considered crucial, and the formation of an International Commission on Medical Imaging under the umbrella of international organizations suggests that partnerships with other diagnostic disciplines are being stimulated to raise awareness of the standing of advanced diagnostics at large and to foster their incorporation into the care trail globally.
63	[144]	2021	Prediction of neonates with low Apgar scores after induction of labor in Northern Tanzania.	Conventional Machine learning	Tanzania	App	Policymakers, healthcare informaticians, and neonatologists must prioritize the deliberate implementation of data preprocessing strategies when making predictions. These strategies are essential for making informed and accurate decisions.
64	[145]	2021	Socio-technical obstacles involving the large-scale deployment of AI-empowered wearable medical devices	An exploratory and inductive approach, and a focus group	China	App	Device suppliers are currently facing significant technological and financial challenges, while elderly users are highlighting the importance of personal and usage-related issues. It has been identified that a lack of clinical trust and collaboration is a central barrier within the network.
65	[146]	2022	Future of immersive technology in global surgery education	Conceptual	India	App	AI will provide autonomous support to apprentices, accelerating their skills development when working on mobile applications. Deep learning algorithms will create models that identify patterns in data and provide feedback, much like a human educator.
66	[147]	2022	A framework for IT-based management against COVID-19	Conceptual	Iran	App	1. Prevention: For proactive health management, utilize M-health, Internet search queries, telehealth, robotics, the Internet of Things (IoT), AI, big data, virtual reality, and social media. 2. Treatment: Telehealth, M-health, AI, robotics, VR, and IoT can be used to deliver effective and efficient treatments. 3. Management and planning: Employ geographic information systems, M-health, IoT, and blockchain for streamlined healthcare management and planning.

							4. Diagnosis: For accurate and timely diagnosis, utilize M-health, drones, telehealth, IoT, robotics, AI, decision-support systems, and electronic health records. 5. Follow-up: Use telehealth, M-health, and VR for comprehensive patient follow-up and care. 6. Protection: Implement IoT, AI, robotics, automatic vehicles, and augmented reality for enhanced safety and protection in healthcare.
67	[148]	2022	Digitally Supported and Real-Time Self-Monitoring	Machine Learning	India	App	Evaluation of digital engagement in establishing an evidence-based, effective intervention.
68	[149]	2023	Barriers and Facilitators to the Sustainability of eHealth Solutions	A qualitative descriptive exploratory study	Tunisia, Ethiopia, Ghana, and Malawi	App	Lack of technology, organizational and human factors, technological infrastructure, economy or funding, and policy and regulations for eHealth implantation and getting results from AI

Table 4: Emerging themes

Classification 1	Classification 2	Classification 3
eHealth	LMICs	AI
mHealth, Telehealth, Electronic EHR, Telemedicine, Wearable Devices	Tanzania (13 times), South Africa (5 times), China (4 times), Peru (4 times), Ghana (4 times), Argentina (3 times), Iran (3 times), Pakistan (3 times), Nigeria (3 times), Kenya (2 times), Brazil (2 times), Chile (2 times), Malawi (2 times), Rwanda (2 times), Malaysia (2 times), Mali (1 time), Mexico (1 time), Philippines (1 time), Afghanistan (1 time), Nepal (1 time), Indonesia (1 time), Tunisia (1 time), Ethiopia (1 time), Bangladesh (1 time), Sri Lanka (1 time), Iraq (1 time), Lebanon (1 time), India (1 time), Gabon (1 time), Estonia (1 time), Egypt (1 time), LMIC (2 times)	Natural Language Processing, Machine Learning, Chatbots

Table 5: Critical characteristics of the included studies' methods

	Method	Usage Percentage
1	Conceptual	0.09
2	Conceptual road map based on expert discussion	0.01
3	Conventional Machine Learning	0.10
4	Cross-sectional	0.04
5	Cross-sectional anonymous web-based survey	0.01
6	Deep Learning	0.09
7	Emotional Control/Pilot Pre-Post Evaluation	0.03
8	Exploratory and inductive approach/ Focus Group	0.01
9	Human-Centered/Hybrid Trial	0.01
10	Machine Learning	0.06
11	Mixed Methods	0.13

12	Open-Label (non-randomized) Trial	0.01
13	Randomized Controlled Trials	0.21
14	Quasi-Experimental	0.06
15	The rest	0.12

3. Results

AI can enhance healthcare access and quality in LMICs by minimizing diagnostic errors and enabling remote consultations [2]. Despite the successful adoption of AI-powered eHealth solutions, challenges persist. Digital infrastructure limitations hinder the adoption of AI in eHealth [5]. Additionally, the need for more AI-trained healthcare workers poses another hurdle [5]. Expanding access to quality healthcare, reducing costs, and improving efficiency are among the transformative promises of AI in LMICs [150]. Collaboration among stakeholders, including governments, healthcare providers, researchers, and technology firms, is vital for the successful implementation of AI in eHealth.

In LMICs, AI in eHealth is nascent [151]. Global AI Index 2020 shows low Government AI Readiness Index ratings for South/Central Asia, Sub-Saharan Africa, the Caribbean, and Latin America [73-152]. Ethical concerns, such as data privacy and algorithmic bias, must be addressed to ensure fair healthcare delivery. AI models primarily employ knowledge-based or symbolic automation for recognition tasks [153], particularly in patient-provider interactions [154]. Studies focus on the efficacy of AI treatment and technical aspects, with limited attention to implementation details [126]. AI's potential to enhance LMIC eHealth outcomes is clear, but ethical considerations and collaborative efforts are essential for successful implementation. To better understand the AI solutions in e-health for LMICs, we categorized the results of Table 2 into three categories: 1. Benefits, 2. Challenges, and 3. Adopting and Determinants, which are reflected in Table 6. This table provides better insights into AI eHealth challenges in LMICs, which could help us answer our research questions. Table 5 presents the key characteristics of the methods employed in the included studies.

Table 6: AI Solutions in eHealth for LMICs

1	**Benefits**	**References**
1-1	Enhanced accuracy and speed of diagnosis	[82 – 149]
1-2	Personalized healthcare	[84 – 97 and [120-140]
1-3	Improved efficiency and cost-effectiveness	[84 - 99] and [120-140]
1-4	Better disease surveillance and outbreak response	[82-88] and [96-110] and [115-140]
1-5	Improved patient outcomes	[89 - 91] and [99-102] and [120-149]
2	**Challenges**	
2-1	Limited digital infrastructure	[93] and [121] and [142-148]
2-2	Inadequate funding	[94] and [142-148]
2-3	Lack of trained professionals	[85-87] and [95-96] and [110-125]
2-4	Low data quality and availability	[100-103] and [110] and [115-140]
2-5	Ethical and social implications	[97-100] and [145-149]

2-6	Ethical and Regulatory	[137]
2-7	Algorithmic Bias	[85-105-146]
2-8	Regulatory frameworks	[101-104] and [140-143]
2-9	Data Privacy	[128]
2-10	Absence of research	[105] and [115-129]
2-11	Adoption and Determinants of AI in eHealth	[115]
2-12	Technological Concerns	[121-145-149]
2-13	Infrastructural Barriers	[137-149]
2-14	Socio-Economic Factors	[122-145]
2-15	Collaborative Efforts and Sustainability	[89-104-149]
3	**Adoption and Determinants**	
3-1	Resistance by patients and healthcare professionals	[107-109] and [125] and [140-149]
3-2	Future job security and professional autonomy	[84] and [140]
3-3	Age, sex, and organizational capabilities	[82-100] and [110-111]

These categories help us identify gaps and, based on them, introduce concepts that could, in the future, enhance the use of AI applications in e-health systems in LMICs. The details of each category are explained as follows:

3.1. Benefits

Medical diagnosis, treatment recommendations, drug discovery, and disease surveillance are just a few of the myriad uses of AI in eHealth. AI can help address healthcare issues in LMICs, including shortages of healthcare professionals, limited access to medical equipment, and limited access to readily available healthcare services. LMICs can gain from the use of AI in eHealth in the following ways:

3.1.1 Enhanced accuracy and speed of diagnoses

AI will never replace medical experts [82-149]. Instead, they will help each doctor accomplish more than they could. By learning from large volumes of patient data, AI systems can assist healthcare professionals in interpreting X-rays, evaluating test results, and identifying and treating uncommon conditions [84]. Diagnoses can be made more swiftly and precisely thanks to AI systems' ability to analyze large volumes of health data quickly and reliably. Patients in remote and impoverished areas can connect with health professionals using AI-powered telemedicine platforms [85]. Diseases predominant in developing countries, such as AIDS/HIV, tuberculosis, and malaria, can be detected using AI [86]. AI systems can review patient information, test results, and imaging data to produce correct and speedy diagnoses.

3.1.2. Personalized healthcare

Based on a patient's health history, lifestyle, and genetics, AI can assist healthcare professionals in delivering personalized care. AI is developing intelligent virtual agents, such as chatbots [87]. The virtual assistant can respond to inquiries about different health ailments and do a preliminary symptom screening using a set of questions based on information from reliable sources [88]. Using wearable sensor data, AI-based digital technology has enabled patients to self-monitor key health metrics, including heart rate, blood pressure, physical activity, and sleep patterns. Babylon Health is an AI-powered chatbot that offers moms aid and guidance on their health throughout pregnancy and after giving birth. The "BABY" chatbot can respond to common inquiries on conception, labor, and maternal and fetal health [89].

3.1.3. Improved efficiency and cost-effectiveness

Improving patient outcomes and reducing prohibitive costs are two significant challenges in providing healthcare services. By 2026, the healthcare sector is expected to save $150 billion annually by implementing AI technologies [154-155-156]. AI technologies might free up time for busy doctors to concentrate on more essential responsibilities. Additionally, it enables consumers to contact medical experts for further assistance and guidance [90-91]. COVID-19 has motivated the healthcare sector to develop robotic systems that can be deployed quickly, allowing separate entry by essential service providers and experts, eliminating the need for them to travel to the front lines [92].

3.1.4. Better disease surveillance and outbreak response

By examining patterns in health data and identifying outbreaks, AI-powered eHealth solutions can aid disease surveillance and outbreak response [93-94]. AI can help find high-risk locations and foresee the potential for disease outbreaks. This can help healthcare professionals plan and give resources more effectively. The COVID-19 pandemic has heightened the emphasis on public health education, leading to a "misinfodemic" [94]. AI can help prevent the spread of erroneous pseudoscientific claims. In addition to reducing the burden on healthcare systems [85] by enabling faster and more affordable COVID-19 detection, screening, and diagnosis, AI has also helped predict future outbreaks, allowing for adequate healthcare preparedness [97-98]. Predictive analytics, task automation, and decision support are all enabled by the integration of AI into healthcare settings [99-5].

3.1.5. Improved patient outcomes

AI-powered eHealth solutions can enhance patient outcomes by delivering personalized healthcare, faster and more precise diagnoses, and improved disease surveillance and outbreak management. AI-powered eHealth tools can educate patients in LMICs about their health conditions and treatment options. This can help to increase patient engagement and empowerment, leading to better health outcomes. Organizations also use social media and modern healthcare tools to quickly reach critical stakeholders [100]. Surgical oncology patients can benefit from high-quality interventions developed through eHealth and AI [101]. While hospitals may employ AI for tasks such as greeting people during an outbreak, delivering disinfectants, and distributing personal protective equipment globally, there is still an opportunity for further development [102]. Using AI in eHealth in LMICs can significantly transform healthcare delivery and improve health

outcomes for millions of people. Therefore, public, private, and healthcare partners must collaborate to address implementation issues.

3.2. Challenges to Implementation of AI in eHealth in LMICs

Despite AI's potential benefits in eHealth, LMICs face several challenges when using eHealth systems [103].

3.2.1. Limited digital infrastructure

AI-powered eHealth solutions can only be adequately implemented with access to digital infrastructure. Implementing AI-powered eHealth solutions requires robust digital infrastructure, including mobile networks and high-speed broadband internet. Unfortunately, the lack of digital infrastructure or restricted availability in many LMICs makes using AI in eHealth complex [104]. The limited availability of digital infrastructure, including broadband internet and mobile networks, is a primary challenge.

LMICs vary widely in their economic, social, and healthcare infrastructure, with some advancing in internet and mobile technology while others struggle with primary healthcare and digital connectivity [193]. Medical data archives in LMICs face quality issues due to training, organizational, and infrastructure gaps, and need support in digital literacy and technology [194]. Other challenges include low computer literacy, resource shortages, weak infrastructure, poor network coverage, cultural norms, and time constraints [195]. Institutional gaps in emerging nations, such as political instability, inadequate infrastructure and resources, weak laws, and corruption, exacerbate these issues for businesses operating there [196]. Due to high IT infrastructure costs and a lack of skilled personnel, the integration and widespread use of eHealth technologies are limited, particularly in developing countries where they are most needed [197]. eHealth services can enhance healthcare quality, but insufficient ICT budgets, security concerns, and privacy issues hinder their integration [198].

3.2.2. Inadequate funding

Creating and implementing AI-powered eHealth solutions requires significant investment [105]. However, healthcare budgets in LMICs are often constrained, and funding for eHealth is typically allocated to conventional eHealth solutions, such as electronic medical records and telemedicine. Another problem is the need for additional financing to develop and implement AI-powered eHealth solutions. Healthcare spending is often constrained in LMICs, and traditional eHealth technologies, such as electronic medical records and telemedicine, typically receive funding.

Limited funding for medical technology, low education levels, and poor infrastructure severely restrict medical decision support and diagnostics in LMICs [199]. Economic and financing issues, including workforce shortages, undermine the sustainability and implementation of eHealth solutions due to high initial costs [200]. Long-term funding is crucial for successfully adopting and implementing eHealth technologies, as a shortage of funds makes this challenging [201]. Many mHealth programs in LMICs, such as emergency lines and mobile telehealth, often stall after the pilot phase due to low adoption, insufficient funding, and a lack of legal regulation

[202]. Technical barriers to integrating eHealth in referral hospitals include insecurity, inadequate funding, and lack of computer proficiency [203]. Additionally, modern networking supports electronic healthcare delivery in developing countries. However, routine preventive maintenance is often neglected due to budget constraints, and service-level agreements frequently do not address the quality of outsourced ICT services [204].

3.2.3. Lack of trained professionals

Healthcare professionals trained in and proficient in employing the technology are needed to apply AI in eHealth efficiently. Unfortunately, there is a shortage of healthcare workers in many LMICs, and those present might not be sufficiently trained in AI [106]. A major global health issue is the burnout of overworked healthcare professionals [107]. Maintaining patient data, using pattern recognition to identify patterns and suggest treatments, estimating mortality risk, and training practitioners are all ways AI can help alleviate the strain on healthcare professionals.

As digital health methods become increasingly prevalent, the health workforce requires specialized skills and knowledge, underscoring the critical shortage of trained professionals [205]. Introducing new technologies is severely restricted by inadequate infrastructure, untrained personnel, and other barriers [206]. Insufficient or non-existent training significantly impacts the success and efficiency of digital health technologies [207]. The primary obstacles to improving eHealth knowledge include limited time and limited training opportunities [208]. Reviews indicate that healthcare providers often experience low self-efficacy with digital health technologies when they lack proper training, which can lead to negative attitudes toward their use [207]. Most healthcare organizations in developing countries have extensive data, but cannot manage and analyze it using ICTs; therefore, annual training is essential for the success of e-health systems[12]. Overall, the sustainability of eHealth solutions is significantly hindered by the lack of trained professionals, low digital literacy, distrust in technology, and resistance to change [209].

3.2.4. Low Data Quality and Availability

AI-powered eHealth solutions rely on the availability of high-quality health data to make correct forecasts and diagnoses [121]. Unfortunately, the usefulness of AI-powered eHealth solutions is constrained by the limited availability, reliability, or completeness of health data in many LMICs. Concerns about a lack of financing for translation into multiple languages and scripts in the developing world are justified, given that many AI technologies are developed primarily for and in high-income countries [137]. It is essential to integrate AI technology appropriately to combat global inequity.

Poor-quality health data and ineffective management in eHealth systems hinder evidence-based decision-making in LMICs, although improving healthcare delivery with better data efficiency remains possible [210]. Research indicates that poor data quality and limited use of health information hinder decision-making, planning, and evaluation of healthcare programs and disease outcomes [211]. Poor data quality hurts the continuity of care, patient safety, clinician

[12] Infrastructural Barriers to e-Health Implementation in Developing Countries: (2013). European Journal of Sustainable Development, 2(1). https://doi.org/10.14207/ejsd.2013.v2n1p163

productivity, and research efforts [212]. While technical barriers are noted, many eHealth datasets in LMICs are of poor quality and consist of small, incompatible datasets [213]. This can lead to incorrect diagnoses, ineffective treatments, and increased risks for both patients and healthcare providers. The reliance on evidence from low-quality data highlights significant risks, as many organizations producing healthcare evidence do not ensure the accuracy, completeness, or traceability of their data[13]. These challenges, including poor data quality, incompatible datasets, and inadequate expertise, are central to the barriers to advancing the big data revolution in healthcare [214].

3.2.5. Ethical and Social Implications

The application of AI in healthcare raises ethical and social concerns, including data security and privacy, algorithmic bias, and the potential for exacerbating existing healthcare disparities [108-109]. AI-powered eHealth solutions may exacerbate existing healthcare inequities, among other unforeseen effects. Concerns about data security and privacy, as well as the potential for algorithmic bias, are also raised by the use of AI in the healthcare industry [110]. A comprehensive framework for developing and applying ethical AI in healthcare has yet to be widely acknowledged. Nonetheless, it is abundantly clear that there are currently no effective ways to evaluate AI-based technologies for their deployment and moral purpose. However, several stakeholder groups, including vulnerable people, healthcare workers, and healthcare administrators, are glaringly underrepresented in the current debate about the morality of AI use in healthcare [111]. For instance, integrating eHealth and AI tools into Africa's healthcare system has been complicated thus far due to regulatory concerns about their use and privacy.

3.2.6. Ethical and Regulatory

Several ethical and legal issues arise from the use of AI in healthcare, including algorithmic bias, which occurs when AI systems exhibit preconceptions based on training data and may result in unequal treatment across demographic groups [37]. Furthermore, the use of AI systems in patient care raises legal questions about accountability and liability, particularly when misdiagnoses or treatment errors occur. As a result, regulations and guidelines are needed to establish who is responsible for what—eHealthcare providers, AI developers, or the technology itself [157-158]. Recommendations to address security, privacy, safety, trust, and ethical issues include mandating the approval of information ethics regulations and legal frameworks by ethics committees before funding any intervention, a responsibility shared by governments, end-users, healthcare providers, and AI developers [137]. Additionally, managing liability presents a significant challenge for healthcare organizations, particularly e-healthcare providers using AI-based solutions [31].

3.2.7. Algorithmic Bias

Algorithmic bias occurs when the bias is not inherent in the input data and is introduced solely by the algorithm [159]. The selection of optimization functions, regularization techniques, whole-dataset or subgroup regression models, and the use of statistically biased estimators in algorithms

[13] SGA. (n.d.). *Why is Healthcare Data Quality Critical in the Age of AI*. Www.sganalytics.com. https://www.sganalytics.com/blog/why-is-healthcare-data-quality-critical-in-the-age-of-AI/

are examples of algorithmic design decisions that may lead to biased algorithmic outcomes, affecting results [160]. AI and machine learning must be applied carefully to avoid issues related to fairness and algorithmic bias. Furthermore, populations in LMICs are particularly vulnerable to such biases due to limited technical capacity, existing social biases against minority groups, and inadequate legal protections [161]. While bias is related to fairness, it is simply a mathematical and statistical consequence of an algorithm and its data. Suppose an algorithm is discovered to have bias. This bias can be assessed against ethical or legal principles to determine whether it is unfair, and the machine learning model can be adjusted to meet specific fairness constraints [161]. Moreover, AI development methods must remain open and accountable [85]. Policymakers and healthcare professionals must insist on comprehensive explanations of the algorithms' decision-making processes and ensure that biases are systematically identified and addressed. By fostering justice, equity, and inclusivity in AI-driven eHealth solutions, collaborative efforts amongst healthcare professionals, data scientists, ethicists, and community representatives might help eliminate algorithmic biases [146]. In conclusion, addressing ethical challenges specific to AI in eHealth for LMICs, such as data privacy and algorithmic bias, requires a balanced approach. Safeguarding patient data through stringent data protection regulations and robust security measures is essential to mitigate risks of breaches and uphold confidentiality. Simultaneously, combating algorithmic bias demands careful algorithm design and oversight to ensure fairness and equity in healthcare outcomes [105]. Collaborative efforts among policymakers, healthcare providers, and technologists are crucial in developing and enforcing standards that protect patient privacy while promoting unbiased AI applications for equitable healthcare delivery in LMICs.

3.2.8. Data Privacy

In the context of health, data management refers to a person's right to protect their private life, thereby preventing unauthorized collection and use of their data. Therefore, AI algorithms and solutions should respect health data privacy, supported by proper patient consent [31]. Healthcare organizations must manage and safeguard personal information, address data privacy risks and legal responsibilities associated with data processing, and comply with diverse and evolving data protection laws across various countries [162]. Ensuring the confidentiality and integrity of patient information is crucial, as breaches can lead to unauthorized access and may result in identity theft, discrimination, and other harms to patients [37]. Healthcare providers and AI developers must adhere to stringent data protection regulations, such as the General Data Protection Regulation (GDPR) in the European Union and the Health Insurance Portability and Accountability Act (HIPAA) in the United States, and implement robust security measures to safeguard patient data [163-164]. Healthcare data breaches have risen in many jurisdictions worldwide, including the United States, Canada, and Europe. While criminal hackers may not widely use them now, AI and other algorithms contribute to a growing inability to protect health information [165]. The challenge lies in striking a balance between the benefits of AI-driven medical advancements and the need to protect patient privacy. Policy and regulatory measures must be implemented throughout the patient data lifecycle—from collection and storage to sharing and analysis—to ensure the security of patient data [128]. This calls for strict access controls, anonymization strategies, encryption protocols, and transparent consent processes [166]. Stakeholders, including policymakers, healthcare providers, and technology developers, must collaborate to establish and enforce robust data protection standards tailored to local contexts [167].

3.2.9. Regulatory Frameworks

AI's potential lies in its ability to analyze and understand vast amounts of data, while also identifying patterns that would be difficult for humans to notice [112]. This AI capability has raised concerns about liability and risks, particularly concerning the level of autonomy allowed to AI applications [113]. Developing eHealth and AI in surgery in Africa following COVID-19 is expected to face several challenges due to disparities in healthcare guidelines across countries, according to a review by [114]. This cost is particularly significant for developing nations, as the obstacles to inclusion in such databases will continue to rise, excluding more populations and exacerbating biases that favor high-income nations. Ethnic minorities and LMICs should all have data incorporated to properly move towards a global information medical system that combines data from all regions to reduce prejudice and promote data justice. Unfortunately, regulatory frameworks governing the use of AI in healthcare in LMICs are often inadequate [115].

Integrating AI technologies into healthcare systems requires a robust regulatory framework that addresses ethical concerns, data privacy, and equitable access, ensuring that all populations benefit from advancements in medical technology [169]. AI's ability to analyze vast amounts of data and identify patterns invisible to humans has revolutionized many industries. However, it raises significant concerns about liability and risks, particularly regarding the autonomy granted to AI applications [169-215]. Health system regulations are not well adapted to rapid technological change because states update their rules slowly [216]. The development of eHealth and AI in surgery in Libya following COVID-19 is hindered by disparities in healthcare guidelines across countries [217]. The risk of unconsented commodification of collected data—where individuals cannot control or access how their data are shared, reused, or commercialized—poses a significant threat, especially in low-resource settings characterized by deep intersectional inequalities and where governments are slow to implement data protection policies and regulatory oversight [218]. Unfortunately, many LMICs lack adequate regulatory frameworks to govern the use of AI in healthcare, which can lead to ethical and safety concerns [216].

3.2.10. The absence of research

The biggest obstacle in the field is the lack of in-depth studies on eHealth and AI advancements in surgery in LMICs, including the Middle East, Asia, and Africa. The lack of relevant data on the many drawbacks of implementing AI in surgery is another issue in this field. The analysis of enormous amounts of health data and the discovery of novel patterns and correlations that can enhance health outcomes are made possible by AI-powered eHealth solutions. AI technologies can combine and analyze data from diverse sources, such as information from wearable sensors, digital symptom tracking, and medical visits, to create a full image of the patient [116].

The lack of research on eHealth and AI in surgery in LMICs poses significant challenges, despite their potential to enhance clinical decision support and treatment planning. Issues such as limited data availability, reliability, and user-friendliness hinder the implementation of AI in these regions [219]. Additionally, telemedicine, which could mitigate barriers to surgical care, remains under-researched regarding its clinical effectiveness in LMICs [220]. The research focus is unevenly distributed, with a heavy concentration in countries such as China, highlighting the need for more diverse geographic coverage [220]. While digital surgical simulation shows promise,

further study is needed to address issues such as image distortion and high costs to ensure its practical implementation in LMICs [221]. Initiatives such as Artificial Intelligence for Global Health (AI4GH) aim to address these gaps by promoting interdisciplinary research and developing AI tools suited to global health needs.[14]. Despite large volumes of data generated by public health institutions, donor-funded programs, and the business sector, this data often remains fragmented or limited to specific uses, impeding access for researchers and AI implementers [219].

3.2.11 Adoption and Determinants of AI in eHealth

The adoption of AI and electronic health systems in LMICs during the pandemic was low, according to a review by [117], due to the pandemic's detrimental effects on these nations. Since the area is still developing and has significant healthcare inequities, the low adoption is primarily due to these factors. The major obstacle to successful AI deployment is resistance from patients and healthcare professionals [118-119]. According to [136], consumers in LMICs are still reluctant to use technology. Healthcare professionals and patients consistently emphasized psychosocial factors as key to the adoption and acceptance of AI technology. These considerations included perceived ease of use, usefulness, perceived effort, performance, and social impact [5-120]. AI adoption is negatively correlated with understanding of the risk to autonomy. Professionals' resistance to AI is primarily linked to the perceived danger to future job security and professional independence [5]. Many doctors who oppose technology believe it threatens their professional autonomy [115]. The adoption of AI technology is heavily influenced by structural aspects, including workflow, organizational size, security, and training [121]. Some earlier studies have identified sex, age, and organizational capabilities as potential factors influencing AI adoption [121, 122]. Additionally, [122] has shown that standard setting and client guidance can enhance AI adoption and acceptability by removing barriers to its usage in healthcare.

The adoption of AI in eHealth within LMICs has encountered substantial challenges, particularly highlighted during the COVID-19 pandemic [222]. Although AI has shown promise in areas such as diagnosis and treatment, its widespread adoption has been hampered by pre-existing healthcare disparities that worsened the pandemic [223]. Despite high interest in eHealth technologies, overall acceptance and integration rates remain insufficient for healthcare systems to fully realize the potential benefits [224]. To improve adoption rates, engaging users early in the design of eHealth interventions and effectively utilizing feedback mechanisms are crucial [225]. The slow progress in LMICs is mainly due to several barriers, including limited computer skills among users, inadequate internet connectivity, poor infrastructure, network failures, lack of prior planning, and the absence of comprehensive eHealth policies and strategies [226]. Furthermore, psychosocial factors such as perceived usefulness and ease of use are significant determinants of AI acceptance [227]. Addressing these challenges is essential for enhancing the adoption and effectiveness of AI in eHealth across LMICs.

3.2.12. Technological Concerns

[14] Artificial Intelligence for Global Health | IDRC - International Development Research Centre. (n.d.). Idrc-Crdi.ca. https://idrc-crdi.ca/en/initiative/artificial-intelligence-global-health

One of the primary obstacles to AI implementation in eHealth within LMICs is the lack of robust digital infrastructure [121]. The digital divide is particularly relevant to the healthcare industry because inequalities in digital literacy and access to resources make it challenging to implement advanced medical technologies successfully in low- and middle-income nations [27]. Limited digital literacy in data collection and management complicates the effective digitization of routinely collected data, hindering overall progress in this area [168]. Ensuring interoperability across diverse platforms and technologies, which often employ unique standards and protocols, is crucial to enhancing coordinated care through AI [145-149]. This requires collaboration among technology developers, healthcare providers, and regulatory bodies to establish universal standards that promote interoperability and seamless data exchange [169-170]. For eHealth solutions to be successfully implemented in low- and lower-middle-income countries, a centralized eHealth policy framework is necessary to address issues such as shortages of healthcare providers, insufficient workforce education, widespread illnesses, inadequate surveillance, and inefficient management [171].

3.2.13. Infrastructural Barriers

Infrastructural barriers are substantial in LMICs, and limited connectivity is a significant impediment to collecting and analyzing health data, as healthcare facilities often lack the hardware and software needed to support AI solutions [172]. Sustainable funding models and cost-effective solutions are essential to ensure the long-term feasibility of AI implementation in laboratory medicine, as insufficient funding and awareness impede the development and application of AI technologies in this field [29]. The high costs of acquiring and maintaining advanced AI technologies can be prohibitive for many healthcare providers in these regions [173]. Healthcare systems in LMICs are often fragmented, with numerous small-scale, uncoordinated projects that do not share data or integrate effectively with national health systems [137-149]. This fragmentation increases inefficiencies and hinders progress toward universal health coverage, resulting in duplication of efforts [174]. Large volumes of high-quality data are needed to train AI-based health applications, but these data are currently unavailable or extremely difficult to obtain in LMICs [175].

3.2.14. Socio-Economic Factors

Numerous socioeconomic factors, including income levels, poverty rates, the state of the healthcare system, and accessibility to resources and services, define LMICs and impact their ability to adopt AI technologies [122-145]. LMICs often face challenges in healthcare delivery, including limited resources, poor infrastructure, and a high disease burden, which can hinder their ability to implement AI solutions [29].

Limited financial resources hinder the acquisition of advanced medical equipment and technologies crucial for modernizing healthcare services. Meanwhile, infrastructural deficits, such as inadequate healthcare facilities and limited digital connectivity, obstruct the seamless integration of AI systems, which is essential for enhancing operational efficiency and patient care outcomes [27].

3.2.15. Collaborative Efforts and Sustainability

Substantial public-private sector partnerships are needed for AI in eHealth to be successfully adopted in LMICs [89]. Governments must fund and implement supportive legislation to facilitate these efforts, while private organizations can provide the necessary technological expertise and creativity. Scaling up and sustaining such initiatives proves challenging due to constrained resources, fragmented funding, and accountability issues. Short-term, narrow focus, coupled with short time horizons, limited research capacity, political interests, risk aversion, data shortages, silos, and high staff turnover, further complicate these efforts [176]. Enhancing the impact and sustainability of solutions can be achieved by involving local communities in their creation and implementation, which helps ensure they are relevant and well-received [104].

Finally, AI adoption in eHealth in LMICs presents several challenges that require a multimodal strategy that accounts for socioeconomic, technological, ethical, and infrastructural factors. It is imperative to have a robust digital infrastructure, all-encompassing legal frameworks, and significant financial resources [149]. The effective integration of AI in healthcare systems in LMICs depends on community involvement and collaboration between the public and private sectors. It will take constant investigation and flexible thinking to negotiate the challenging terrain of AI use in these areas. To fully realize the promise of these technologies, implementing AI in eHealth delivery in LMICs faces several vital obstacles that must be addressed.

3.5. Perspectives of the end-users of AI-driven eHealth solutions

End users' perspectives on AI-driven eHealth solutions in LMICs offer critical insights into the effectiveness and challenges of these technologies. End users, including patients, healthcare providers, and community health workers, bring diverse perspectives that are essential to the successful implementation and sustainability of AI in eHealth.

3.5.1 Patient Perspectives

Patients in LMICs often have a positive attitude toward AI-driven eHealth solutions because of the potential to improve access to healthcare services. AI technologies that enable remote consultations and diagnostic services are particularly valued in rural and underserved areas where healthcare facilities are scarce [177]. Data privacy and security are critical for protecting the interests of patients, healthcare providers, and researchers, as AI applications depend on extensive access to sensitive information. Maintaining the confidentiality of patient data is paramount because breaches can result in severe consequences for individuals and undermine public trust in healthcare systems [27]. Facilities with more staff members who were driven, more resources, and higher digital literacy were more willing to use eHealth technologies, resulting in better, more coordinated service delivery and increased patient satisfaction. However, sociocultural norms already in place, geographic differences in access to technology, and gaps in digital literacy can limit the potential of eHealth [34].

3.5.2. Healthcare Provider Perspectives

Healthcare providers, including doctors, nurses, and community health workers, generally recognize the potential benefits of AI in enhancing diagnostic accuracy, streamlining administrative tasks, and providing decision support. AI tools that analyze medical images or

predict patient deterioration are valuable additions to clinical practice [178]. In 2016, the UK-based digital health company Babylon began operating in Rwanda, where there was much interest in leveraging AI to improve the healthcare system. Despite registering 2 million users and handling 3,500 consultations per day, Babylon's progress underscores the challenges and debates surrounding digital healthcare, including concerns about unequal access and the potential overhyping of AI benefits[15].

Despite these benefits, healthcare providers often need help integrating AI tools into their existing workflows. Extensive training and support are necessary to ensure providers can use AI systems effectively. Additionally, some providers express concerns about the reliability of AI recommendations and the risk of overreliance on technology at the expense of clinical judgment [179]. These problems can be resolved by ensuring AI technologies are user-friendly and by involving healthcare practitioners in the design and deployment phases.

3.5.3. Community Health Worker Perspectives

Community Health Workers (CHWs) in LMICs are increasingly supported by AI-driven eHealth solutions, which have the potential to significantly enhance their ability to deliver primary healthcare, especially in remote areas. These AI-powered tools can assist CHWs in various aspects of their work, including refining clinical assessments, facilitating accurate patient identification, and aiding in disease diagnosis[16]. For instance, machine learning platforms bolster clinical logic for CHWs in Nigeria, facial biometrics streamline patient identification in Uganda, and computer vision facilitates the interpretation of rapid malaria diagnostic tests in Rwanda[17]. However, implementing AI technologies for CHWs in LMICs faces several challenges. These include context-specific solutions tailored to local needs, comprehensive training for CHWs to understand and use these new technologies effectively, and addressing concerns about the potential erosion of clinical skills or misalignment between AI recommendations and local healthcare realities [180–181]. Moreover, infrastructure constraints, such as limited device access, unreliable internet connectivity, and inconsistent electricity supply, must be carefully considered when deploying AI solutions for CHWs [182]. Despite these challenges, AI offers a promising avenue to reduce burdensome workloads for CHWs, potentially leading to more efficient and effective care delivery in resource-constrained settings [180–181].

End-users in LMICs generally have an optimistic view of the potential advantages of AI-driven eHealth solutions, but there are also substantial constraints to consider. Addressing concerns about training, digital literacy, data protection, and the integration of AI tools into existing healthcare

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[15] wdlhi. (n.d.). *Rwanda venture tests digital health potential in developing world – RHIA*. Retrieved July 15, 2024, from https://rhia.rw/rwanda-venture-tests-digital-health-potential-in-developing-world/

[16] *Transforming Healthcare: Unleashing the Power of AI for Frontline Workers | Innovations in Healthcare*. (n.d.). www.innovationsinhealthcare.org. https://www.innovationsinhealthcare.org/transforming-healthcare-unleashing-the-power-of-ai-for-frontline-workers/

[17] *Transforming Healthcare: Unleashing the Power of AI for Frontline Workers | Innovations in Healthcare*. (n.d.). www.innovationsinhealthcare.org. https://www.innovationsinhealthcare.org/transforming-healthcare-unleashing-the-power-of-ai-for-frontline-workers/

systems is crucial. Stakeholders can enhance the adoption and efficacy of AI in improving healthcare delivery in LMICs by incorporating input from patients, healthcare professionals, and community health workers in the design and implementation of AI solutions. It will take constant investigation and flexible thinking to negotiate the challenging terrain of AI use in these areas.

4. Examples of AI implementation in eHealth within LMICs

4.1. Ayushman Bharat Digital Mission (ABDM) in India[18]

ABDM is an innovative attempt to use AI technologies to change healthcare delivery. According to PricewaterhouseCoopers' research on leveraging technology to enhance healthcare in India, ABDM aims to improve the quality and accessibility of healthcare services nationwide. AI-driven solutions play a crucial role in achieving this aim by enabling streamlined healthcare administration, personalized treatment plans, and accurate diagnostics. This initiative demonstrates India's commitment to leveraging digital advancements to bridge the healthcare gap, empower patients, and optimize resource utilization. India establishes a global standard for advancing technology to create inclusive healthcare ecosystems by integrating AI into e-health systems under the ABDM. AI solutions have greatly enhanced the detection and treatment of tuberculosis (TB) and Chronic Obstructive Pulmonary Disease (COPD). Advanced spirometers and analytical tools enable early warning systems for COPD, as well as inhalers driven by AI, to track drug delivery and prescription compliance. Furthermore, Computational Fluid Dynamics techniques visualize lung characteristics, improving treatment accuracy. To support India's national TB program in its fight against the disease, the Central Tuberculosis Division of the Ministry of Health and Family Welfare uses AI in TB diagnosis to identify disease clusters, perform vulnerability mapping, and enhance screening and diagnostic methods (**Fig. 2**).

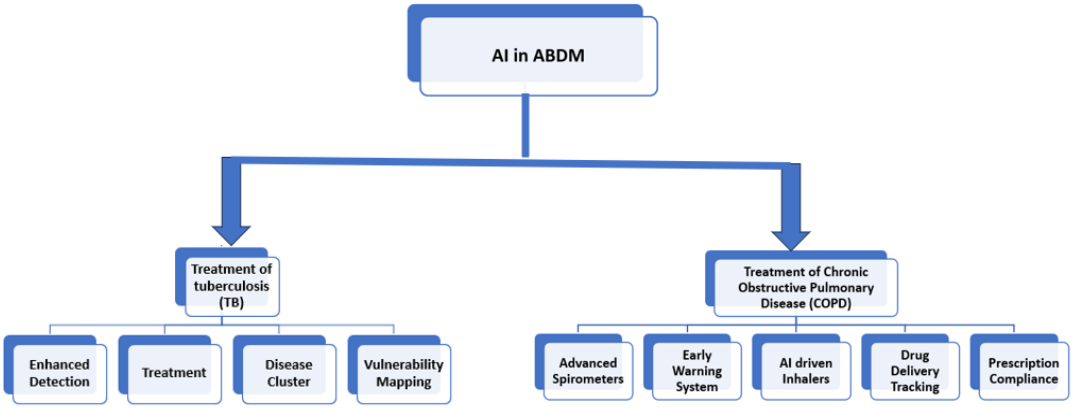


Figure 2: AI implementation in ABDM

4.2.AI-Driven Drone Delivery in Rwanda

The successful implementation of AI-driven drones for medical supply delivery in Rwanda, through a partnership between Zipline and the Rwandan government, has revolutionized healthcare logistics [183]. Since 2016, Zipline has been operating in Rwanda, utilizing drones to

[18] Enabling healthcare with technology. (2023). https://www.pwc.in/assets/pdfs/healthcare/enabling-healthcare-with-technology.pdf

deliver blood, medical products, and vaccines to hospitals in remote regions[19]. These drones leverage AI algorithms for autonomous navigation, ensuring efficient delivery and return trips. Previously, transporting blood from Kigali to remote hospitals could take 4-5 hours; however, with drone delivery, the time has been significantly reduced to 15-20 minutes, enhancing response times crucial for saving lives, especially in emergencies such as postpartum hemorrhage, a leading cause of maternal mortality in Rwanda [184]. Over the past six years, Zipline has completed more than 500,000 deliveries, running around the clock and covering distances of up to 150 miles round-trip. This scale has dramatically improved healthcare access, reducing delivery times, minimizing blood wastage, and enhancing the availability of critical medical resources in underserved areas. The Rwandan government views this initiative as integral to its broader healthcare improvements, embracing innovative technologies to save lives and improve healthcare efficiency. While the exact number of lives saved remains unquantified, the impact on Rwanda's healthcare system underscores the effectiveness of AI and drone technology in overcoming logistical challenges and ensuring timely medical support for remote communities **(Fig. 3)**.

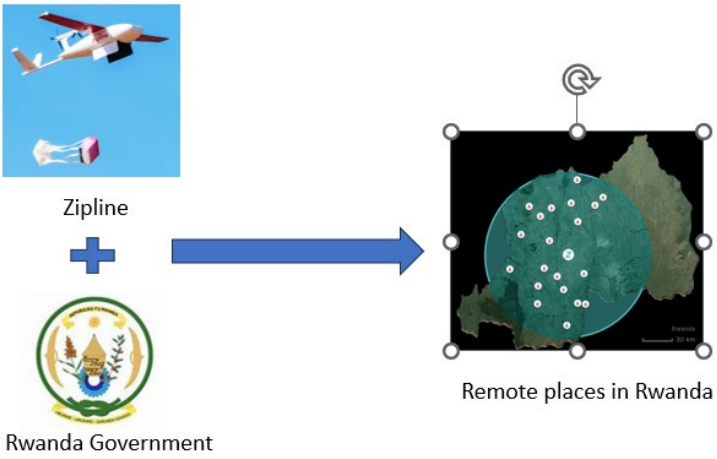


Figure 3: AI-driven drone delivery by Zipline in Rwanda

4.3. CarePay's mobile health wallet in Kenya - M-TIBA

M-TIBA, a mobile health wallet developed by CarePay in partnership with Safaricom and PharmAccess Group, has significantly transformed healthcare in Kenya by enabling users to save, send, and receive funds for medical expenses, thereby improving financial access to healthcare and reducing barriers to care [185]. CarePay has evolved into a comprehensive solution provider, catering to a diverse range of payers, including insurers, public bodies, donors, corporations, and individuals, while serving healthcare providers and patients. CarePay's platform can effectively administer, automate, and manage diverse healthcare schemes and programs, ensuring that designated healthcare funds are utilized by the appropriate individuals for the correct care at suitable locations and at minimal transaction costs[20]. This platform, which supports millions of users and integrates with over 300 medical institutions, demonstrates how AI can optimize healthcare systems by improving financial access and streamlining payments, ultimately providing patients with necessary medical services [186].

[19] How drones are delivering lifesaving medical supplies in Rwanda. (2019, April 16). PBS NewsHour. https://www.pbs.org/newshour/show/how-drones-are-delivering-lifesaving-medical-supplies-in-rwanda
[20] https://www.carepay.com/

4.4. Smart Health Applications in Uganda for CHWs[21]-[22]

The Smart Health app, developed by Medic in partnership with Living Goods, is an AI-powered eHealth solution designed for community health workers (CHWs) in Uganda. Medic's user-centered design approach involved extensive research in Ugandan communities to tailor the applications to specific local needs. Key features include intelligent workflows for accurate health assessments, automated SMS messaging to engage patients, AI-driven task lists that prioritize high-risk patients, and real-time performance management for supervisors. The application operates in low-connectivity areas and seamlessly integrates with government health systems for efficient data sharing. Supporting over 7,800 CHWs, Smart Health has improved healthcare delivery by shifting from geographic canvassing to data-driven prioritization. Adaptations during COVID-19 enabled the application to give prevention messages and national guidelines, ensuring safe service delivery. Comprehensive health services covered by the application include pregnancy care, childhood diseases, nutrition, family planning, immunization tracking, and COVID-19 response.

In conclusion, the use of AI in eHealth in low- and middle-income nations has made notable advances in improving the accessibility and delivery of healthcare. The Ayushman Bharat Digital Mission in India exemplifies how AI-driven technologies are transforming healthcare delivery, leading to improved patient outcomes and diagnostic accuracy. Similarly, Zipline's deployment of AI-driven drones in Rwanda to transport medical supplies highlights the impact on healthcare logistics, as it cuts delivery times and improves access to vital medical resources in remote locations. These projects demonstrate AI's capacity to transform healthcare in resource-constrained environments and its crucial role in saving lives and improving overall effectiveness.

5. Discussion

Together, governments, healthcare providers, and the private sector will need to develop policies [123] and regulatory frameworks to address the ethical and social ramifications of AI in eHealth, increase funding for eHealth, invest in digital infrastructure, train healthcare professionals, improve data quality and availability, and train healthcare professionals to address these issues. AI may significantly alter how resources are given. Several potential solutions exist to address the challenges of implementing AI in eHealth in LMICs. Some of these solutions include:

5.1. Investment in digital infrastructure

To facilitate the adoption of AI-powered eHealth solutions in LMICs, substantial investment is needed in digital infrastructure, including broadband internet and mobile networks. To stimulate investment, LMICs may consider offering incentives to foreign tech companies, enabling them to conduct research and construct facilities that support infrastructure development. The development of open-source software to aid proper data handling, data anonymization tools, and AI governance guidelines should consider these investments. Dependable connectivity and

[21] Living Goods' Smart Health App. (n.d.). DHealth Compendium. Retrieved July 18, 2024, from https://fpdigitalsolution.org/case-study/living-goods-smart-health-app/

[22] Smart Health in Uganda. (n.d.). www.exemplars.health. https://www.exemplars.health/emerging-topics/epidemic-preparedness-and-response/digital-health-tools/smart-health-in-uganda

internet access are essential to providing free, straightforward access to health information. Open-access publishing should be widely promoted to overcome copyright and financial barriers, and more health sciences journals in developing countries should be published in this manner [187]. Governments and organizations have a significant role in funding and implementing these efforts.

5.2. Healthcare professional training

Healthcare professionals must receive training in AI technology to implement AI-powered eHealth solutions efficiently. Governments, academic institutions, and organizations have developed programs for training healthcare personnel in AI.

5.3. Partnership with the private sector

Implementing AI-powered eHealth solutions in LMICs can benefit significantly from business-sector involvement. Collaboration with IT firms can facilitate the development and implementation of AI-powered eHealth solutions tailored to the specific needs of LMICs. Private organizations have been actively involved and are the main factors behind mHealth efforts. The first issue we must tackle from the standpoint of the right to health is the connection between for-profit businesses and health equity. To balance individuals' diverse needs while improving the healthcare system, clear direction on cooperation between the private and public sectors is crucial.

5.4. Improved data quality and availability

The effectiveness of AI-powered eHealth solutions depends on improving health data quality and availability [121] in LMICs. Governments should enhance health data collection and sharing, and businesses can invest in data management solutions to use AI more effectively. Leaders in LMICs should strive to ensure compliance with rules and regulations governing publicly available datasets, while also facilitating accurate data collection, if they aim to produce objective datasets that accurately reflect the global community. With this aid, these nations can use their data to address clinical issues specific to their populations and enhance current global datasets by more accurately representing their populations' diversity. The perspectives of marginalized and vulnerable groups must be considered when LMICs establish digital health infrastructure to define how their data will be collected and used, and how they might benefit. So, when fostering digital literacy in LMICs, involving patients and the local community is crucial. The creation of governing bodies must include representatives from various demographic groups, such as laborers, the urban poor, Indigenous peoples, the elderly, and women, to ensure their perspectives are heard.

5.5. Ethical and social considerations

Patients and healthcare professionals seek AI devices that perform effectively, enhancing transparency and trustworthiness [124]. To address these issues, policymakers must investigate specific solutions to integrate online hospitals into the hierarchical healthcare system, improve local governance at all levels, enact legislation to protect individuals' rights, and define the role of the private sector in the healthcare industry [125]. Governments and organizations can create legislative frameworks [115] to address issues such as algorithmic bias, healthcare disparities, and

data privacy and security concerns. Health policies that broaden access, enhance population health, reduce barriers to care for patients in LMICs, and align incentives and reimbursement to support the technology needed to provide these services are backed by research [126]. These frameworks should encompass algorithmic bias [127], data privacy and security, as well as the moral and societal ramifications of AI in healthcare.

Additionally, regulations should be implemented to address medical professionals' concerns and ensure their involvement in the development and deployment of AI-powered eHealth solutions. Healthcare personnel must receive AI training and participate in the creation of AI-powered. To ensure the efficacy and ethical use of AI-powered eHealth solutions, healthcare professionals must be trained to use them and participate in their design and development. Future studies should focus on standardizing AI in eHealth and developing new regulations and incentives that promote its application [128]. Health policy can have unrestricted access, boost population health, and ease obstacles to patient care in developing nations [129]. Despite the rise in eHealth use during the pandemic, researchers still need to define universal standards that apply everywhere to ensure the proliferation of eHealth and AI in unstable regions.

5.6. Funding for eHealth

This may help LMICs plan and distribute their healthcare resources to prevent the collapse of healthcare systems [130]. Therefore, it could be effectively used by LMICs to reduce the burden on their healthcare systems in several ways, including planning, mitigation, diagnosis, and patient treatment. The implementation and development of AI-powered eHealth solutions in LMICs can be enabled by increasing funding for eHealth [45]. Governments should allocate more funds to eHealth, and private-sector companies can invest in eHealth solutions that could improve health outcomes in LMICs.

Addressing the challenges of implementing AI in eHealth in LMICs will require a multi-stakeholder approach that involves collaboration among governments, healthcare providers, academic institutions, the private sector, and other relevant stakeholders. By working together, these stakeholders can help unlock the potential of AI to improve health outcomes in LMICs. Deploying AI-driven tools in LMICs can eliminate health inequities and reduce the strain on health systems.

5.7. Investment in research

To help students, researchers, and public health authorities understand the new world of technology and automation, we highly recommend that they be exposed to AI approaches and models. Many LMICs are working to integrate AI across all levels of their education systems [131]**.** We also recommend that investigators assess understanding and patient care outcomes in response to guidance in eHealth [132-133]. The COVID-19 pandemic highlights the importance of eHealth guidance, as the necessity for groundbreaking healthcare initiatives is both a prospect and an opportunity [134-135]. These developments will enable faster, higher-quality, and more affordable healthcare delivery by organizations. The biggest obstacle in this field is the lack of in-depth studies on eHealth and AI advancement in LMICs, including several Asian countries, the Middle East, and Africa.

6. *Actionable recommendations and practical steps for implementing AI in eHealth for policymakers*

LMICs should adopt a comprehensive strategy that accounts for several key variables to successfully implement AI-driven eHealth solutions. To ensure the effective integration of modern technologies into healthcare systems, policymakers must adopt clear and achievable actions. This synopsis provides essential guidelines and actionable steps for successful execution, supported by citations to relevant journals.

6.1. Strengthen Data Privacy and Security Frameworks

The security and privacy of data are critical when deploying AI-driven eHealth solutions. Legislators should create and implement stringent data protection laws tailored to the needs of LMICs. Ensuring adherence to these standards through frequent audits is crucial for upholding public confidence in healthcare systems. Highlights the need for strict procedures to protect sensitive information and the significance of data privacy in eHealth [27].

6.2. Enhance Digital Literacy and Training Programs

In LMICs, digital literacy poses a significant barrier to AI technology adoption, impacting the uptake of eHealth tools. Facilities with higher digital literacy show greater adoption of AI-driven healthcare technologies. Assessing the impact of digital health interventions underscores the critical role of digital literacy. Disparities in digital skills can limit the potential of eHealth, especially in rural areas. Policymakers should consider digital literacy levels within the digital ecosystem when implementing digital solutions. However, the document should provide more detailed recommendations for widespread digital literacy programs and partnerships with educational institutions and NGOs. Additionally, an explicit discussion on training for patients, healthcare providers, and community health workers should be included. Improving digital literacy remains crucial for the effective implementation of eHealth in LMIC [34].

6.3. Integrate AI Tools into Existing Healthcare Systems

To integrate AI tools into existing healthcare systems, healthcare organizations should focus on several key steps. First, they should prioritize data standardization and interoperability by adopting frameworks such as Fast Healthcare Interoperability Resources (FHIR) to ensure consistent data formats across platforms and vendors. Implementing robust data-sharing protocols while maintaining patient privacy is crucial to creating anonymized benchmarking datasets that can be regularly updated and calibrated. Healthcare providers should demand transparency from AI vendors on algorithm development and decision-making processes to ensure patient safety and detect potential biases. Organizations should also establish clear accountability frameworks and quality-control mechanisms for AI technologies, such as those used in clinical laboratories. Financial considerations are essential, so healthcare systems should develop sustainable funding models for ongoing AI maintenance and updates. Finally, integrating AI tools into clinical workflows requires careful planning and potentially redesigning processes to optimize the synergy between human providers and AI technologies [188].

6.4. Ensure Context-Specific AI Solutions

AI solutions must be tailored to the specific healthcare needs and infrastructure of LMICs. Policymakers should collaborate with local healthcare providers and technologists to create AI solutions that address local challenges. Emphasize the need for context-specific AI in eHealth, noting that technologies must be adapted to local realities to be effective [175].

6.5. Address Infrastructure Constraints

Infrastructure constraints, such as unreliable internet connectivity and inconsistent electricity supply, pose significant challenges to deploying AI solutions effectively in LMICs. Addressing these challenges is crucial for harnessing AI's full potential in healthcare. Investing in targeted infrastructure development initiatives that improve connectivity and power reliability in underserved regions is imperative. By prioritizing these efforts, policymakers can pave the way for successful AI integration, thereby enhancing healthcare delivery and outcomes in LMICs [182].

By implementing these recommendations, policymakers in LMICs can enhance the acceptance and effectiveness of AI-driven eHealth solutions, ultimately improving healthcare delivery in these regions. These steps will help address the unique challenges LMICs face and leverage AI's potential to transform healthcare.

7. Limitations

As with the other research, our work has some limitations. Any papers excluded because they were written before 2018 likely require a complete interpretation of the current state of the field. Also, all articles in our review were written in English (we have some papers in Farsi, Chinese, and Hindi that we did not consider). We focused exclusively on completed studies, which may have significantly reduced the number of papers, excluding ongoing research endeavors that may have been reported through other channels. The field of AI research is promptly progressing. Consequently, our review has also excluded relevant new research published between our database search and this paper's publication. Articles also had to have been peer-reviewed, excluding a few recently published manuscripts on https://arxiv.org/.

8. Conclusion

AI in eHealth is gradually attracting the attention of academics and professionals, both as a phenomenon and as a means to explain how LMICs are improving their healthcare systems while considering the rapidly evolving AI landscape [93]. Although there is an emphasis on related concerns and the complementarity of suggestions, the AI-based eHealth literature has received little attention from the AI and eHealth communities. A review of AI and eHealth papers on LMICs published in reputable journals reveals a need for greater theoretical and analytical integration between the two domains. AI-based solutions are already being explored for use in LMICs to alleviate the burden on resource-limited settings [64] and improve outcomes. This technological development may enhance the population's approach to e-healthcare and the efficacy of care provided to patients. Simplifying processes and improving accessibility can also enhance medical

research and education. Our study has highlighted the need for credible, high-quality research that provides a core dataset to evaluate the literature effectively. AI holds significant promise for optimizing healthcare procedures, enhancing access to and delivery of reliable health information, and relieving the burden on healthcare professionals [67]. Concerns about how AI might unintentionally exacerbate healthcare disparities [45] in LMICs should not be ignored, as this technology is widely integrated into clinical practice [135].

LMICs should conduct assessments to show their specific challenges in delivering e-healthcare services. This assessment should show the areas where AI can be most beneficial. Based on the needs assessment, LMICs can develop roadmaps that outline how AI will be incorporated into their eHealth systems. The roadmap should include clear goals, timelines, and implementation strategies. LMICs should build the necessary capacity to implement AI. This can involve training healthcare professionals in AI technologies and ensuring enough skilled professionals to develop and maintain AI systems [107]. LMICs should partner with other organizations and countries that have experience implementing AI in eHealth. These partnerships can provide LMICs with technical aid, funding [108], and knowledge-sharing opportunities. To scale up digital solutions, governing authorities, healthcare professionals, patients, and health organizations should collaborate more closely with the technology industry [104]. AI relies on high-quality data to be effective [121]. LMICs should ensure that their data is of high quality, collected, managed, and standardized.

AI also raises ethical issues on bias, data security, and privacy. By creating laws and regulations that regulate AI use in eHealth, LMICs can alleviate these fears [115]. LMICs should pilot and evaluate AI applications before scaling them up. This can help show challenges and ensure the AI system is effective and meets the population's needs. Following the epidemic, research in this field is expected to increase, as many LMICs have learned from the shortcomings of COVID-19. Implementing AI in eHealth in LMICs effectively and efficiently can accelerate progress toward the United Nations Sustainable Development Goals. By following these recommendations, LMICs can effectively integrate AI into their eHealth systems, thereby improving healthcare outcomes for their populations.

The most significant findings from the reviewed literature indicate that application designs are underway in LMICs, diverse e-health systems are being developed, and various methods are being applied to support application development, both qualitatively and quantitatively, or in mixed approaches. Researchers in LMICs need to pay more attention to the following behavioral theories when designing their applications to make them user-friendly. Regarding key takeaways and emerging trends, LMICs have not paid enough attention to big data analysis due to limited infrastructure, and their governments have not yet demonstrated project leadership and commitment to AI. AI talent causes more delays in adoption, job security, and Machine-Human interactions. To solve these problems, they must reduce high implementation costs and the lack of interoperability, mitigate resistance to change, and secure both short-term and long-term funding. Users have numerous social contexts that influence their decision to use AI data-gathering devices. Level and exercise style influence users' decision to use data-gathering devices should be considered based on the TAM (Technology Acceptance Model) and UTAUT (Unified Theory of Acceptance and Use of Technology) on adoption part contexts (Human–Technology Interaction, Technology-Organization-Environment, Stimulus-Organism-Response and Decomposed Theory

of Planned Behavior), Virtual and Augmented Reality, Digital and System Twin. The impact of data-gathering devices on users must be evaluated in light of cultural differences, and innovative pricing is a missed opportunity.

Finally, developing predictive AI models trained on data that does not reflect the context of algorithm use is the so-called "contextual bias" [59] (which aligns with our findings). In other similar works [58-189], the authors do not focus on the design needs of the architectural framework or discuss the technological lens. E-health service providers need to clearly explain their needs. We should remember that LMICs have begun to pay significant attention to foreign direct investment (FDI). FDI positively affects the recipient country by creating employment and transferring technological knowledge, which is risky. In addition, based on ownership, location, and internationalization, multinational companies expand their markets. Investors consider the accessibility of natural resources in a host country a key factor in their FDI decisions for sustainable development. Based on the above discussion, e-health expansion in LMICs requires an understanding of market segmentation, and multinational enterprises can use different models to position themselves more effectively for the FID. Additionally, client behavior in LMIC markets should be considered in light of relevant research.

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