Systematic Review on AI-Based Diagnosis and Appointment Management in Under-Digitalized Healthcare

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***Abstract*– This systematic literature review (SLR) aims to analyze the impact of the use of intelligent systems in preliminary diagnosis and appointment management in healthcare settings with low technological adoption. The PICOC method and the PRISMA protocol were applied, selecting 26 relevant studies from an initial total of 658 articles. The results show that AI significantly improves diagnostic accuracy, optimizes appointment scheduling, and promotes equity in access to care, even in settings with limited infrastructure. Six key types of solutions were identified, including predictive models, automated triage systems, and conversational assistants, which are more efficient and adaptable than traditional methods. The analyzed technologies have been shown to reduce bias, accelerate clinical processes, and expand access in rural or low-tech areas. In conclusion, this SLR validates the transformative potential of AI in decentralized healthcare, provided it is implemented with ethical criteria, contextual governance, and adequate staff training.**

***Keywords*-- artificial intelligence, healthcare, diagnosis, low resource settings, automation**

I. Introduction (Heading 1)

The integration of artificial intelligence into intelligent systems for preliminary diagnosis and healthcare appointment management has been a striking topic in the scientific literature in recent years [6],[7],[8]. Despite reviews on AI developments in clinical care applications, specifically in automated diagnosis and decision making [9],[10], much of these studies are, however, primarily based on digitalization, where technology integration, data interoperability, and regulation are well established [6].

Currently, there are significant obstacles that hinder the effective adoption of intelligent systems in contexts with low digitalization in healthcare [13],[14]. Among the main challenges are ethical aspects related to the protection of personal data, the confidentiality of medical information and the possible decrease in the active role of the professional in clinical decision-making [1],[2],[11],[12]. These challenges are aggravated by the lack of adequate technological infrastructure, the absence of specific regulations for the use of artificial intelligence in healthcare, and the scarce practical validation of these systems [3],[4],[5], which widens the digital divide and compromises their effective application [14].

Despite the progress made in the development of AI-based technologies, there is still a limited number of systematic reviews that address these difficulties in contexts with limited digital infrastructure [4],[5],[6]. Therefore, it is pertinent to conduct a new systematic review that allows a comprehensive examination of current knowledge, detect little-explored areas, and offer guidelines to guide the implementation of these systems in environments with technological restrictions [1],[2],[11]. In this order of ideas, the research problem for this review study arises: what is the impact of the use of intelligent systems in preliminary diagnosis and appointment management in health contexts with low technological adoption?

Therefore, this SLR aims to analyze the impact of using intelligent systems on preliminary diagnosis and appointment management in healthcare settings with low technology adoption. It should be noted that this review article is structured into five sections. The first section addresses the PICOC methodology and PRISMA protocol. This is followed by a second section focusing on the results of this study. This is followed by a third section discussing the findings. A fourth section explains the conclusions. Finally, a fifth section addresses the references used in this study.

II. Methodology

A. PICOC Method

Table I below shows the formulation of the questions and motivation that systematically guide this review study through the application of the PICOC method [16]. It focuses on localities and users who face difficulties due to limitations in technological infrastructure. The intervention consists of implementing automated diagnostic and appointment scheduling solutions using AI, comparing them with traditional manual methods. The study seeks to identify improvements in medical care, diagnostic efficiency, and optimization of the appointment process, also evaluating the specific contexts where these technologies present the greatest benefits.

In this sense, the following general equation was obtained as a result: (TITLE-ABS-KEY("health system" OR "medical institution" OR "low technology adoption" OR "limited infrastructure" OR "preliminary diagnosis" OR "appointment management" OR "challenges") AND TITLE-ABS KEY("artificial intelligence" OR "machine learning" OR "predictive models" OR "medical diagnosis" OR "triage" OR "automation") AND TITLE-ABS-KEY(("AI in healthcare" OR "traditional methods" OR "manual diagnosis" OR "conventional management" OR "comparison" OR "impact" OR "benefits" OR "limitations")) AND TITLE-ABS-KEY(("AI implementation" OR "healthcare improvements" OR "outcomes" OR "performance metrics" OR "patient scheduling" OR "success factors")) AND TITLE-ABS KEY(("AI deployment" OR "low-resource settings" OR "underdeveloped healthcare" OR "rural health" OR "case studies" OR "best practices"))).

TABLE I
PICOC METHOD

Component	Motivation	Ask	Search equation
P (Population / Problem)	Identification of problems in institutions and users of the health system with low technological adoption.	What types of challenges do healthcare institutions and users with low technology adoption face in improving preliminary diagnosis and appointment management?	"health system" OR "medical institution" OR "low technology adoption" OR "limited infrastructure" OR "preliminary diagnosis" OR "appointment management" OR "challenges"
I (Intervention)	Implementation of intelligent AI systems for automated preliminary diagnosis and appointment scheduling.	What types of AI-based intelligent systems will improve the efficiency of preliminary diagnosis and appointment scheduling?	"artificial intelligence" OR "machine learning" OR "predictive models" OR "medical diagnosis" OR "triage" OR "automation"
C (Comparison)	Identifying the effects of using AIbased technologies compared to manual processes and/or traditional systems without artificial intelligence.	What are the effects of using AI-based technologies compared to traditional health management and diagnostic methods?	("AI in healthcare" OR "traditional methods" OR "manual diagnosis" OR "conventional management" OR "comparison" OR "impact" OR "benefits" OR "limitations")
O (Result)	Improved preliminary diagnosis and optimized patient care.	What improvements have been achieved in healthcare after implementing AI in diagnosis and appointment management?	("AI implementation" OR "healthcare improvements" OR "outcomes" OR "performance metrics" OR "patient scheduling" OR "success factors")
C (Context)	Limitations and specific characteristics of environments with low technological infrastructure that affect the adoption of AI in healthcare.	In what contexts, specific conditions, or types of institutions with low technological infrastructure are AI technologies implemented in medicine?	("AI deployment" OR "low-resource settings" OR "underdeveloped healthcare" OR "rural health" OR "case studies" OR "best practices")

B. *PRISMA Protocol*

Fig. 1 presents the structure of the PRISMA protocol, which systematically and in detail describes the stages of identification, filtering, eligibility assessment, and inclusion of studies in this systematic literature review [15]. It demonstrates the rigorous screening process applied to ensure the methodological soundness of the study. Out of a total of 659 initial records, only 26 met the strict criteria established. Automatic filters were applied by year, subject area, document type, language, and access, complemented by a manual evaluation based on relevance and availability. This protocol ensures that the selected studies are relevant, current, and consistent with the research objectives in the field of systems engineering. It is worth noting that these criteria are shown in the following Table II.

TABLE II
INCLUSION AND EXCLUSION CRITERIA

INCLUSION CRITERIA	EXCLUSION CRITERION
IC1: original articles	**EC1** : period 2021-2025
IC2: related topics	**EC2** : engineering area
IC3: Studies focused on healthcare institutions with low technological adoption	**EC3** : Research and conference papers
IC4: Studies written in English or Spanish	**EC4** : Spanish or English language
IC5: Full access to the text (not just the abstract)	**EC5** : open access
	EC6 : Review articles
	EC7 : items not found
	EC8 : unrelated topics

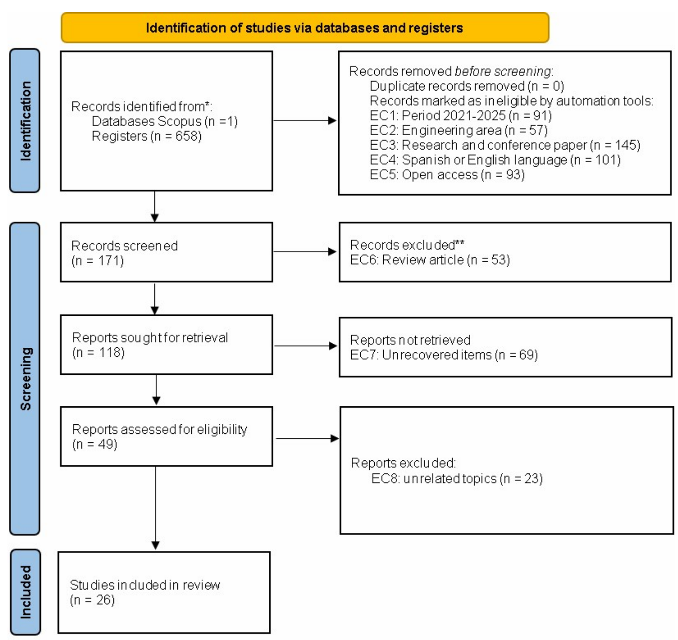

Fig. 1 PRISMA protocol.

III. ANALYSIS OF THE RESULTS

A. Biometric Analysis

The bibliometric analysis, based on the SCOPUS database, reveals significant growth in academic output related to the use of AI-related systems for preliminary diagnosis and appointment management in poorly digitalized healthcare settings. Figure 2 shows a notable increase in the number of publications associated with this topic starting in 2023, peaking in 2024 and continuing to grow steadily throughout the year.

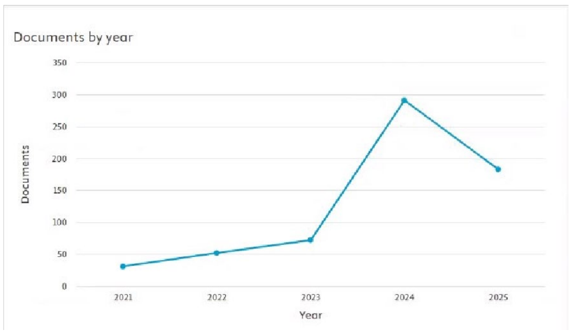

Fig 2. Contribution on the methodology of processes and digital transformation.

In Fig. 3, it is evident that the US is positioned as a central node in scientific production on the use of AI for preliminary diagnosis and management of medical appointments in healthcare contexts with low digitalization, with frequent links with China.

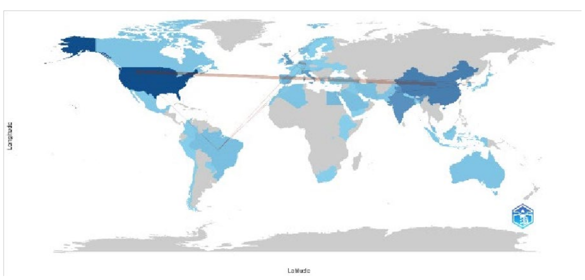

Fig. 3 Contributions by country.

Figure 4 shows keywords related to the use of AI in preliminary diagnosis and appointment management in lowdigital medical settings. Key terms such as Artificial Intelligence, Machine Learning, and Deep Learning are identified, organized into thematic clusters. This visualization highlights the main areas of study and how they connect with each other.

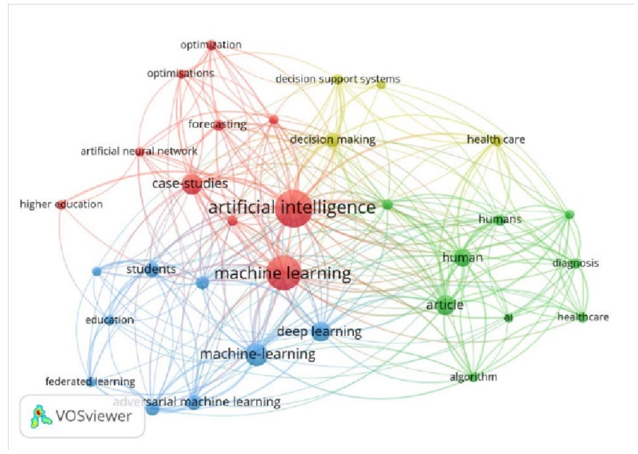

Fig 4. Interrelation between keywords.

Process methodology in low-digitalization healthcare contexts is defined as the systematic approach that integrates artificial intelligence tools to optimize data collection, processing, and use, improve clinical decision-making, and automate both administrative and healthcare workflows [19], [31]. This methodology not only promotes interoperability and operational efficiency [19], [25], [31], but also drives equity and transparency by reducing bias and using explainable models [20], [21], [24]. Furthermore, it structurally transforms medical roles and the dynamics of hospital services [22], [28], and expands the reach of the healthcare system through remote accessibility and real-time monitoring [26], [27], [29]. Finally, it favors more personalized and patient-centered care by assisting in adaptive clinical decisions [23], [30].

On the other hand, the incorporation of this methodology allows to accelerate primary care through automatic diagnostic systems [32], [33], optimizes the scheduling of medical appointments according to specialty, symptoms and urgency [34], [35], [39], [44], and uses intelligent assistants to guide the patient in real time throughout the care process [36], [41], [43]. In addition, it promotes the dynamic allocation of resources based on clinical priority and the availability of the health system [38], [40], while also contributing to the early detection of diseases, improving the efficiency in referral and specialized treatment [37], [42].

P: Types of problems presented by institutions and users of the health system with low technological adoption to improve preliminary diagnosis and appointment management

The analysis shows that healthcare institutions with low technological adoption face six major types of problems. First, the lack of infrastructure and connectivity limits the implementation of basic technologies such as digital surveillance systems, mobile applications, and remote monitoring platforms, which directly affects access to preliminary diagnosis and appointment management [19], [24], [40].

Second, the absence of predictive and automated systems prevents the timely detection of medical complications, the optimization of clinical agendas and the proactive management of resources, generating inefficient waiting lists and delays in priority care [25], [28], [32], [36], [38], [42], [43]. Third, ethical, legal and governance limitations are identified that generate institutional resistance towards the adoption of AI, hindering its use in diagnosis and intelligent triage [26], [27], [41], [44].

On the other hand, many institutions lack technological integration that allows combining voice, image, text and clinical sensor data, which restricts the automated processing of symptoms and affects the accuracy of preliminary diagnoses [19], [23], [31], [33], [37]. Furthermore, low digital literacy and limited professional training in emerging technologies restrict the ability of professionals to use smart tools in clinical practice [21], [30].

Finally, inequality in access to care and the presence of biases in diagnostic processes affect vulnerable populations, perpetuating health gaps by not having algorithms that consider equity [20], [29]. This is aggravated by the lack of specialized models for complex diseases or critical contexts such as transplants, mental health or pandemics [22], [34], [35], [39]. Fig. 5 shows that the main barriers in institutions with low technological adoption are the absence of automated systems, low digital integration and limited data management, thus hindering the effective implementation of solutions based on artificial intelligence.

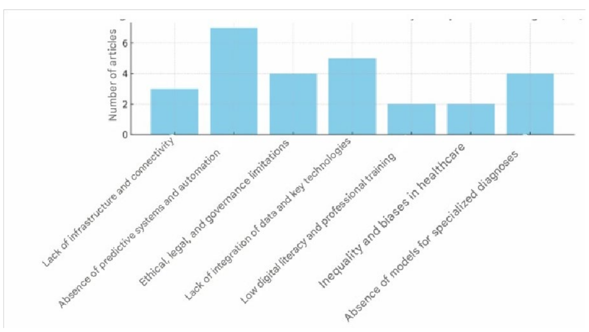

Fig 5. RQ1 Problems.

Table III below highlights multiple challenges in AI adoption in healthcare, from technological gaps to biases in predictive models. These problems, supported by recent studies, underscore the urgency of comprehensive solutions that address infrastructure, governance, and digital training for effective implementation in vulnerable contexts.

TABLE III
MEDICAL PROBLEMS AND MANAGMENT IN SUBDIGITAL ENVIRONMENTS

METHODOLOGY	PROBLEM	IEEE
Documentary analysis of technological gaps	Lack of infrastructure and connectivity to implement basic technologies (digital surveillance, mobile apps, remote monitoring).	[19], [24], [40]
Review of clinical systems and flows	Lack of predictive and automated systems to manage complications, schedules, and resources.	[25], [28], [32], [36], [38], [42], [43]
Regulatory and institutional governance assessment	Ethical, legal, and institutional governance barriers to AI adoption.	[26], [27], [41], [44]
Technical review of clinical data integration	Lack of technological integration between voice, image, text, and medical sensor data.	[19], [23], [31], [33], [37]
Diagnosis of professional skills and digital literacy	Poor staff training in emerging technologies and low digital literacy.	[21], [30]
Health equity analysis and population approach	Presence of biases in AI and lack of models for critical contexts (mental health, transplants, pandemics).	[20], [22], [29], [34], [35], [39]

I: Types of AI-based intelligent systems that will improve the efficiency of preliminary diagnosis and medical appointment scheduling

Based on the analysis, six main groups of AI-based intelligent systems were identified that contribute to improving the efficiency of preliminary diagnosis and appointment scheduling. First, systems focused on the integration and processing of complex clinical data allow combining information from various sources, such as medical records, diagnostic images, and sensors [19], [31], [32], [33], [34], [43]. Thanks to their ability to centralize and analyze this data, they facilitate faster and more accurate diagnoses, in addition to allowing automated appointment assignment based on the detected urgency.

Secondly, predictive and automated classification models [20], [25], [36], [38], [42] stand out, which are capable of anticipating clinical risks and classifying patients by severity level. These systems allow reorganizing agendas, prioritizing critical care and improving the use of clinical resources, especially in contexts of high demand or complex hospital care. In addition, approaches based on explainable and ethical AI [21], [26], [27], [41], [44] provide transparency to automated decision-making processes. The presence of governance frameworks facilitates institutional and professional acceptance, which favors the implementation of solutions such as intelligent triage or the automated assignment of medical shifts with fair and understandable criteria.

Likewise, clinical decision support and automated triage systems [22], [28], [29], [30], [35] use AI to analyze symptoms and history, proposing automated clinical referrals. These tools are essential in sensitive specialties, such as mental health or chronic diseases, since they contribute to reducing errors, accelerating diagnosis and optimizing appointment management based on real urgency. On the other hand, remote monitoring and automated response technologies, supported by IoT and artificial intelligence [23], [24], [39], [40], allow the detection of clinical alterations in real time and proactively scheduling appointments. These solutions are especially useful in rural areas or in home care models, facilitating preventive care and reducing response times to emergencies.

Finally, conversational and natural language processing (NLP) systems [30], [31], [35], [37] represent an important innovation by allowing patients to describe their symptoms in natural language, which is interpreted by AI to offer preliminary diagnostic guidance and automatically schedule appointments. These systems improve the user experience, reduce the operational burden on medical staff, and ensure more agile, accessible, and patient-centered care.

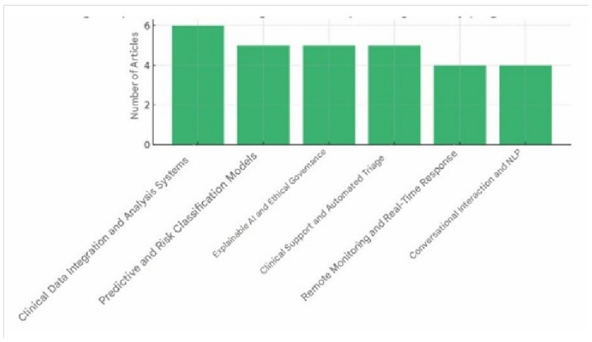

Fig 6. RQ2 Types of intelligent systems.

Table IV presents six key categories of intelligent systems applied to healthcare, highlighting their role in preliminary diagnosis and appointment management. These technologies, from NLP to explainable AI, optimize clinical processes, improve care, and promote more accurate, transparent, and ethical decisions in complex healthcare settings.

TABLE IV
INTELLIGENT AI SYSTEMS FOR DIAGNOSIS AND APPOINTMENTS

Type of AI system	Description	Reference (IEEE)
Integration and processing of clinical data	Systems that combine heterogeneous medical information (images, medical records, sensors) to facilitate centralized analysis.	[19], [31], [32], [33], [34], [43]
Predictive and automated classification models	Algorithms capable of anticipating risks and classifying patients according to severity.	[20], [25], [36], [38], [42]
Explainable and ethically focused AI	Solutions with transparent decisions and institutional governance frameworks.	[21], [26], [27], [41], [44]
Clinical decision support and automated triage	AI that analyzes symptoms and history to generate automated clinical referrals.	[22], [28], [29], [30], [35]
Remote monitoring and automated response (IoT + AI)	Technology that detects clinical changes in real time and proactively schedules appointments.	[23], [24], [39], [40]
Conversational systems and natural language processing (NLP)	They allow patients to describe symptoms in natural language, automatically interpreted by AI.	[30], [31], [35], [37]

C: Effects of using AI-based technologies compared to traditional health management and diagnostic methods

The use of AI-based technologies has profoundly transformed healthcare diagnosis and management processes, overcoming several limitations inherent to traditional methods. First, AI's ability to integrate disparate clinical data such as electronic medical records, diagnostic images, or sensor signals allows for faster and more accurate diagnoses, reducing common human errors in manual procedures [19], [32], [33]. This accuracy is further enhanced by visual analytics tools such as Vision Transformer and GRU, which detect clinical patterns more reliably than human observation, especially in areas such as ophthalmology or dermatology [34], [43].

Additionally, improvements in fine-grained learning and natural language processing have facilitated more personalized and explainable clinical decision-making. Unlike traditional approaches, which tend to be generalist and opaque, AI systems can explain their recommendations, increasing the confidence of healthcare professionals [21], [31], [37]. Furthermore, the incorporation of synthetic data and multi-criteria analysis allows for the optimization of clinical management even in complex scenarios such as pandemics or transplants [38], [42].

From an operational perspective, AI is a useful tool to improve hospital care. Technologies such as the fusion of IoT with AI, or predictive models of hospital stay, optimize the use of resources and reduce the saturation of medical services, in contrast to traditional methods that depend on the intuition and experience of the staff [23], [24], [36], [39]. Likewise, automated epidemiological surveillance systems make it possible to anticipate outbreaks more quickly than manual systems, thus strengthening the response capacity [24].

In terms of health equity, AI has the potential to correct diagnostic biases associated with age, gender, or ethnicity, which represents a substantial improvement over traditional practices that often perpetuate these inequalities [20], [29], [41]. By more fairly identifying at-risk patients, more inclusive and effective care is promoted.

On the other hand, AI has enabled the use of chatbots and conversational systems such as ChatGPT, which provide continuous and accessible assistance. This has been particularly useful in contexts where face-to-face medical care is limited, and contrasts with traditional, more fragmented and reactive methods [22], [30], [35].

Finally, it is important to highlight that the implementation of these technologies requires appropriate ethical frameworks and governance. Unlike traditional methods, AI poses regulatory challenges that, if addressed responsibly, can improve transparency, security, and institutional trust in its use [26], [27], [40], [44].

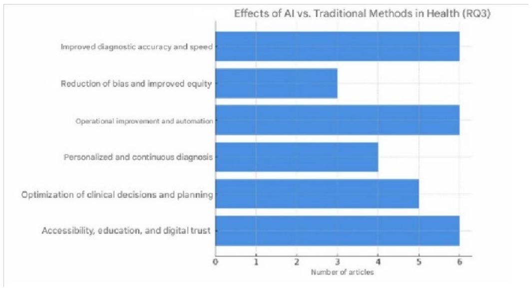

Fig 7. RQ3 effects.

Table V shows key AI technologies applied in healthcare, such as computer vision, NLP, and chatbots, focused on improving diagnostic accuracy and continuity of care. These solutions drive personalized clinical decisions, promote equity, and strengthen health surveillance in increasingly demanding clinical environments.

TABLE V
AI TECHNOLOGIES APPLIED IN CLINICAL HEALTH

Applied AI technology	Description	Reference (IEEE)
Clinical data integration + computer vision	It unifies medical records, diagnostic images, and sensors using models such as Vision Transformer and GRU, improving diagnostic accuracy.	[19], [32], [33], [34], [43]
Deep learning + natural language processing (NLP)	Facilitates personalized and explainable clinical decision-making, increasing the confidence of professionals.	[21], [31], [37]
Synthetic data and multicriteria analysis	It allows for optimizing clinical decisions in complex scenarios such as transplants or pandemics by combining multiple variables.	[38], [42]
Fusion of IoT with AI + predictive models	Optimizes the use of hospital resources and predicts length of stay, reducing overcrowding in healthcare centers.	[23], [24], [36], [39]
Automated epidemiological surveillance	Detects and anticipates outbreaks faster than manual systems, strengthening the health response.	[24]
AI for diagnostic equity	Identify gender, age, or ethnic biases, promoting fairer and more inclusive diagnoses.	[20], [29], [41]
Chatbots and conversational systems (e.g. ChatGPT in healthcare)	They provide ongoing mental health and primary care assistance, especially in settings with limited medical access.	[22], [30], [35]
Ethical and governance frameworks for AI in health	They promote the responsible, safe, and transparent use of AI in clinical and institutional settings.	[26], [27], [40], [44]

O: Improvements in healthcare achieved after implementing AI in diagnosis and appointment management

The implementation of artificial intelligence (AI) in diagnosis and appointment management has generated substantial improvements in the efficiency, equity, and personalization of the healthcare system. First, the integration of multiple sources of clinical data has enabled more accurate diagnoses and fairer prioritization of medical appointments [19], [20]. Furthermore, AI has reduced bias in diseases such as breast cancer [20] and improved interdisciplinary collaboration [21].

In mental health, it has facilitated continuous monitoring through automated scheduling [22], while its combination with IoT has enabled more proactive healthcare [23]. Furthermore, explainable AI has increased patient confidence [24], and its application in epidemiological surveillance has optimized the response to outbreaks [25].

AI-based clinical prediction enables smarter appointment scheduling [26], and its responsible adoption has strengthened transparency and efficiency [27], [28]. Even in low-resource settings, it has improved accessibility [29], promoting more inclusive diagnoses [30]. Tools such as ChatGPT support appointment scheduling and preliminary query resolution [31], while natural language processing and chatbots improve the patient experience [32], [36].

Furthermore, it has been possible to accelerate diagnoses with limited data [33], optimize appointments in complex diseases such as brain tumors or retinopathies [34], [35], and reorganize care according to clinical urgency and length of stay [37]. During the pandemic, AI helped prioritize critical diagnoses and distribute appointments equitably [39].

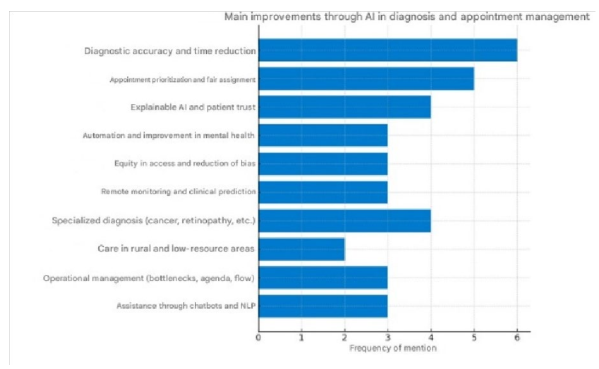

Fig 8. RQ4 AI improvements.

Table VI presents specific artificial intelligence technologies applied to diagnosis and appointment management, detailing their functionality and context of use. It clearly summarizes how these solutions improve clinical care by optimizing time, reducing errors, and adapting to resource-limited environments.

TABLE VI
IMPACTS OF AI ON DIAGNOSIS AND APPOINTMENTS

Applied AI technology	Description	Reference (IEEE)
Clinical data integration	Combines multiple clinical sources for more accurate diagnoses and fair appointment prioritization.	[19], [20]
AI for bias reduction	It improves equity in diagnoses, for example, in breast cancer, by eliminating gender or condition biases.	[20]
AI for interdisciplinary collaboration	It facilitates interaction between different medical specialties, optimizing joint decisions.	[21]

AI in mental health + automated programming	Allows continuous patient monitoring through intelligent appointment scheduling.	[22]
IoT and AI for proactive care	Improve preventive healthcare through remote monitoring and early appointment scheduling.	[23]
Explainable AI	Increases patient confidence by providing transparency in automated decision-making processes.	[24]
AI in epidemiological surveillance	Optimize early detection and response to outbreaks through automated analysis.	[25]
Clinical prediction and intelligent scheduling	Schedule appointments based on the patient's clinical risk and expected progress.	[26]
Responsible and ethical implementation	Increase system efficiency by ensuring transparency and fairness in the use of AI.	[27], [28]
AI in low-resource settings	Improves diagnostic and appointment accessibility even in environments with limited infrastructure.	[29]
AI-based inclusive diagnosis	Promotes care that considers a diversity of clinical and social profiles.	[30]
ChatGPT as a preliminary medical assistant	Supports appointment scheduling and initial query resolution using natural language.	[31]
Chatbots and NLP in patient care	They improve the patient experience by offering automated, accessible, and continuous guidance.	[32], [36]
AI for diagnosis with limited data	Accelerates disease identification even when limited clinical information is available.	[33]
AI in complex diseases	Optimize appointment scheduling and prioritization in cases such as brain tumors or retinopathies.	[34], [35]
Clinical reorganization due to emergency and hospital stay	Restructures care based on severity and estimated length of hospitalization.	[37]
AI during the pandemic	It facilitated the prioritization of critical diagnoses and equitable distribution of appointments in the context of a health crisis.	[39]

C: Contexts, specific conditions or types of institutions with low technological infrastructure where AI technologies will be implemented in medicine

The implementation of artificial intelligence technologies in environments with limited technological infrastructure has been established as a viable and adaptive strategy to improve healthcare in vulnerable regions. First, in hospitals with fragmented systems or paper-based storage, AI allows integrating and processing clinical data without requiring advanced infrastructure [19], [25], [31]. Similarly, in healthcare centers with limited staff and resources, lightweight algorithms or low-computational models are used to reduce diagnostic biases and support clinical tasks without the need for high-performance computers [20], [26].

In rural clinics, indigenous areas or regions with poor connectivity, mobile applications, digital forms or even SMS are used as means to apply AI in epidemiological surveillance and assisted diagnosis [22], [24], [40]. These solutions are possible thanks to academic collaborations or the use of nocode platforms, which allow their adoption even without specialized IT personnel [21], [28], [33]. Likewise, in health posts equipped with basic sensors (IoT), vital data is collected for automated analysis using models embedded in mobile devices [23], [34].

On the other hand, the use of chatbots has been reported in centers without sufficient administrative staff, providing immediate assistance through basic cell phones [35]. In contexts where only medical records are available in PDF or Word, AI facilitates the automated extraction of useful information [31]. In institutions with scarce historical data, synthetic data are generated to train predictive models adapted to local contexts [32].

Furthermore, AI has been implemented through open source tools in public hospitals or developing centers, accompanied by basic training and ethical processes to prevent misuse [27], [26], [41]. In regions without advanced medical planning, simple models help prioritize critical resources such as beds or oxygen [38]. During mobile campaigns, AI is used to detect visual or skin pathologies with just a cell phone or tablet [34], [43].

Finally, the responsible adoption of AI in these contexts relies on modular, accessible, and progressive solutions that build trust in healthcare personnel and the population, adapting to the technological and sociocultural reality of each environment [29], [36], [39], [44]. Table VII shows how different adaptive artificial intelligence applications respond to technological limitations in healthcare. From chatbots to lightweight algorithms, each technology allows for the optimization of diagnoses and clinical processes in environments with low connectivity, demonstrating that AI can be effective even without advanced infrastructure.

TABLE VII
ADAPTIVE AI APPLICATIONS IN LIMITED HEALTHCARE

Applied AI technology	Description	Reference (IEEE)
Clinical data integration without advanced infrastructure	It allows processing medical information from fragmented or paperbased systems without the need for networks or complex hardware.	[19], [25], [31]
Lightweight and low computational algorithms	They are applied in centers with limited resources to reduce diagnostic bias without requiring powerful equipment.	[20], [26]
Mobile applications, digital forms or SMS	Used in areas without constant connectivity to apply AI-assisted surveillance and diagnosis.	[22], [24], [40]
No-code platforms and academic collaboration	They allow AI to be implemented without the need for IT staff, facilitating adoption in remote centers.	[21], [28], [33]
Embedded models in mobile devices with basic sensors (IoT)	They collect vital data at rural post offices and enable automated analysis without direct connection to servers.	[23], [34]
Chatbots on basic cell phones	They provide automated care in centers without administrative staff, accessible from simple devices.	[35]
Extracting data from PDFs or Word	AI that converts unstructured medical records into useful information for clinical analysis.	[31]
Generation of synthetic data	It allows training predictive models in contexts without extensive medical histories.	[32]
Using open source tools with basic training	Facilitates responsible implementation in public hospitals or developing centers, with minimal training.	[27], [26], [41]
Simple templates for basic medical planning	They help prioritize resources such as beds or oxygen in regions without advanced management systems.	[38]

AI in mobile campaigns with cell phones or tablets	Detect visual or skin pathologies in the field with low-cost portable devices.	[34], [43]
Modular, accessible and progressive solutions	Modular, accessible and progressive solutions	[29], [36], [39], [44]

IV. DISCUSSION

The systematic review showed that the implementation of artificial intelligence (AI) in healthcare settings with low digitalization offers substantial improvements in clinical efficiency, equity, and personalization of care [19], [20], [26], [31]. Some main types of intelligent systems were identified, such as predictive models, automated triage, and conversational assistants, which allow optimizing diagnoses and appointment management even in environments with limited infrastructure [23], [32], [34], [35].

The findings align with recent research highlighting the effectiveness of advanced AI architectures such as recurrent neural networks, as well as the use of natural language processing (NLP) to facilitate patient interactions [30], [33], [37]. Furthermore, the importance of ethical and governance frameworks was emphasized, as a lack of regulation and professional training limits safe and fair adoption [11], [12], [27], [41], [44]. Barriers such as institutional resistance and low digital literacy are also recognized, making it difficult to integrate these solutions into clinical practice [21], [24], [28].

However, the review presents methodological limitations on the sustained impact of these technologies [22], [25], [40]. Therefore, future research is proposed to address the sustainability, acceptance, and real applicability of these tools, especially in vulnerable populations and regions with limited connectivity [29], [36], [38]. Overall, AI represents a transformative opportunity for lagging healthcare systems, provided its implementation is ethical, contextualized, and accompanied by appropriate public policies [17], [39].

While the findings of this SLR reveal significant advances in clinical efficiency and equity, it is important to acknowledge methodological limitations. First, the reliance on open-access studies and those in English/Spanish could bias the results, excluding relevant research in other languages or databases. Furthermore, the heterogeneity of the evaluation methods in the articles analyzed prevents a uniform quantitative comparison of clinical effectiveness. Therefore, it is recommended that future research incorporate more robust statistical analyses, longitudinal studies, and field validations to confirm the sustainability of these solutions over time. There is also little evidence regarding the cultural acceptance of AI in healthcare, a crucial aspect for its actual adoption.

V. CONCLUSIONS

The findings of this systematic review show that artificial intelligence (AI) can play a transformative role in strengthening preliminary diagnosis and appointment management in low-digital settings. Through the analysis of 26 relevant studies, six key categories of intelligent solutions were identified that, together, have demonstrated significant advantages over traditional methods: increased diagnostic accuracy, efficient automation, remote monitoring, and reduction of clinical bias. These technologies allow not only to optimize healthcare resources but also to expand access and personalize care, even in settings with limited connectivity or poor technological infrastructure.

The study also provides critical and up-to-date evidence that addresses the need to guide future AI implementations in healthcare under principles of equity, transparency, and ethical governance. It highlights the importance of adapting these solutions to local sociotechnological realities, training healthcare personnel, and evaluating their operational feasibility and community acceptance. In short, AI represents not only an innovative tool but also a strategic avenue for closing structural gaps and moving toward a more equitable, accessible, and patient-centered healthcare model.

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