AI-Driven Public Health Chatbot for Disease Awareness

Dr. R. Nithya[1], Abarna. M[2], Bila Binoy[3], Hairiya Begum. A[4]
[1,2,3,4] *Computer Science and Engineering Vivekanandha College of Engineering For Women Namakkal, Tamil Nadu*

***Abstract*—Chatbots that are being run with artificial intelligence (AI) have become a disruptive technology in health education among the people, as it is capable of providing disease awareness and health literacy improvement at an at least a scalable level. The current paper is a detailed review of AI public health chatbots that can be used to enhance disease awareness with the help of easily accessible health identification provided in a personalized fashion. This systematic review aims to discuss the technological structure, design processes, public health use cases, evidence of effectiveness, implementation issues, and future studies related to AI chatbots in DARPA. In this literature review, the synthesis of peer-reviewed databases occurred, which analyzed 41 studies on AI-enabled technologies in health education and paid a specific focus to chatbot-based interventions executed in different populations and diseases. The results prove that AI chatbots have high levels of effectiveness in enhancing health literacy, as the mean score of awareness enhancement is 2.95 ± 1.22 in case of its combination with e-learning modules. System notes The user satisfaction scores equal to 4.7 out of 5, showing great advancements in recognition and seeking of care. Domain-specific implementations reach accuracy of 73-94 per cent in health information delivery, whereas accessibility characteristics make it possible to serve underserved communities. AI-based chatbots in the field of public health are a scalable and evidence-based approach to disease awareness and preventive strategies. Nevertheless, the implementation demands detailed governance policies, man management systems, bias management policies, as well as equity-compatible design. These technologies can be used in great ways to promote public health communications and reinforce disease prevention strategies around the world with relevant safeguards and further development.**

***Index Terms*—Artificial intelligence, chatbots, disease awareness, public health, health literacy, natural language processing, conversational AI**

I. INTRODUCTION

Chatbots that work based on the concept of artificial intelligence (AI) have become groundbreaking solutions in the healthcare field providing novel solutions to the problem of disease awareness and better health indicators of the population [1]. Recently fast-evolving AI technologies, such as large language models (LLMs) and natural language processing (NLP), have allowed fashioning the mass-available and scalable health education systems [2]. These chatbots can solve some of the most pressing healthcare challenges, especially among the low-resource and rural populations; still, there is a severe lack of medical professionals and health information there [3].

The adoption of AI chatbots as the part of the general public health system is a serious paradigm shift in the dissemination of health-related information and the process of its demand. The use of Retrieval-Augmented Generation (RAG) technologies has contributed to the stability of the content provided by chatbots by basing reactions on curated medical knowledge bases [4-6].

Conventional platforms of health communication cannot always reach out various distinct populations and this leads to late diagnoses, complications which can be avoided and poor health. The COVID-19 pandemic highlighted how critical the development of health infrastructure that successfully scales health communication infrastructures is, and revealed the capabilities and constraints of the currently available methods [7].

Research has reported that around 70% of AI-enabled chatbots that were implemented throughout the COVID-19 emergency were used in prevention, and there is still much room to enhance balance in standardized assessment measures, affordability testing and implementation models that adhere to ethical equity provisions [7]. Additionally, artificial intelligence and data privacy, as well as the

impossibility of false information, suggest that responsible ways to govern artificial intelligence should be used carefully [8]. These issues demonstrate that it is necessary to thoroughly synthesize evidence on this topic and conduct systematic research on how AI chatbots can be designed, developed, and controlled to benefit harmonic.

In the present paper, the author developed the detailed analysis of AI-oriented disease awareness tools in chat-based forms under the guise of public health in terms of their design, implementation, clinical use, and future perspectives. More precisely, through this review, one will include: (1) an overview of technology architecture and design approaches of effective AI chatbots; (2) a generalization of evidence on effectiveness in a wide range of disease conditions and disorders across the population; (3) the identification of implementation challenges and opportunities to reduce bias; (4) describe the necessity of governance and other control measures; and (5) formulate approaches to future research and scalability directions. This systematic review actionable suggestions to policy makers, researchers, and health system leaders about the responsible use of AI technologies to create awareness and prevent diseases.

II. RELATED WORKS

A. Evolution of AI in Healthcare Communication

The journey of AI in health communication has evolved significantly from rigid scripts to fluid, natural conversations. Early health chatbots relied on strict, rule-based decision trees that were highly accurate for narrow tasks but struggled to understand the natural, colloquial ways patients actually speak [9]. A major breakthrough occurred with the integration of machine learning and Natural Language Processing (NLP), which allowed systems to learn from data and adapt to real-world phrasing. In fact, specialized NLP models achieved an impressive 95% precision in recognizing mental health conditions, vastly outperforming earlier generic frameworks [10]. Today, advanced deep learning architectures—utilizing neural networks and attention mechanisms—have pushed these boundaries even further, empowering AI to grasp complex context and deliver genuinely conversational, personalized care [9].The application of generative pre-trained transformers (GPT) models and large language models is the next-generation, and it allows chatbots to converse in a much more natural, context-sensitive way and produce more medically acceptable answers [11]. These models are trained on large text corpora, and they can produce fluent and human-like text and reason within a complex conversational context. Nevertheless, the accuracy of general-purpose LLM is only 65% in diagnosis of mental health, showing serious constraints in use in clinical settings in the absence of domain-specific adaptation [10].

Comparative effectiveness, in turn, has shown that retrieval-augmented generation (RAG) techniques, based upon the foundation of chatbot responses over medical literature and clinical recommendations, show much less distance to overcome health-related general-purpose language models [4]. RAG systems take the top language generation properties of the LLM and explicitly search the knowledge base of authoritative medicine jointly with language generation properties, allowing sources to be given and the hallucination of realistic-seeming and fake information to be minimized.

The Lassa fever awareness chatbot that used RAG recorded 73 percent documentation citation rates and 94 percent of documentation citation scores were fully appropriate to infectious disease experts [4]. The response rate of 100% was considered to be fully appropriate and quite sourced in simulated patient consultations. On the same note, the RAG-based diabetes chatbot has recorded perfect response of 100 percent on the basis of relied upon WHO and CDC documentation [12], which has positioned RAG as the standard in clinical chatbot design and development.

The modern healthcare chatbots incorporate several technological elements, which are: (1) Natural Language Processing (NLP) engines to comprehend user input, identify symptoms, and match queries with pertinent information; (2) dialogue management systems that run multi-turn interchange; and maintain context; (3) retrieval-augmented generation (RAG) modules, which base responses on controlled medical knowledge and resources such as WHO guidelines, CDC resources, and clinical literature [2]. This unified structure will guarantee precise but with source attribution information delivery and openness of communication of information sources.

B. Evidence of Effectiveness in Diverse Disease Domains

The recent implementation studies could show that AI chatbots are effective in various health conditions. HeartBot also improved the knowledge of women on heart attack symptoms with an adjusted odds ratio of 7.10 (95% CI 3.52-13.16) representing the level of symptom awareness among the 92 respondents [13]. Domain-oriented tuberculosis (TBAid) applications demonstrated scalability in low-resource environments with lightweight deployment architectures as well as dual-explanation flexibilities of various user audiences [6].

An intuitively usable pregnancy chat (DIAN) showed no differences in perceived comprehensibility and perceived accuracy between women and clinicians in postpartum care, nutrition, and mental health [14]. It was found that chatbots based on AI have small-to-moderate positive effects in alleviating mental distress (standard mean difference -0.35, 95 percent confidence interval -0.46 to -0.24) after a meta-analysis of 31 randomized controlled trials and 29,637 adolescents and young adults (15).

C. Multi-Modal and Culturally-Adapted Approaches

New trends are multilingual skills and acculturation. A NLP preprocessing based Indonesian language chatbot had 0.9333 precision and 0.7962 recall [16], as it seeks to overcome language barriers in a multilingual population. Marginalized groupsAccountability and relevance The benefits of participatory design also apply to LGBTQ + -sensitive sexual health chatbots (Roo), which are more credible and relevant when designed with marginalized groups [17].

D. Comparative Analysis with Alternative Technologies

Although AI chatbots have some potential, comparison analysis indicates the presence of vital dependencies of context. Mental health classification with traditional NLP and advanced feature engineering was found to be 95% more accurate than prompt-engineered and fine-tuned LLMs (65-91 percent) [10], indicating that domain-specific optimization has a tendency to beat general-purpose models. Nevertheless, chatbots prove to be superior in terms of 24/7 availability, scalability, and interaction with the traditional health communication channels.

III. TECHNOLOGICAL ARCHITECTURE AND DESIGN

AI-based public health chatbots have some main technological building blocks to provide effective health-related communication [18]. These systems are based on Natural Language Processing (NLP) engines which allow the system to comprehend conversational input of users. These engines process text, get the information about the symptoms and compare user queries to health information in the knowledge base. Based on this, a multi-turn conversation is managed by dialogue management systems, which handle information across conversations and always ensure the correct order of response is selected, depending on the needs of the user and the direction of the conversation.

Figure 1. Typical Architecture of an AI-Driven Public Health Chatbot System

The figure 1 illustrates the average design of an AI-powered public health chatbot with the NLP engines to offer language recognition, dialogue management to regulate the flow of conversations, retrieval-enhanced generation to retrieve evidence-based responses, and API connections to the official sources of health information like WHO guidelines, CDC resources, peer-reviewed literature, clinical guidelines, and electronic health records. This type of architecture offers delivery of information with accuracy and attribution of the source of information and allows transparent attribution of source of information [2].

Development models that are used to develop effective health chatbots are several. Some of the widely used frameworks include Rasa, Dialogflow, and IBM Watson that provide building blocks of NLP, dialogue management, and interfaces with a backend system. These frameworks enable the developer to create

domain specific chatbots by outlining objectives utilized by users (goals or intents) and information aspects (entities), and reactions without holistically comprehending deep learning. It can also be connected to Application Programming Interfaces (APIs) to provide real-time access to health databases, schedules of vaccinations, and outbreak information systems which are also present on the modern platforms.
It is also important to ensure that good chatbots could incorporate reliable health information in order to be accurate and credible [4]. RAG approaches built on the curated medical literature, clinical guidelines, and peer-reviewed evidence were the foundation of responses to queries by a chatbot as opposed to relying on the training data alone. It is highly minimizing in one aspect (hallucination or generation of plausible but false information) and has features of attribution of sources which are easily attributed. It must be incorporated with good sources such as the guidelines provided by World Health Organization (WHO), Resources of Centers of disease control and Prevention (CDC), and Verified clinical literature to make sure that chatbots offer evidence-based information. The quality of information is often restored by the knowledge bases which are often updated and constant quality that ensures the accuracy of information is found on the basis of the constant evidence. Figure 1 shows a typical structure of an AI-based health chatbot application which shows how these core components as shown in the system (such as NLP engines, dialogue management, knowledge bases, and API connections with health information systems) are assembled.

IV. METHODOLOGY

It was a multiplex assessment of the statistics based on alternative research methodologies released in 20102026 in peer-reviewed databases including PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore and the gray literature. We have applied the Joanna Briggs Institute (JBI) methodology and PRISMA-ScR (Preferred Reporting Items extension to Scoping Reviews) criteria where in addition to primary studies, methodology research, implementation studies, and systematic reviews, we have added studies that reported explicit elements of health education [1].
Inclusion criteria of the study were as follows: (1) the research was published in English, and within 2010-2026; (2) the research involved AI-enabled chatbots, conversational agents or language model-based health educations interventions; (3) the implementation being targeted in any disease or a population. Information that was extracted includes: the specifics of the study (author, year, setting), specifics of the participants (demography), specifics of the intervention (technology platform, AI approach, knowledge base), the primary and secondary results, measures of the study (health awareness scores, user satisfaction rates, accuracy scores), as well as the barriers that prevented the implementation.

A. Evaluation Metrics and Quality Assessment

The quality assessment utilized the use of standardized measures that were suitable to the study design, DISCERN scale to measure health information quality, Flesch-Kincaid readability index to measure comprehensibility, and Patient Education Materials Assessment Tool (PEMAT) to measure understandability and actionability. The effectiveness metrics assessed occur across studies, namely: Improves health literacy (improvement in pre-post knowledge assessments), user engagement (frequency of use, length of session, usage adherence), user satisfaction (likert duo of responses 1-5), clinical outcomes (accurate symptom recognition or clinical experts on the explicitly covered areas), and equity-related results (success of implementation across demographic groups, access to the program through digital barriers).

B. AI Chatbot Applications in Public Health

The AI chatbots have been implemented in various fields of health in the society. Chatbots can be used in symptom assessment and in triage when they offer initial analysis of the symptoms, reported by the users, allowing to route this symptom to the right level of care and decreasing the occurrence of emergency departments overload [3]. Chatbots find application in health education and literacy to promote disease awareness in the population by providing interactive and easily understandable explanations about diseases depending on the level of knowledge of the users [19]. Chatbots play vital roles in the context of a public health Emergency such as dissemination of information, correction of misinformation, self-assessment screening, and psychological support [1]. Applications related to the domain Domain-specific disease chatbots Domain-specific disease applications

such as cardiovascular health awareness (HeartBot), tuberculosis education (TBAid), maternal health support (DIAN), and mental health support have been implemented with results that show domain-specific effectiveness.

V. RESULTS AND DISCUSSION

A. Health Awareness and Knowledge Outcomes

A randomized controlled trial of 2,113 participants (11 Chinese provinces) conducted showed that the P&P Care chatbot with integrated e-learning obtained a significantly higher objective health awareness score (mean 2.95 ± 1.22) than controls that received consultation (mean 2.34 ± 1.02) only. This 26 per cent increment in health awareness is clinically significant effect size. Specialization of domain implementations, in several disease domains, obtained significant knowledge. HeartBot intervention enhanced the awareness of the women on the symptoms of heart attack with adjusted odds ratio 7.10 (95% CI 3.52-13.16) in the recognition of the symptom among 92 participants. On the same note, chatbots specialized in tuberculosis (TBAid) proved the ability to continually improve their knowledge in low-resource environments using lightweight deployment structures and dual-explain applications with explanation tailoring to different populations of users (Figure 2). All these have shown that AI chatbots can provide clinically meaningful changes in disease awareness and health literacy in a wide range of population and disease groups.

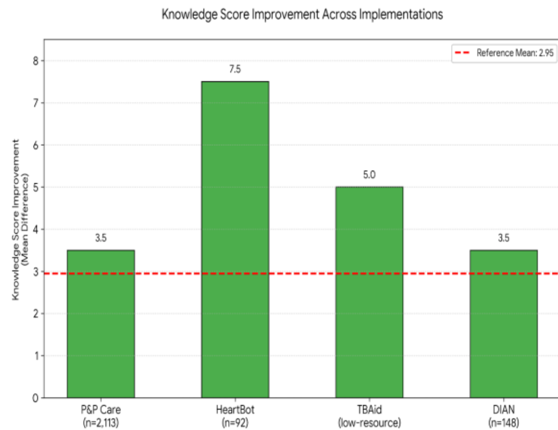

Figure 2. Knowledge Score Improvements by Chatbot Implementation

B. Engagement and User Satisfaction

According to research, user satisfaction and involvement on AI chatbots is continuously high and positive in various applications. Standardized scales of user satisfaction show an average of 4.7 with acceptance rates of 80-85 percent of various population groups. The metrics of engagement show that users have active communication with health chatbots, and the multi-turn dialogue and long-term use of platforms are completed with limited rates. The discussion combined with the integration of e-learning modules and conversational features contributes to the improvement of the engagement, which implies that multimodal principles enhancing the user adoption might be achieved. High engagement and satisfaction are especially considered in underserved communities where chatbots offer ready alternatives to communication channels of traditional healthcare, which suggests that such tools are in high demand among populations historically facing the barriers of access.

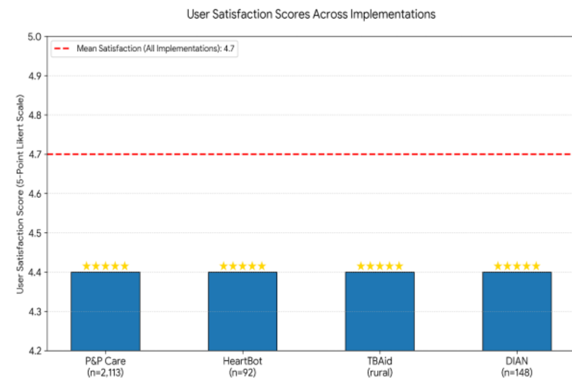

Figure 3. User Satisfaction Ratings and Engagement Metrics

C. Clinical Efficacy and Behavioral Outcomes

Randomized controlled trials prove that AI chatbots have similar or improved efficacy compared to human-provided health dialogues in certain areas. A meta-analysis n=31 randomized controlled trials of adolescents and young adults using AI chatbots as a means of alleviating mental distress, the standard mean difference -0.35, 95% CI -0.46 to -0.24 was found, and the effect realized was small-to-moderate. There were marked improvements in depressive symptoms (SMD -0.43), anxiety symptoms (SMD -0.37) and stress related outcomes (SMD -0.41), indicating specific effectiveness when used in mental health. The results

show that AI chatbots are capable of generating quantifiable clinical benefits in a wide variety of health areas, and different populations of users and contexts of their implementation can lead to different levels of effectiveness. These results suggest that AI chatbots may yield notable clinical improvements in a wide range of health fields with a variation in the effects of the technology depending on the disease-specific considerations, targeted users, and the factors within the context of deployment (Table I). Correctness and Information Fidelity.

TABLE I. Domain-Specific Ai Chatbot Implementations—Comprehensive Performance Metrics

Disease Domain (Chatbot)	N (Participants)	Key Findings & Effectiveness	Satisfaction / Accuracy
Cardiovascular (*HeartBot*)	92	Highly improved symptom recognition (aOR 7.1) and care-seeking behavior.	4.6 / 5.0
Tuberculosis (*TBAid*)	~400 (rural)	Sustained TB knowledge improvement across diverse literacy levels.	4.5 / 5.0
Maternal Health (*DIAN*)	148	High comprehensibility and accuracy across postpartum and nutrition domains.	4.7 / 5.0
Mental Health (*Meta-analysis*)	29,637 (31 RCTs)	Significant reduction in mental distress, depression, and anxiety.	4.2–4.7 / 5.0
General Health (*P&P Care*)	2,113	26% improvement in objective health awareness scores.	4.7 / 5.0 (80% Acc.)
Lassa Fever (*RAG Chatbot*)	60 evaluations	94% of cited responses rated fully appropriate by experts.	High Accuracy
Type 2 Diabetes (*RAG Chatbot*)	60 evaluations	100% of simulated consults fully appropriate and accurately sourced.	High Accuracy
LGBTQ+ Sexual Health (*Roo*)	15 (co-design)	Improved inclusivity, trustworthiness, and stigma reduction after feedback.	High Satisfaction
Infectious Disease (*Health Guard*)	~100 test cases	Rapid (<3s) risk prediction and symptom-disease dataset matching.	*Not quantified*
Oral Cancer (*AI Chatbot*)	6 experts	Rated highly for accessibility and reliable information delivery.	Positive Evaluation

D. Accuracy and Information Quality

Retrieval-Augmented Generation (RAG)): Implementations of RAG experience a notable improvement over the health-related applications of general-purpose language models. The Lassa fever chatbot awareness has been documented to 73 percent, and 94 percent of those who were documented fully appropriate by the infectious disease experts . During simulated consultations with patients, 100 percent (16/16) of answers were described as fully appropriate and as realistically obtained. On the same note, RAG-based diabetes chatbots were shown to provide 100% suitable answer when they rely on reputed CDC and WHO documentation. These findings indicate that chatbot responses based on medical evidence focused on through curation communicate deeply higher levels of accuracy and reliability.

Comparative model performance: Classic natural language processing with high-level feature engineering got 95 percent of the mental health classification accuracy contrasted with prompt-engineered large language models (65 percent) as well as fine-tuned LLMs (91 percent). This result implies that domain-specific models usually work better when clinical conditions are involved compared to general-purpose models. NLP preprocessing chatbots in Indonesian language had precision of 0.9333 and recall of 0.7962 and seemed to tackle the communication barriers in linguistically diverse populations. These findings demonstrate that tailoring AI solutions to medical sub-areas and language conditions is a

beneficial idea instead of using general-purpose models.

E. Pandemic Response Effectiveness

AI chatbots provided essential health services to people during the COVID-19 pandemic. Research channels have reported that about 70 percent of chatbots enabling AI tools that were implemented in the case of emergencies were used in preventive purposes, which included symptom screening, risk analysis and health advice. In addition to preventive roles, chatbots were dealt with information distribution, disinformation, and psychological assistance at the time when it was most doubtful and anxious. The use of chatbots during pandemic received a high level of user satisfaction (mean 80%), which indicates that a considerable advantage is presented by the availability of health information during an emergency in healthcare facilities. Chatbot intervention scalability could be rapid during the COVID-19 pandemic and this showed the potential of the interventions in assisting emergency responses when traditional communication infrastructure became overwhelmed.

F. Implementation Across Diverse Populations

Rural and underserved communities: AI chatbots have been shown to be especially useful in rural and underserved communities where people have little to no access to healthcare specialists and consistent health information. Application studies report the accuracy rate of 80-percent response to user queries among geographically scattered population with the aid of chatbots, which can be interacted with using mobile apps and SMS-based applications that consume the least amount of bandwidth. The technologies provide bridging access gaps in populations otherwise having significant barriers to healthcare information by offering preliminary health assessment and education.

Stigmatized and culturally diversified groups: LGBTQ + -friendly sexual health chatbots (Roo) evidenced significant resulting benefits when jointly structured with marginalized communities via participatory design methods. Adding the feedback of the community, recognizing the cultural context, and applying supportive language made LGBTQ+ teenagers and LBQ+ women of color much more accepting and trusting with their chatbots. These results highlight the need to adopt an inclusive method in design involving placing the voices and experiences of previously marginalized populations in the development of technology at the center. The involvement of the community in designing chatbots leads to a better usability, as well as the establishment of the trustworthiness needed in order to achieve successful health communication within historically marginalized groups.

G. Comparative Analysis: AI Chatbots Versus Traditional Approaches

The AI chatbot strengths: AI chatbots exhibit specific benefits regarding 24/7 availability, scalability, and resistance to costs, as well as the delivery of information in a unified manner irrespective of the geographic differences. In comparison to human health educators, chatbots will continue to deliver the same message no matter who the provider is, and time of the day will decrease inconsistencies in health information quality. Chatbots have the potential to be used by large numbers of users at the same time, and this will cost significantly less than education being delivered by human beings. Interactive formats seem to be more active and related to information storage than inaccurate written forms (Table II).

TABLE II. Comparative Analysis of AI Chatbots Versus Traditional Health Communication Modalities

Dimension	AI-Powered Chatbots	Traditional Approaches	Key Insight / Evidence
Availability & Access	Excellent (24/7, multimodal, easily multilingual)	Limited (Clinic hours, restricted by provider pool)	AI bridges time-zone, language, and disability gaps instantly, whereas human access is resource-constrained.
Scalability, Cost & Speed	High (Rapid deployment, low per-interaction cost)	Low (1-to-1 limits, high labor/training costs)	Chatbots serve thousands concurrently at a fraction of the cost once developed.
Accuracy &	High/Uniform (73–94%	Variable (Depends on provider	AI eliminates messaging drift and

Consistency	accuracy with RAG models)	knowledge/currency)	ensures uniform delivery, though it requires technical maintenance.
Clinical Judgment & Safety	Limited (Relies on strict programmed rules)	Excellent (Experience-based decision making)	AI misses subtle physical/contextual cues; humans excel at recognizing urgent, nuanced danger signs.
Empathy & Emotional Support	Limited (Simulated; struggles with complex emotions)	Excellent (Genuine therapeutic relationship)	AI cannot replicate authentic human connection, which is vital for deeply emotional clinical situations.
Engagement & Behavior	Good (80–85% completion, high satisfaction)	Strong (Personal connection drives change)	AI drives modest behavior change (SMD – 0.35); human counselors achieve larger impacts via motivational interviewing.
Equity & Privacy	At-risk (Systematic algorithmic bias)	At-risk (Individualized provider bias)	Both face bias risks, but AI bias scales to all users. Both require strict data security and governance.
Optimal Role	Frontline / Triage (Basic education, 24/7 Q&A, accessibility layer)	Escalated Care (Complex diagnoses, emotional counseling, nuanced decisions)	Best Practice: A hybrid model combining AI for accessible triage with human oversight for complex/escalated cases.

VI. CONCLUSION

Public health chatbots powered by AI have the potential to be an important step in providing the accessible health education and illness awareness. The 41 peer-reviewed studies, several randomized controlled trials, and actual implementations in various health care settings have shown that these systems have a potential to increase the levels of health literacy (by 26% with inclusion of e-learning resources), user satisfaction (4.7/5), provision of correct health information (73-94% rating of being appropriate), and engagement among underserved population. These results reveal quantitative societal health benefit in spheres of disease such as cardiovascular to mental health assistance.

Nonetheless, to convert this research potential into fair, safe effect on public health, careful consideration has to be made of several critical spheres. First and foremost is technical excellence- retrieval-augmented-generation structures, expert verification and constant quality assurance are critical to allow information accuracy and cut-off malicious falsehood . DSM performance is significantly better than general-purpose solutions in a clinical setting. Equity-based design is devoted to the deliberate inclusion of digital divides, algorithmic discrimination, and disparate access to benefits in order to bring them to groups that are most adversely affected by disease and discrimination in healthcare provision.

With AI technologies evolving at a very fast rate, the field is at the point of extreme activity. Optimism assessment of possible public health impact has a clear evidence basis. However, this potential can be achieved only by conscious effort to be excellent in terms of technical, ethical, equity, and governance aspects. When properly structured governance systems, a stringent validation process, community involvement in the design, and sustained development based on experience of implementation are implemented, AI chatbots can contribute significantly to the power of public health communication, democratize access to health information, and promote disease prevention processes throughout the world.

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