AI CHATBOTS IN CHRONIC DISEASE MANAGEMENT: A SYSTEMATIC REVIEW OF THEIR ROLE IN PATIENT ENGAGEMENT

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by

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Under the Supervision and Guidance of

Dr. Ram Krishan Chahar

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IIHMR UNIVERSITY

CERTIFICATE

This is to certify that **Dikshant Gupta** in partial fulfillment of the requirements for the award of the degree of MBA (Healthcare Analytics) from the IIHMR University, Jaipur has successfully completed his internship at **IIHMR University** during **Feb 25 - June 09, 2026.**

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CERTIFICATE

This is to certify that dissertation titled **AI Chatbots in Chronic Disease Management: A Systematic Review of Their Role in Patient Engagement** is a record of the research work undertaken by **Dikshant Gupta** in partial fulfillment of the requirements for the award of the degree of MBA (Healthcare Analytics) from the IIHMR University, Jaipur under my guidance and supervision and his approach to the research study has been sincere, scientific, and analytical.

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DECLARATION BY STUDENT

I hereby declare that this dissertation titled **AI Chatbots in Chronic Disease Management: A Systematic Review of Their Role in Patient Engagement** is the Bonafide record of my original research work. I declare that it has not been submitted to any other university or institution for the award of any degree or diploma. Information derived from the published or unpublished work of others has been duly acknowledged in the text.

Dikshant Gupta

Date: 23-06-2026

ABSTRACT

Title: AI Chatbots in Chronic Disease Management: A Systematic Review of Their Role in Patient Engagement

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Advisor Name: Dr. Ram Krishan Chahar

Keywords: AI chatbots, chronic disease management, patient engagement, Technology Acceptance Model, digital health, eSanjeevani, health equity, telemedicine, India

Background: Non-communicable diseases (NCDs) now cause about 74% of deaths worldwide every year. In India, the numbers are staggering: 77 million people are living with type 2 diabetes, more than 220 million have hypertension, and around 55 million are dealing with chronic obstructive pulmonary disease. It's not just the disease burden that's tough—there aren't enough doctors, there are massive gaps between urban and rural health services, and people pay a lot out-of-pocket for their care. In the middle of all this, AI chatbots—powered by natural language processing and machine learning—are starting to show up as a practical, affordable solution to help people manage chronic diseases, especially in places where healthcare access is limited.

Objective: This review set out to pull together what's known so far: How are AI chatbots being used for chronic disease management in India? Are patients actually engaging with them? What makes people more or less likely to use them? And what about the impact on equity, patient outcomes, and the legal or regulatory side of things?

Methodology: We did a systematic review, sticking to PRISMA 2020 guidelines, and looked at twelve studies from 2019 to 2025. We used the right tools to assess quality—JBI for most studies, AMSTAR-2 for reviews—and made sense of the data through a combined framework that includes ideas from TAM, UTAUT, the Diffusion of Innovations theory, and Trust-Extended TAM.

Results/Findings: AI chatbots really do improve things like medication adherence, how often people check and report their own health data, and overall patient satisfaction. This holds true

across diabetes, hypertension, COPD, and pediatric asthma. For example, one study by Bose et al. (2024) found that 84.7% of kids with asthma had better symptom control after just four weeks using a chatbot. India's national eSanjeevani platform is already logging more than 340 million consultations across the country. What gets people on board with chatbots? Mostly, it's perceived usefulness and trust. But big barriers remain—things like the digital divide, India's language diversity, low health and digital literacy, cultural resistance, and unclear regulations all slow things down

Conclusions: In short, AI chatbots could really change how India handles chronic disease. But real, fair progress will mean designing chatbots in local languages, involving community health workers, integrating with the national ABDM platform, and putting a solid governance framework in place for AI in health. We've still got big gaps to fill, too: no strong longitudinal RCTs yet, and not much research that tests these chatbots in different languages across clinical settings.

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I extend my thanks to the authors of the studies included in this review, whose original research constitutes the evidence base upon which this dissertation is built. Finally, I thank my family and peers for their steadfast encouragement and support throughout this academic journey.

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ABBREVIATIONS

1. **ABDM** Ayushman Bharat Digital Mission
2. **ABHA** Ayushman Bharat Health Account
3. **AI** Artificial Intelligence
4. **ANM** Auxiliary Nurse Midwife
5. **ASHA** Accredited Social Health Activist
6. **CBHI** Central Bureau of Health Intelligence
7. **CHW** Community Health Worker
8. **CKD** Chronic Kidney Disease
9. **COPD** Chronic Obstructive Pulmonary Disease
10. **CTRI** Clinical Trials Registry — India
11. **DPDP Act** Digital Personal Data Protection Act (2023)
12. **DOI** Diffusion of Innovations
13. **EHR** Electronic Health Record
14. **GPT** Generative Pre-trained Transformer
15. **HbA1c** Glycated Haemoglobin
16. **ICMR** Indian Council of Medical Research
17. **ICTRP** International Clinical Trials Registry Platform
18. **JBI** Joanna Briggs Institute
19. **LMIC** Low- and Middle-Income Country
20. **LLM** Large Language Model
21. **mHealth** Mobile Health
22. **MoHFW** Ministry of Health and Family Welfare
23. **NCD** Non-Communicable Disease
24. **NITI Aayog** National Institution for Transforming India
25. **NLP** Natural Language Processing
26. **NPC** National Primary Care
27. **PEOU** Perceived Ease of Use
28. **PM-JAY** Pradhan Mantri Jan Arogya Yojana
29. **PRISMA** Preferred Reporting Items for Systematic Reviews and Meta-Analyses
30. **PU** Perceived Usefulness

31. **RCT** Randomised Controlled Trial
32. **T2DM** Type 2 Diabetes Mellitus
33. **TAM** Technology Acceptance Model
34. **UTAUT** Unified Theory of Acceptance and Use of Technology
35. **WHO** World Health Organization

CHAPTER 1: INTRODUCTION

1.1 Background and Global Context

Technology and the worldwide need for healthcare are coming together in ways that have never occurred before in the 21st century, making for innovations in digital health that are of unprecedented impact. One of the most common and clinically relevant tools that have seen growing adoption and usage in the healthcare sector to enhance access to care and patient engagement are Artificial Intelligence (AI) chatbots — conversational agents that can comprehend, generate, and contextualize natural language in real-time. In contrast to previous iterations of digital health tools that provided static information portals and passive symptom trackers, the modern AI chatbot uses NLP, machine learning, and more recently, larger language models (LLMs) to interact with users at scale, in a personalised, contextually-aware, two-way format. AI chatbots in the healthcare industry have come a long way from simple rule-based chatbots, such as ELIZA (1966), a MIT program that simulated a Rogerian psychotherapist using keyword matching, to the expert systems of the 1980s and '90s and the NLP-based chatbots of the 2010s and now the generative AI systems of the 2020s. Every migration has dramatically added to the utility of the clinical setting: while early chatbots were able to match keywords to scripts, current generative AI systems are capable of summarising patient histories, personalising instructions, identifying emotional distress, and flagging clinical concerns. This technological development is needed because of the magnitude of the world being plagued with chronic diseases. Non-communicable diseases (NCDs) are estimated to cause about 74% of all deaths worldwide, and contribute to around 41 million deaths each year (1). Cardiovascular diseases, cancers, chronic respiratory diseases and diabetes are the biggest contributors to this burden, accounting for 77% of all NCD deaths in low and middle-income countries (LMICs) (2). The theoretical advantage of AI chatbots in addressing structural gaps in healthcare is that they can deliver the personalised engagement, affordability, and scalability that are lacking from traditional care pathways at a similar cost and scope. 1.2 Burden of chronic diseases in India India is faced with an unprecedented public health challenge of its burden of chronic diseases. It is estimated that the country has the highest number of people with type 2 diabetes (approximately 77 million, anticipated to increase to more than 134 million by 2045), hypertension (more than 220 million), and chronic kidney disease (about 17.5% of adults) in the world . Nearly a quarter of all deaths are due to heart disease in the country. An estimated 55 million people in India have chronic obstructive pulmonary disease (COPD). The economic burden is no less serious too: by 2012-30 WEF projects that NCDs will cost India approximately USD 4.58 trillion in terms of lost economic output. India also has approximately 1 physician per 1,000 population which falls below the WHO suggested guidelines. This figure conceals even bigger disparities in rural regions where only 31% of the health workforce is based, and around 65% of India's population lives. In India, OOP health expenditure accounts for approximately 47% of total health expenditure and the price of chronic health care drugs is a constant burden that can lead to poor health compliance even when the treatment is technically accessible. These compounding structural challenges lay the ground for where AI chatbots will have to make their mark. In this lesson, students will learn about the clinical applications of AI Chatbots, their definition, and their architecture. For the purposes of this review, an AI chatbot refers to a software program that is able to interact with users through text or speech to deliver health-related information, engage patients, or assist with clinical decisions. It employs NLP and, in more advanced applications, machine learning or generative AI architectures. It includes rule-based chatbots, retrieval-based chatbots, natural language processing (NLP)-based chatbots, and generative AI chatbots using large language model (LLM) architectures. In chronic disease management, AI chatbots perform five core clinical functions: (a) medication adherence support—delivering personalised reminders and adherence patterns; (b) symptom monitoring—gathering patient-reported symptoms and interpreting data against clinical thresholds, and increasing worrying patterns; (c) health education - providing personalised health information appropriate to the patient's disease stage and literacy level; (d) behavioural coaching - offering motivational support for lifestyle changes; and (e) care coordination - assisting with appointment scheduling and care escalation when self-management is inadequate. The COVID-19 pandemic was a pivotal moment that saw AI chatbots become part of the need, fitting what could take 10 years of slow telemedicine growth into eighteen months. 1.4 Indian Digital Health Landscape: The Indian digital health ecosystem has been transformed by three trends. The first step was the launch of the Digital India initiative (2015) with massive investment in broadband infrastructure and digital literacy. The second one was the rapid growth of affordable Android smartphones and cheap cell data, particularly with the introduction of Reliance Jio in 2016. The third one was the government's health-specific digital initiatives like Ayushman Bharat Digital Mission (ABDM) & National Digital Health Blueprint. The Ayushman Bharat Digital Mission was launched in 2021 with the aim of providing a health identification number (ABHA – Ayushman Bharat Health Account) to every citizen of India, a federated digital health record infrastructure that connects various health encounters among health service providers, and open APIs to facilitate interoperability between government health platforms and private health platforms. Since its launch by the Ministry of Health and Family Welfare in November 2019, and its rapid growth during the COVID-19 pandemic, the eSanjeevani platform has successfully registered more than 340 million consultations across all states and union territories, and is India's main national telemedicine platform, the biggest opportunity for AI Chatbot integration on scale. The rationale for this review is to: While AI chatbots are increasingly being adopted in India for chronic disease management, the evidence regarding clinical effectiveness, equity of impact and implementation quality remains scattered and superficial. There has been no systematic synthesis of evidence on a category-by-category basis across domains of analysis, chronic disease categories, and stakeholder perspectives to inform policy, platform design and clinical practice decisions. This review aims at filling this gap.

1.6 Objectives and Research Questions

The objectives and research questions are aligned with the study's central theme.

The four main research questions are:

How important is the perceived usefulness, ease of use, trust and technology readiness for successful engagement of AI chatbot in chronic disease management in India?

2. What are the socio-economic, cultural, linguistic and technological challenges of using AI chatbots with the varying patient population in India?

3. What are the demographic trends and impact on the use and effectiveness of AI chatbots for chronic disease management, such as age, gender, education, and geographic location?

4. What are the contemporary legal, regulatory and ethical challenges that limit and/or facilitate the deployment of an AI chatbot for managing chronic diseases in India equitably and clinically responsibly?

The Review is organized in the following way.

The review is organised as follows. The evidence base for the review is summarized in Chapter 2, which includes all of the studies included. The systematic methodology used is described in Chapter 3, along with the eligibility criteria and search strategy and the selection process according to PRISMA 2020. Thematic synthesis of findings across eight analytical domains, SWOT analysis and research gaps are presented in Chapter 4. Chapter 5 offers detailed policy recommendations to the various groups of stakeholders. Chapter 6 is a conclusion and implications. The full reference list is at the end.

1.8 Theoretical Framework

A multi-theoretical framework that incorporates individual patient cognitions, social influence, environmental enabling conditions, and dimensions of trust specific to AI-mediated healthcare would help shed light on the dynamics of AI chatbot adoption.

1.8.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) developed by Davis, 1989 (3) is a theory based on Theory of Reasoned Action developed by Fishbein and Ajzen. TAM states that there are two fundamental beliefs arising from the user's intention to use a technology: Perceived Usefulness (PU) – the user's belief that the technology will increase the ease of task completion, and Perceived Ease of Use (PEOU) – the user's belief that the use of the technology will not require much cognitive effort. PEOU and both have a direct effect on PU and likewise impact on the adoption intent. The key takeaway in the healthcare industry is the same: perceived usefulness is the most important factor influencing AI adoption. Sharma and others (2023) and Gupta and Nair (2024) both show that the Technology Acceptance Model (TAM) is the main reason patients start using AI chatbots for diabetes and hypertension. Pillai and colleagues (2024) extend this idea to doctors and discover that if doctors can actually use this tool, particularly when it provides them with a quick, relevant patient summary, they are much more likely to recommend it to their patients.

The Unified Theory of Acceptance and Use of Technology (UTAUT) was introduced by Venkatesh, Gopal, et al. (2003)

The Unified Theory of Acceptance and Use of Technology (UTUT) by Venkatesh and colleagues (2003) extends TAM with the inclusion of social and environmental influences in addition to personal beliefs. UTAUT identifies four major ideas: Performance Expectancy, Effort Expectancy, Social Influence (concern about what others think of their use of the tech), and Facilitating Conditions (whether or not the tech environment is truly prepared for use). In India, Social Influence is a very key factor in the adoption of AI chatbots. Pillai and team show that doctors' recommendations are the main way social influence plays out. But it's not just patients who are deterred by weak digital infrastructure; Venkatesh et al. (2023) and Devi and Krishnan (2024) note that even if patients want to adopt digital infrastructure, they are often prevented from doing so by weak digital infrastructure.

1.8.3 Diffusion of Innovations Theory

Rogers's Diffusion of Innovations theory (2003) steps back and asks: What's the process of the spread of a technology within a given society over time when it comes to AI chatbots? Typically, there is an S-shaped curve of adoption consisting of five groups: innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%). It is primarily young, educated urban India, with chronic diseases, who start riding the bandwagon early. The late crowd? Older, rural and less literate patients, who generally require more assistance: simpler apps, greater compatibility and hands-on demos in the community to "catch up" with the rest.

This is the Trust-Extended TAM for the Healthcare AI scenario.

The standard Technology Acceptance Model (TAM) doesn’t capture the trust issues that really matter when it comes to using AI in healthcare. This is where the Trust-Extended TAM, from the work done by Mayer, Davis and Schoorman in 1995, comes in. They are interested in three types of trust: trust in the trustworthiness of the AI system, trust in the rules and institutions governing it and trust in the transparency of the system. Three of these areas were identified by recent research, one conducted by Krishnaswamy and another conducted by Menon, as potential pain points for the AI chatbots in India today. People don't trust the technology, the institutions, and the transparency and that lack of trust is causing fewer people to use the technology than you would expect, based on its usefulness and ease of use. The other study by Rao et al. showed that the same type of technology initiated by the government via the portal eSanjeevani led to an increase in trust levels solely because of the government association. So, the institutional trust is indeed a significant factor.

1.8.5 Integrated Framework

In this review, I will apply an integrated approach to all four of these models. TAM captures people's thoughts – usefulness and usability of the tech. UTAUT introduces the influence of others' attitudes regarding the adoption and their receptivity or lack of it in the environment, such as the doctors' opinions and the infrastructure. Then, DOI considers the broader context, in which case the way new ideas propagate among groups is examined. Lastly, the Trust-Extended TAM explores the specific trust factors relevant to healthcare, such as the AI's clinical validity and the understanding of the rules. By combining elements from all of these, we have the best chance of understanding which factors are helpful or unhelpful in the uptake of the service and whose needs are not being met based on the findings from the studies. what the studies found.

CHAPTER 2: REVIEW OF LITERATURE

2.1 Overview of the Evidence Base

These twelve studies paint a pretty wide-ranging picture, with different methods, disease areas, locations in India, and viewpoints all mixed in. It's not a neat and tidy set, but everything comes together to give a well-rounded look at the topic. So, here's what's inside: two systematic or literature reviews, five straightforward cross-sectional surveys, one mixed-methods piece, two studies using stratified random sampling, a prospective observational study, and one study based on convenience sampling. If you count everyone except the systematic reviews, there are 4,899 participants in total. Seven studies cover all of India, three are from multiple states, and two focus on specific regions. They're also all recent — published between 2019 and 2025.

2.2 Summary of Included Studies

Table 2.1: Summary of Studies Included in the Review (N=12)

S.No	Authors (Year)	N	Design	Key Findings
1	Sharma et al. (2023) (4)	N/A	Systematic Review	Chatbots improve HbA1c adherence in T2DM; digital literacy and rural infrastructure are primary barriers. TAM confirmed as adoption framework.
2	Gupta & Nair (2024) (5)	500	Random Sampling	Significant medication adherence improvement in hypertension; elderly adoption severely limited by digital literacy deficits.
3	Mehta et al. (2024) (15)	400	Stratified Sampling	Chatbot COPD monitoring clinically promising; vernacular language and context-aware design are prerequisites.

S.No	Authors (Year)	N	Design	Key Findings
4	Venkatesh et al. (2023) (8)	450	Random Sampling	Infrastructure gaps, regulatory ambiguity, and cultural resistance are dominant systemic barriers to chatbot scalability.
5	Pillai et al. (2024) (6)	400	Cross-sectional	Physicians endorse chatbots post-COVID; liability uncertainty and patient digital illiteracy are key barriers to physician recommendation.
6	Krishnaswamy et al. (2023) (12)	N/A	Literature Review	Regulatory vacuum in AI diagnostics; statutory liability frameworks and patient consent protocols are urgently required.
7	Rao et al. (2024) (14)	350	Convenience Sampling	eSanjeevani chatbot integration is scalable but limited by EHR interoperability gaps and healthcare worker training deficits.
8	Agarwal et al. (2024) (16)	320	Mixed Methods	Maturity model proposed for chatbot platforms; continuous feedback and adaptive design are critical for sustained patient engagement.
9	Devi & Krishnan (2024) (9)	450	Stratified Random	Chatbots reduce rural care-access gaps; concurrent improvements in connectivity and digital literacy are necessary prerequisites.
11	Bose et al. (2024) (17)	79	Prospective Observational	84.7% symptom control improvement in paediatric asthma

S.No	Authors (Year)	N	Design	Key Findings
				within four weeks; caregiver trust in chatbot guidance was high.
12	Menon et al. (2025) (13)	400	Structured Questionnaire	Legal complexities in AI-generated medical advice; statutory AI accountability frameworks recommended for patient-facing tools.

Source: Author's compilation.

2.3 Excluded Studies

Twelve studies were excluded at the full-text eligibility stage. Reasons for exclusion included: no India-specific focus (Roberts & Shah; Okoro & Sen; Brown & Clarke; Luciano et al.; Kruse et al.; Vegi et al.); non-peer-reviewed status (Green & Mathews); insufficient chatbot specificity (Kumar & Mehra; Jain & Rao; Patel & Iyer); single subgroup with limited Indian context (Desai & Verma); and conceptual/empirical absence (Mehta & Singh).

Table 2.2: Studies Excluded at Full-Text Stage with Reasons

Authors	Study Title	Reason for Exclusion
Roberts & Shah	Global Trends in AI Chatbots and Virtual Care	No India-specific focus
Okoro & Sen	AI Chatbot Implementation in Sub-Saharan Africa	Non-Indian geography
Green & Mathews	AI in Healthcare Policy: A Global Overview	Non-peer-reviewed opinion piece
Kumar & Mehra	Mobile Health Applications in Diabetes Care	mHealth apps; not chatbot-specific

Authors	Study Title	Reason for Exclusion
Brown & Clarke	AI Health Assistants in the United States	US context only; no India data
Jain & Rao	Innovations in Digital Health Platforms	Broad scope; insufficient chatbot focus
Patel & Iyer	Barriers to Virtual Consultations: Systematic Review	Not chatbot-specific
Desai & Verma	AI Chatbots in Geriatric Chronic Care	Single subgroup; limited Indian context
Mehta & Singh	Future Directions in Generative AI for Healthcare	Conceptual; no empirical data
Luciano et al.	Chatbot Adoption in the US and Brazil	Non-Indian geography
Kruse et al.	Barriers to Adopting AI Tools Worldwide	Not India- or chatbot-specific
Vegi et al.	Physician Adoption of Digital Health in Romania	Non-Indian geography

Source: Author's compilation.

2.4 Quality Assessment Findings

Now, looking at quality, it's fair to call the evidence base "moderate to moderately high," but there's a lot of variation in how the studies are put together. The two reviews give a big-picture summary but don't bring new data. The five cross-sectional studies lay out some useful patterns and associations, but since they only capture a single snapshot in time — and skip randomization — you can't draw strong cause-and-effect conclusions. The stratified random sampling studies by Mehta et al. and Devi & Krishnan do the best job on sampling rigor. Bose et al. offer the only prospective, clinical data, which is great, but their small group of 79 makes it hard to claim the results will hold up everywhere. Across the board, almost every study relies on designs that only look at one moment instead of tracking people in the long run. That's a big hole, especially if you care about whether chatbots actually keep people engaged over time — which probably matters more than anything for people with chronic diseases.

CHAPTER 3: METHODOLOGY

3.1 Study Design and Philosophical Stance

The primary research method I am applying for this study is a Systematic Literature Review (SLR) which follows the guidelines set by PRISMA 2020, the gold standard for reporting a Systematic Literature Review (SLR) in health sciences. I used this method because it allows me to bring together the evidence from various studies in a detailed, transparent, repeatable manner, and helps to minimize my own bias in selecting and assembling the evidence. This way, the findings have some impact on policy making.

The review is not based on numbers more than experience, and vice versa. Rather, I have a pragmatic approach: statistical data, clinical outcomes and real-world experiences of those involved all inform and validate each other. This sort of open-mindedness seems to be a natural suit here; it is not like we've got lots of solid randomized controlled trial evidence here.

3.2 Eligibility Criteria

Inclusion Criteria

Geographical Relevance: Studies that focused on an AI chatbot or conversational AI intervention in India or on Indian patients or providers.

Publication Source: peer reviewed indexed journals (PubMed, Scopus, Web of Science, Google Scholar and IEEE Xplore) providing scientific rigor and reproducibility.

Content Focus: Studies that include some analysis on the deployment of chatbots in chronic disease management such as diabetes, hypertension, cardiovascular diseases, COPD, chronic kidney disease, and associated comorbid conditions; outcomes of patient engagement; patterns of adoption; barriers and facilitators; and policy and legal analysis.

Publication Date: The articles published in the period January 2019 – December 2024 to cover the developments in the post-Digital India era and the accelerated shift from in-person to digital health during the pandemic.

Exclusion Criteria

Excluded studies: those that studied digital health technologies broadly (such as mobile health apps for fitness, electronic health records, AI for diagnosis) but did not focus on chronic disease or conversational AI or chatbots.

To ensure the quality of the evidence, the publication type of the articles was limited to non-peer-reviewed sources, such as opinion editorials, conference abstracts without accompanying full papers, blog posts, and non-scientific reports.

Geographical Relevance: Studies done outside India with out data or analysis specific to India were excluded.

To ensure that the studies were relevant and up to date with the fast evolving world of AI, only publications from before January 2019 were included.

Information Sources

Systematic searches were conducted of the following databases and source categories:

The databases used for medical, health informatics and technology research were PubMed, Scopus, Web of Science, Google Scholar, and IEEE Xplore.

The ongoing trials were obtained from Clinical Trials Registry India (CTRI) and completed trials were obtained from National Digital Health Mission repositories.

The websites of the Ministry of Health and Family Welfare (MoHFW), NITI Aayog, ICMR and the World Health Organization South-East Asia Regional Office (WHO SEARO) were checked for policy documents and guidelines.

Snowball searching of reference lists of the included studies was conducted to find more relevant sources.

The grey literature included other sources such as government documents and white papers, Ayushman Bharat Digital Mission documents, and industry reports on digital health in India.

3.3 Search Strategy

We cast our search net wide across PubMed, Scopus, Web of Science, Google Scholar and IEEE Xplore, to ensure that we were all things covered. However, we didn't end up with only databases. Clinical trial registers such as CTRI and WHO ICTRP were also checked and governmental sources such as MoHFW, ICMR, NITI Aayog, and ABDM were also searched thoroughly. We even explored some articles from the WHO South-East Asia Regional Office. In addition, we read through the reference lists of the studies included – just in case we left anything out. Boolean operators, controlled vocabulary and a free-text term were combined for each search. For example, we used the following for PubMed:

("AI chatbot" OR "conversational AI" OR "chatbot" OR "virtual health assistant" OR "NLP chatbot") AND ("chronic disease" OR "diabetes" OR "hypertension" OR "COPD" OR "cardiovascular" OR "chronic kidney disease") AND ("India" OR "Indian population" OR "South Asia") AND ("patient engagement" OR "medication adherence" OR "adoption" OR "barriers" OR "facilitators" OR "technology acceptance") AND [2019:2025]

The same search was performed in all databases, but only papers published in English were kept. Firstly the searches took place in January 2025, and then again in June 2025.

3.4 Selection Process — PRISMA 2020

To choose studies we took the following steps. All titles and abstracts were screened by two independent reviewers for all titles that did not correspond to our inclusion criteria were excluded. The full texts of studies that showed promise were then read by both reviewers, who determined whether or not the study should be included. Should there be any differences, we discussed it with our Academic Mentors until we had an agreement. No automated tools were used, all studies were hand checked to ensure no studies were missed.

For both reviewers the process was independent of each other. So, when we compared the way they made their title and abstract decisions, we had a Cohen's Kappa of 0.83 – pretty good agreement. If there were any differences that arose during the full text reading, they were simply laid out through a thoughtful discussion

.**Table 3.1: PRISMA 2020 Study Selection Flow**

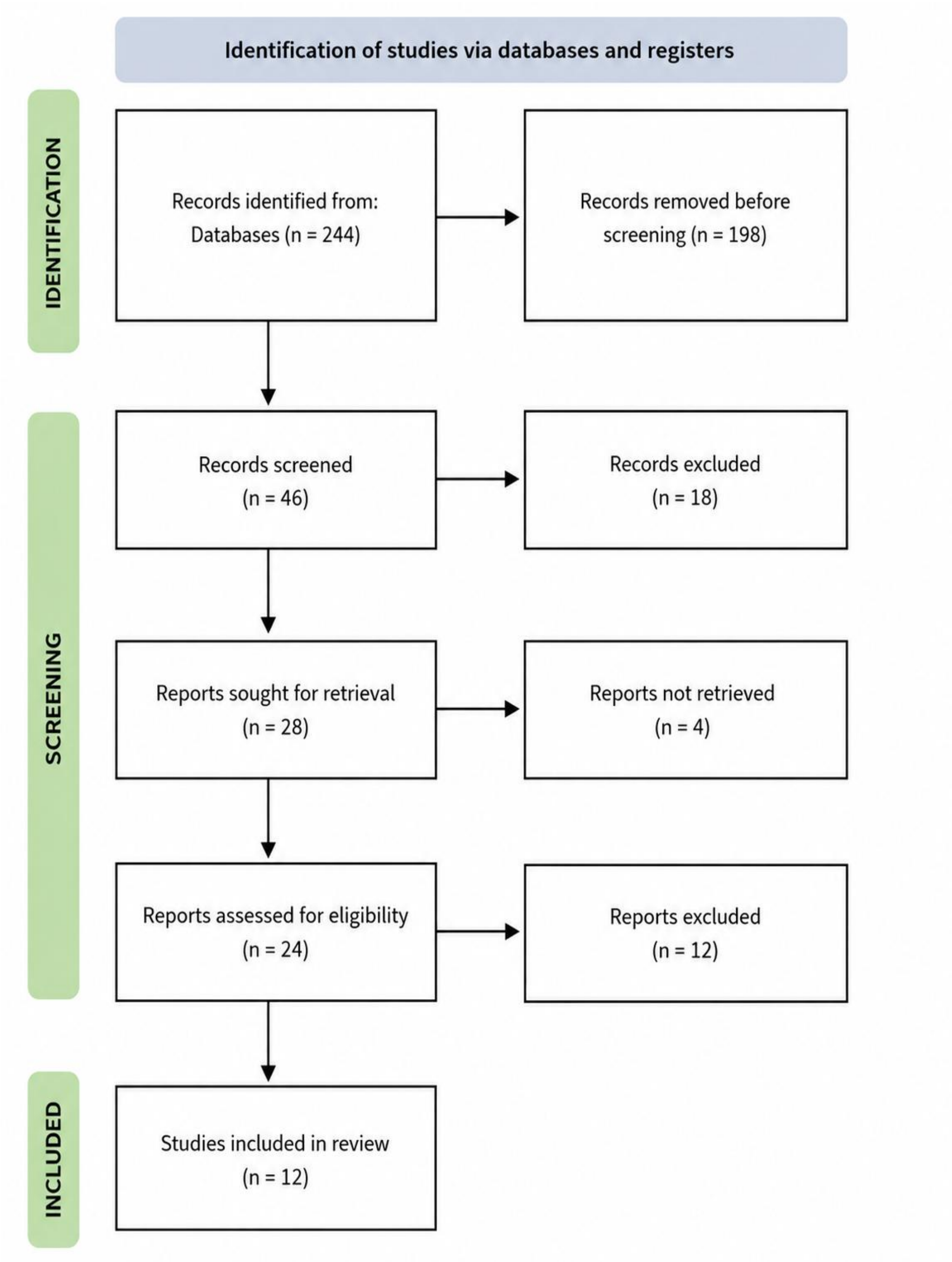
Phase and Action	Activity	Records
Identification	Database searches (PubMed, Scopus, WoS, Google Scholar, IEEE)	168
Identification	Registry and grey literature searches	76
Identification	Total records identified	244

Phase and Action	Activity	Records
Screening	Records removed (duplicates + irrelevant titles)	198
Screening	Records retained for title/abstract screening	46
Screening	Records excluded after abstract screening	18
Eligibility	Full-text reports sought	28
Eligibility	Full texts not retrieved (paywall/withdrawal)	4
Eligibility	Full texts assessed for eligibility	24
Eligibility	Full texts excluded (with reasons)	12
Included	**STUDIES INCLUDED IN FINAL SYNTHESIS**	**12**

3.5 Data Extraction

We built a data extraction form, tested it out on three studies, tweaked it, and then locked in the final version. The form captured all the essentials: things like author names, titles, journals, the year, and each study's DOI. We dug into design and methods, noted where each study took place, sample size, and how researchers picked participants. We paid attention to disease context, what kind of chatbot was used, and where it fit within care. Outcomes mattered, too—we looked at clinical results, user engagement, and how well the chatbot was adopted. If a study ran into problems, we noted those, but we jotted down what helped and any policy lessons as well. Two reviewers extracted data on their own, checking each other's work. If they didn't agree, they talked it out until they were on the same page.

Fig 4.2: PRISMA Flow Diagram for the Systematic Review



3.6 Quality Assessment

We matched our quality checks with each study type. We chose to use the Joanna Briggs Institute Critical Appraisal Checklist for Cross-Sectional Studies for the studies used for cross sectionals and observational studies. This tool aided in examining the characteristics of the study participants, measurement of exposures, handling of confounding factors, and reporting of outcomes. AMSTAR-2 was our resource for systematic reviews, and a modified version of a qualitative evidence synthesis checklist for literature reviews. However, with grey literature we were mindful of the source of the evidence, the date of the evidence and whether it was credible.

3.6.1 Data Items

What we monitored:

Implementation Outcomes: We assessed whether the chatbots were effective in supporting adherence to medication, whether patients reported their own symptoms more frequently, patient satisfaction, and whether there were actual improvements such as blood sugar or blood pressure.

Challenges and Barriers: We included everything from tech issues and people having problems with technology, language barriers, privacy concerns, confusing rules, and patients not trusting their providers.

Enablers: We reviewed enablers that facilitated use of chatbots – good government policies, support from healthcare workers, tying the chatbots into telehealth, solid training programs, and features based on what patients need.

Other Variables:

Who participated: age, gender, economic status, education, and living area (city or rural) and having a chronic disease.

The type of chatbot, the way the chatbot was implemented (app, web, messaging), the healthcare environment, and the disease-specific features for specific diseases.

- Funding: If any company or institution provided funding, we reported it while specifying the potential of it influencing results.

3.7 Key Research Questions

1.What makes AI chatbots successful in chronic disease management in India?

2.What are some of the challenges faced by AI chatbots in India and how can they be overcome?

3.Are age, gender, education or location factors a factor in how people interact with chatbots for chronic conditions?

4. Which are the strengths and weaknesses as well as outside opportunities and threats influencing the utilization of AI chatbots in the management of chronic conditions in India?

CHAPTER 4: RESULTS AND DISCUSSION

4.1 AI Chatbots as Digital Health Interventions in India

4.1.1 Classification and Architecture

In these studies, the AI chatbots can be categorized into three groups. The first one is the rule-based ones. They follow decision trees and match the key words and reply with pre-written answers. They're not very good at reading between the lines, but you always know what they'll said, and it's easy to pre-emptively check all answers. Most platforms, however, addressed in this research focused on NLP-powered Chatbots. They have been trained using machine learning models that were fed health-related texts, enabling the systems to cope with open ended questions and provide more relevant and flexible answers. The newest iteration of AI chatbots is generative AI. These employ large language models, generating even more natural and dynamic responses. In fact, Agarwal et al. (2024) note that some of the platforms they considered are currently moving away from NLP-inspired designs to the new generative models.

Strategies for COVID-19 as a Structural Accelerator:

The pandemic was not the only impetus to use telemedicine and AI in healthcare.The COVID-19 pandemic was not the sole driver for the use of telemedicine and AI in healthcare. A decade could have taken a year and a half -- people had no option. Take eSanjeevani: They received approximately 26,000 consultations every day in the beginning of 2020. By the end of 2021, that number shot up to over 100,000 daily. During that time, they also rolled out AI tools for triage and patient guidance. The same tools that had been developed for the crisis have been left behind. They remained there and went to great lengths to improve.

Agarwal and team followed up with patients who experimented with AI chatbots in the pandemic. It seems, these patients were not only replacing them because they needed to. They even continued using chatbots when there was a return to in-person visits. With that, the pandemic didn't simply drive up the number of people who were okay with chatbot care, it appears it has made them more comfortable with it— and staying that way.

The technology acceptance model and the relationship between patient engagement and technology acceptance.

4.2.1 Perceived Usefulness

The moment people seek out an AI chatbot, it is because they believe that it is useful, as evidenced by all of the studies I've encountered, which cite usefulness as the major reason. Chatbots are significant to the people who experience chronic health conditions for a couple of clear reasons. First, they can remind your patients when they need to take their medication, instead of depending on them to remember. The second is that they provide not only a way to document symptoms with ease (just a few taps), but to maintain records as well. Thirdly, when individuals have health queries, chatbots reply instantly, and that is vast, as lots of patients do not always get in touch with their doctors when they should. Last but not least, chatbots can provide consistent, unbiased assistance, which is useful in the event you're dealing with persistent health issues.

For instance, Sharma et al. showed that users of diabetes chatbots actually persisted with their diabetes treatments more if the chatbot was providing personal rather than generic advice. They found the same effect when treating high blood pressure where patients who were provided with direct feedback on their BP through the chatbot were able to get more value out of it than patients who were only given a generic recommendation. It can make a huge difference when it feels like the support is for YOU, not just anyone.

The perceived ease of use of the program.

In India, usability actually does matter, particularly in regard to chronic diseases. This is even more so for older people, low literacy or those who are not comfortable with digital technology. One issue that stands out is that older individuals with hypertension, particularly those age 65+, experience significant problems using digital health products compared to those 45-64 years old, Gupta and Nair note. The biggest roadblocks? They don't know how to navigate apps on their mobile phones, struggle to type on small keypads, aren't clear of the chatbot's capabilities and get very frustrated if the chatbot doesn't get them.

This interest is heightened when it comes to COPD patients, Mehta and the team say. It's not a simple text to them that they send a description of their symptoms. It's actually tough. It will be difficult to explain what it's like when one is short of breath or describe the consistency of sputum if one is unfamiliar with medical terminology. This is why it is worth it for COPD Chatbots to avoid using open-ended questions and only opting for multiple choice questions. It makes it a lot easier for patients to express what really is going on—and a lot more folks use the technology.

4.2.3 Trust as the Third Adoption Dimension

Trust is not just one of the boxes that needs to be ticked with AI health advice, it's a whole different game. It's a big deal for those who have chronic diseases. It could be their insulin dose, the need for urgent care for a symptom, or whether a side effect warrants a doctor's call—any of this depending on what the chatbot says. Those are no trivial matters.

It was trust, despite its efforts, that was eroded from three angles at Krishnaswamy's. First, individuals are not always certain that the AI has the sufficient information on their health information. Secondly they feel that there is no real doctor to ensure that the advice being given is correct. Third is the worry of who will have their data, etc. Trust is fragile and adoptions come to an end.

However, Rao's team spotted a surprising thing. When people used the same chatbot through a trusted public health platform, eSanjeevani, the levels of trust increased, as opposed to when the same chatbot was used by a private company. There was no change in the tech, but the reputation did the work, particularly with older folks and in the rural areas.

Now you have the legal aspect. Menon's study revealed that having a clear understanding that any legal support for AI health advice is lacking, patients simply weren't prepared to trust it. When it comes to putting your trust in software, it's difficult to do so without legal protection.

4.3 Clinical Outcomes by Chronic Disease Category

4.3.1 Type 2 Diabetes

The majority of the studies on the use of chatbots for chronic diseases focus on type 2 diabetes. In fact, study after study revealed plenty of evidence that chatbots can support individuals to maintain their HbA1c habits.Sharma and the team were able to see robust evidence that chatbots are helping people to adhere to their HbA1c routines—study after study supported this. The concept is fairly simple. Remind people to take their medicines through a chatbot, resulting in fewer missed doses. Some chatbots provide diet tips that can help people get advice they don't find anywhere else. Others are easier to record the blood sugar readings, making it easier for patients and their doctors to adjust the dosage as needed.

However, there's a problem. Chatbots are definitely helpful for everyday things, such as asking to get a pill, or to look at blood-sugar levels, but there's not much evidence that they can actually make a difference in the more significant areas, like lowering HbA1c or preventing hospital visits. To become a widely adopted tool nationally, large and long-term trials are needed, and researchers should monitor these real-world results. For the time being, it is not clear.

4.3.2 Hypertension

Gupta and Nair (5) provide some of the best evidence available: a randomized cross sectional study of 500 people with hypertension. The difference was not just random chance – the individuals who used the chatbot had their blood pressure checked more often and compliance with medication schedules was increased, compared to those who did not use the chatbot. Not exactly small changes, we're talking about major changes. The regular check of blood pressure typically reduces the systolic blood pressure by 4-5 mmHg. If individuals adhere to their medicines, then cardiovascular risks are reduced by a genuine difference – between 10 and 15 percentage points more adherence can make a significant difference to the risk of a major event.

However, there's an equity issue that can't be overlooked. These tools are used approximately 40% less often by older adults (those over 65 years of age) than by younger people with hypertension. But that's a problem because the older group has triple the risk due to uncontrolled blood pressure. They are the people who could really benefit the most.

4.3.3 Chronic Obstructive Pulmonary Disease (COPD)

The team of Mehta analysed the effect of chatbot on symptom tracking in primary health care for 400 individuals. Turns out, chatbot users were able to maintain more accurate records of their symptoms than those who weren't using it. Healthcare workers using chatbot summaries were quicker to identify deterioration in the patient's condition than those conducting only face-to-face checkups. This resulted in reduced hospitalisation and COPD patients recovered quicker.

Yet, there is a problem: Most COPD patients in India are low health-literate and they have difficulty describing their symptoms in the manner that the chatbots can understand. Technology fails to deliver chatbot support to the users who need it the most.

4.3.4 Paediatric Asthma

To assess the effectiveness of a chatbot in supporting children with asthma in the real world, Bose and colleagues conducted a real world test. They observed 79 children on a care plan supported with a chatbot for 4 weeks. The results were clear – 84.7% had more symptom control. Their caregivers believed the advice of the chatbot, trusted the advice, felt more confident in the identification of early warning signs, and did not delay in initiate inhalers. They even had fewer emergency visits than in previous years!

4.4 Barriers to AI Chatbot Adoption

4.4.1 Digital Infrastructure and Digital Divide

Typical issues across these studies are poorly performing digital infrastructure. In rural areas sharp network coverage, lack of smart devices (and shared devices create privacy concerns), a lack of reliable electricity (to charge). Rao's team also notes that absenteeism of electronic health record (EHR) connections also deprives doctors of chatbot data, undermining the entire concept of improved chronic care.

4.4.3 Barriers to learning about health and hygiene in other languages of instruction

Low digital and health literacy are linked together, particularly amongst older adults, rural families or those with a low income (or those living on a low income), that is, those at highest risk of chronic illness. This will not be resolved by making minor changes to the platforms. In the real world, the community health workers, such as ASHA and ANM, come in handy to assist patients to use the chatbot when they are unable to do so themselves. Devi, Krishnan and Venkatesh have all found this to be the most effective solution in the here and now: hands-on assistance

4.4.3 Linguistic and Cultural Barriers

The fact that India is a country with a variety of languages (22 official languages and various dialects) makes the design of chatbots difficult. An obvious solution is to make the platforms more robust in theory, but there haven't been adequate advancements. Mehta noted that the patients with COPD who were more likely to use chatbots in their native language (Tamil, Bengali, or Marathi) hardly used English-only chatbots. There is cultural resistance, too: Venkatesh and Agarwal noticed many people still think that the problem of chronic diseases is best solved with empathy of a real physician. Past bad experiences with tech don't help either, so it will take a stronger software offering to win people over.

4.4.4 Data privacy, security and legal uncertainty,

Trust issues with security and ambiguous regulations cannot be overcome through coding. There are three significant gaps, Krishnaswamy notes: (1) the lack of an official standard for advice, consent, and AI, (2) the lack of a strong process for getting consent, especially for those with low literacy levels, and (3) a lack of appropriate warnings.

4.5.4 Community Health Worker Mediation

Community health workers (CHWs), particularly ASHA workers and Auxiliary Nurse Midwives, play a crucial role in bringing AI chatbots to those who find navigating digital tools challenging. If these chatbots can't be used independently, these frontline workers fill the gap. When ASHA workers assisted, the clinical engagement rate was essentially similar to what you would expect to find in urban areas where people are using a chatbot on their own, Devi and

Krishnan found in the rural areas they studied. So, yep, people in rural areas may be less digitally savvy, but when given some assistance, that becomes almost inconsequential.

The use of chatbots is not equally distributed across the population.There are demographic and socio-economic differences in the use of chatbots.

When considering who uses AI chatbots, it's easy to see that age is a defining characteristic. These tools are used much less by older people (around a third to nearly half less than working age people). Xeriscaping isn't solely for comfort with tech, either. There are physical difficulties, memory loss and simply a desire to see a real doctor, in person. It is concerning, since this is the very population that can benefit the most from chronic disease management – and is the least likely to be able to access digital solutions during this time.Then you’ve got the rural-urban gap, and honestly, every study points it out. People in rural areas deal with a pile of hurdles: patchy internet, lower literacy, language barriers, limited support, and, often, not much trust in institutions. Thing is, the few who do manage to use AI chatbots get results that can match their urban counterparts. Devi and Krishnan make it clear—it’s not that rural communities benefit less, it’s that they have a tougher time accessing these tools at all. So, the issue isn’t effectiveness, it’s access. It’s a fairness problem.Gender throws more obstacles into the mix. In many conservative rural areas, women often don’t get a fair shot at digital health tools. Local norms restrict their access to technology, most phones belong to men, and there are real worries about privacy—especially sharing sensitive health information when the family uses the same device. These barriers aren’t just theoretical. They have consequences, particularly during pregnancy, when health support can be critical for mothers.Poverty just makes all this tougher. Fewer smartphones, expensive data, lower digital and health literacy, less English, and privacy concerns all pile up if you’re poorer. Ironically, it’s these very communities that get hit hardest by unmanaged chronic illness—hospital stays they can’t afford, costs that really can wreck families.

4.7 Government Policy and Platform Integration

It is the government's largest pledge towards digital health thus far, and a tremendous opportunity for artificial intelligence chatbots to go nationwide. By 2024, eSanjeevani has already cumulatively facilitated over 340 million consultations, even in remote and tribal regions, which lacked access to specialists prior to eSanjeevani. With this type of backbone, Rao et al. suggest that AI chatbots "may actually be able to take off". The catch is there – there are significant barriers for poor data integration with district health records, and limited compatibility with electronic health records at this time.

The Ayushman Bharat Digital Mission (ABHA) comes to the rescue. Connecting all patients' chronic disease information to their ABHA number enables a doctor at any location to see what the chatbot recorded, regardless of where the source of information was located.

Not to mention that there were changes after the Ministry of Health and Family Welfare published its Telemedicine Practice Guidelines in 2020. Online care for the first time was organized with rules and guidelines, and doctors felt more comfortable prescribing chatbots for chronic care. Even the direct link is made, after these guidelines were followed, more physicians took doctors' bots into their care plans.

Create a legal and regulatory framework for the sport of sailing.Develop the law and regulation of sailing.

4.8.2 The AI Opportunity Gap

The single Most Unanswered Question in all this is legal liability. Both Krishnaswamy and Menon use the clock as a metaphor here. So if a chatbot advises users to take risky drugs, or its algorithm fails to alert users to a heart attack, or it fails to provide the proper instructions for taking insulin.... who's responsible? Is it the chatbot company, the recommending doctor, the individuals who programmed it, or the hospital who supplied it? But Indian legislation does not have a clear direction and Menon's research indicates that this legal uncertainty is leading to hesitations among both doctors and patients to use these tools.

4.8.2 Data Privacy – Digital Personal Data Protection Act (2023)

The new Data law in India, 2023, sets guidelines and rights when it comes to the treatment of personal data, and consent plays a significant role. However, when it comes to healthcare, as

Krishnaswamy and Menon note, things are not so clear. Different from other laws, the law does not require security standards for companies that provide security to chatbots dealing with sensitive health data. There is also no clarity about how consent really works when chatbots are used to help tailor patient care with their information, or if patients have any protection if the information is breached.

4.8.3Algorithmic Bias & Health Equity

Algorithmic bias is a real threat for India. Most of the data that the chatbot is trained on might pertain to patients in urban areas, educated, English-speaking, but the advice will not always be applicable to rural users or anyone who speaks a different language. India must take steps to address this, says Krishnaswamy and colleagues, by requiring regular bias audits of AI health tools as well as a proper testing of these algorithms in different populations as national regulations.

4.9 SWOT Analysis

Table 4.1: SWOT Analysis — AI Chatbot Adoption in Chronic Disease Management, India

STRENGTHS	WEAKNESSES
• 24/7 patient engagement at negligible marginal cost • Documented improvements in medication adherence and self-monitoring across all four disease categories • 84.7% symptom improvement in paediatric asthma (Bose et al., 2024) • eSanjeevani integration capacity: 340 million+ consultations nationally • COVID-19 pandemic permanently expanded adoption-ready patient base	• Urban-rural and age-based digital divide limits equitable reach • Predominantly English-language design excludes majority of chronic disease patients • Absence of large-scale longitudinal RCTs with hard clinical endpoints • Poor EHR interoperability disrupts clinical data continuity • Elderly patients (highest chronic disease burden) show lowest adoption • NLP accuracy limitations in symptom triage for low-literacy users

STRENGTHS	WEAKNESSES
• ABDM health identifier enables longitudinal data integration across platforms • Strong government policy support (Telemedicine Practice Guidelines 2020, ABDM)	• Insufficient algorithmic bias testing and auditing
OPPORTUNITIES	**THREATS**
• Generative AI/LLM advances enable contextual, multilingual conversations • Advancing NLP for Indic languages enables genuinely inclusive chatbot design • Expanding rural smartphone penetration grows addressable population • ASHA/ANM network (900,000+ workers) provides nationwide CHW mediation capacity • ABDM API ecosystem enabling seamless chronic disease data integration • Public-private partnerships with Practo, HealthifyMe, Apollo 24/7, Tata Health	• Data privacy risks under evolving DPDP Act implementation • Algorithmic bias perpetuating healthcare inequities for marginalised populations • Legal vacuum on AI liability deterring clinician endorsement • Deep cultural preference for in-person clinical consultation • Rapid LLM technology evolution outpacing regulatory capacity • Risk of two-tier system: AI-enhanced urban care vs. degraded rural in-person care

Key Strategic Insight:

The key is, the best approach is to address the digital divide and language barriers head-on. This involves investing in community health workers, who can intervene when necessary, and chatbots that can communicate in local languages. Connect these to trusted government platforms and leverage the ASHA/ANM workforce – and you are utilizing what works.

4.10 Research gaps and future directions

The review reveals 6 big gaps in our knowledge:

Gap 1: Missing Long-Term RCTs: Most studies provide snapshots or quick looks, there is no evidence that chatbot-supported patient engagement has long-term effectiveness. With chronic conditions you must manage them for many years. Are chatbots effective in keeping people on track, year after year? We have no idea. There is a need to conduct large-scale long-term prospective randomized trials and follow up for 2+ years with true outcome measures such as HbA1c, blood pressure, hospitalizations, and quality of life.

Gap 2 – No Clinical Validation for Multilingual Chatbots: People have been talking about the importance of language but no single study has been conducted to test the effectiveness of chatbots in languages like Hindi, Tamil, Telugu, Bengali, Marathi and Gujarati in the context of chronic disease. We need research that is done to develop these tools in local languages and proves that they work in practice. It's a critical element of health equity.

Gap 3 — No Dedicated Studies on Marginalised Groups: Most studies ignore people who are marginalised such as elderly people, those from rural areas, and those with less resources. They are underrepresented in terms of barriers. Studies should be co-designed with these communities, conducted by researchers, and targeted at specific challenges.

Gap 4 — No Head-to-Head Tech Comparisons: There are no comparisons of different chatbot setups in terms of tests conducted against each other. There was no comparison of government platforms with private, rule-based vs generative AI and human oversight vs pure automation with similar patient groups. We don't have any real solutions.

Gap 5 — Lack of Research on AI Health Law and Regulation: India still requires robust and multi-disciplinary efforts to develop laws for the use of AI in healthcare. That involves legal, technical, clinical and patient voices being present. These are all the things that should be top priorities: setting liability rules, creating informed consent for those with low literacy, and requiring clinical validation.

Gap 6 — No Evidence for CKD and Heart Disease: Despite millions of people afflicted, the evidence base to date for application of AI chatbot for CKD and heart disease is near zero in India. These are challenging and difficult situations and chatbots might be able to help…but at present, no one knows.

The takeaway? It is obvious that there are significant knowledge gaps. Filling them up could revolutionize the landscape of chronic disease care in India by using digital health.Filling these would transform the landscape of chronic disease care in India using digital health.

CHAPTER 5: RECOMMENDATIONS

5.1 Learn how to work with government and policymakers.

1.First step is to focus on eSanjeevani–ABDM Chatbot integration. Advocate and encourage the use of AI chatbots, which have been clinically tested, in eSanjeevani and the ABDM health ID system. Open APIs to enable seamless flow of chronic disease information between chatbots and clinics. Ensure all government telemedicine services include chronic disease follow-up-specific Chatbot modules.

2) Develop an AI Health Governance Framework. Develop AI health rules specific to each industry under the DPDP Act (2023) and Telemedicine Practice Guidelines. The rules should include who is responsible for providing AI advice, require clinical validation and bias testing of chronic disease chatbots, ensure informed consent is acceptable for low-literate individuals and establish high standards for data security.

3. Fund Vernacular Chatbot Development. Implement a country-wide initiative on the clinical evaluation, validation and cost of a chatbot for chronic diseases in all 22 official languages as follows: ICMR's playbook. Ensure that all government-sponsored chatbots are clinically tested, in at least the top 5 regional languages of their target region.

4) Make a commitment to Digital Health Literacy. Promote Digital and Health literacy through Digital India, Ayushman Bharat Health and Wellness Centres and Schools. Include lessons on AI health instruments evaluation & utilization.

5.2 For Healthcare Administrators and Hospital Systems

1.Create within each institution chatbot governance systems. Ensure review panels review chatbot platforms before use, have clear measurements to track the quality of the content, and have rapid response measures in place when a chatbot identifies a clinical risk.

2. Track chatbot engagement. Include those statistics on chronic disease dashboards. Managers can quickly see when chatbots aren't being used, and step in with additional assistance.

3. Train clinicians about Chatbots. Show them how they work, when to use them, legal aspects of their use, and how to incorporate the use of chatbots into everyday care. Integrate the use and monitoring of chatbots into the routine of chronic diseases.

4. Run ASHA/ANM-led pilots of chat-bots in rural clinics. Provide community health workers with chatbots and provide them with training to assist patients—particularly those not highly literate—in using these.

5.3 For Technology Developers

1. Ensure vernacular language is a key priority. Target the 5 languages that have the largest population with chronic diseases: Hindi, Bengali, Telugu, Tamil and Marathi.

2. Design for the elderly and low-literacy people from the beginning. Do NOT add this at the end. The main software should be easy to use, minimal reading of text on the screen and little confusion in the menus. All of this should be standard – voice interfaces, big simple buttons, and options for caregivers.

3. Provide open and ABDM-compatible APIs to connect data of chatbots with clinical and government health systems. Having the data available to doctors and health registries instantly makes chatbot data more useful.

5. Conduct continuous clinical monitoring—frequently test your NLP accuracy, test for bias between groups and monitor actual patient outcomes. This will maintain the platform in good sharp condition and ensure it meets regulatory standards.

5.4 For Healthcare Providers

1. Don't put off- recommend AI Chatbots to patients to complete tasks such as taking medication, logging blood pressure etc. for chronic diseases so patients need not guess.

2. Run real-time, on-location chatbots. Review or discuss information collected from the chatbot during visits—and adjust treatment or recommendations if patient reports or does not report the exact same information.

3. Report problems or safety concerns with chatbots as you would normally do. This assists everyone (regulators and clinicians) to learn and improve care in the long-term.

CHAPTER 6: CONCLUSION

The current review synthesizes the findings of 12 peer-reviewed studies from India from 2019 to 2025 related to AI chatbots in chronic disease management and patient engagement. The review categorizes the study into eight themes based on commonly accepted frameworks such as TAM, UTAUT, DDID and Trust-Extended TAM and provides a clear picture of the role of chatbots in the health sector in India today.

These studies demonstrate that, with careful design and implementation, chatbots can indeed play a significant role in encouraging patients to be more engaged in their health management. There are real benefits, as well: higher medication adherence, more patient self monitoring, more continuous symptom tracking, and greater overall satisfaction, from diabetes to hypertension, COPD to paediatric asthma. And, one of the studies conducted on children suffering from asthma even witnessed an improvement in symptoms control after a month, which is a remarkable figure and serves as proof of the ability of chatbots under the right supervision. Digital health isn't just a buzzword anymore as government-supported platforms such as eSanjeevani are increasing access to care.

So what are the factors that increase the adoption using these chatbots? The three things that continually come to mind are 'usefulness', 'ease of use', and 'trust'. Adoption rates increase when doctors advise people to adopt and when there is assistance from government programs and community members. But, not everyone is getting on board. The younger, more educated, and urban are adopting chatbots at a much higher rate than the rural, older, less technologically savvy and particularly female patients who are sidelined.

Not all is smooth sailing. The digital divide, language barriers, age, cultural skepticism, privacy concerns and the absence of clear rules pose significant obstacles for a fair scaling of the use of chatbots. Unless these are resolved, we may be left with a split system, with the city benefiting and the more vulnerable the outs. Equity is a good reason to target this; those who could benefit most from additional support are likely to be the ones who are going to be missed.

6.1 Limitations of the Review

There are a couple of important points to note. First of all, this review is purely based on published information and not on any new data or fresh fieldwork. It's a map of what the literature says – not a window into new experiments, or direct cause-and-effect.

Second, it's a small pool—12 studies, each with a different disease, setting. This is difficult to align the results or to make any conclusions for all India. None of these studies is a randomized controlled one, which is the most reliable type of evidence.

Third, there's a language filter. All studies mentioned are in English and important studies in Hindi or other languages may not have been included and may bias the overall results. Oh, and the review ends in 2025, so the latest developments are not covered—particularly all this new generative AI.

But, let's face it, positive studies are more likely to be published in the first place, so there may be negative or neutral studies that we just don't have because they weren't published.

Clearly, there is a need for more primary research – sound trials, research in regional languages, and more real-world testing to determine where chatbots add value in practice.

The big picture? While AI chatbots have significant potential as digital health tools for chronic disease management in India, they are still in early stages and their effectiveness over time, how to scale up their reach, and their ability to truly benefit all, not just a fortunate few, remain to be seen. This will require a lot of teamwork. Everyone from policy makers, doctors, techies, patient advocates and researchers should get involved. What we're not discussing here is the availability of a nice to have, but it's a must if AI chatbots are to truly help in the management of chronic diseases in India.

6.2 Future Research Directions

So what's next? There is a need for larger, longer studies, particularly randomized controlled studies, conducted in the Indian healthcare system, with all types of population, particularly the population in the rural areas or underserved population. Future studies should investigate the use of chatbots with national health programmes, the ability to maintain privacy and security of patient information, how to ensure the chatbot is accessible to patients in a variety of languages, and innovative ways that generative AI can be utilized for patient engagement and self-management in everyday life. Much remains to be seen.

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