# Original Research Article

# Artificial Intelligence in Healthcare: A Systematic Review of Virtual Healthcare Assistants

## Abstract

Health is one of the most important basic needs of people. With the advent of the information age and the deepening of AI technology, artificial intelligence is playing a vital role in various fields regarding people’s demands and work, like transport, service, finance, manufacturing, gaming, entertainment, agriculture, and healthcare. With improved health awareness, increasing concern over general health and well-being is becoming a popular demand. Therefore, the health system must address this concern and answer the related expectations of the people. Health systems and delivery of health services must follow an easy and simple process for their end-users. This would be time-consuming and cumbersome in an analog process of health service delivery. To address this complexity as well as providing an understandable service, the introduction of various virtual health assistants (VHAs) is a feasible option. Virtual health assistants are artificial intelligence-based options that can respond to the health-related queries of people in a simplified way and in real-time (G Curtis et al., 2021). The well-accepted examples of VHAs are Alexa and Siri, which answer the queries of people making their lives easier and comfortable in sectors like banking, shopping, serving, and entertainment. The intersection of this technology in going one-step forward to the well-being of people regarding health must be valuable. With time, the demand for VHAs regarding people’s health is increasing for general fitness, diet, exercise, anxiety, depression, COVID-19, chemoprotective agents, personal health records, medicine prescriptions, communication with healthcare professionals, planning, and scheduling. The introduction of VHAs would bring the health care system closer to the health needs and health behavior of the people, especially with the growth of mobile devices. The perceived effectiveness of compound micro-counseling on the prevention of sexual risk behaviors (SRBs) among students is an important knowledge gap for adolescents aged 10-19, which is a transitional group from childhood to adulthood. They would receive adequate health content triggered by their surroundings through their perceptions.

Keywords: Health Systems, Micro-Conseling, COVID-19, Virtual Health Assistant, Sexual Risk Behavior, Alexa, Siri, Health Related Queries.

## 1. Introduction

The healthcare sector is facing challenges caused by the increasing global population such as emergency responses, limited healthcare professionals, long waiting hours, overworked professionals leading to burnout, and an increasing number of patients with chronic diseases. To address these issues, healthcare institutions are looking for Assistive Digital Intelligence (ADIs) technologies. One type of widely explored ADIs in healthcare to ease the workload is conversational agents in the form of chatbots. The proposed chatbots generally aim to screen patients, provide medical recommendations, gather medical history for reporting purposes, and supply psychological support and therapy. Chatbots provide consistent responses and can be accessed by multiple patients at once. They are cheaper to maintain than human agents once implemented. However, as patient safety and data confidentiality are issues raised by the introduction of ADIs in healthcare, experts are now emphasising ‘Trustworthy’ and ‘Ethical’ AI. The first concern with machine-dependent healthcare is patient safety. Healthcare professionals fear that their life-saving recommendations may lead to fatalities and lawsuits if they are produced by an uncontrolled machine. Additionally, patient data confidentiality is a major hurdle as several chatbots either collect personal data or are connected to EMRs (Sen Bhattacharya & Sinai Pissurlenkar, 2023). Chatbots are an attractive proposition as they can act as the first point-of-contact automation with patients before they interact with healthcare professionals. Users encounter a chat interface with text or speech input where they can engage in a conversation. The goal of the user is to explain their concerns such that the chatbot can provide useful information or guidance. The chatbot must map the user input to an appropriate response from its knowledge-base. An important step would be to establish a dialogue system based on a type of machine learning technique. There are primarily two modes of incorporating AI in chatbots. The first is supervised learning, where the knowledge-base of the machine is finite and annotated queries must be added to its knowledge-base. Induction requires operations to produce a Q&A machine based on data that are stored in a database. The second is unsupervised learning, where the machine learns by itself to respond to unknown ground truths. Reinforcement learning can be an additional approach where the response policy of a Q&A system is improved based on the rewards given.

## 2. Background

In recent years, Artificial Intelligence (AI) technologies have gained even more traction (Bajwa et al., 2021). The growing capabilities of AI, combined with ongoing improvements in computer science and availability of data, have allowed AI to be integrated in diverse applications (Khinvasara et al., 2024; Dave & Patel, 2023). Health and healthcare are not an exception to this trend. Starting in 2020, several countries all around the world faced challenges related to the limited capacity of their health systems in dealing with the COVID-19 pandemic. AI technologies addressed these challenges, for instance through the analysis of data from hospitals, even large-scale hospitals, to guide resource allocation (Alowais et al., 2023; Nallamothu & Cuthrell, 2023). Virtual Health Assistants (VHAs) used in patients’ homes also decreased the burden on the health systems and, in some cases, improved health outcomes. Likewise, for some time now, text-based chatbots were being integrated into electronic health record systems. AI-driven chatbots were developed for patient appointments, medication reminders, and storage of patient information, amongst others.

In general, these applications became common during the COVID-19 pandemic exclusively or, at least, in combination with other technologies, in response to a sudden need in some cases. These VHA applications and their use in health have received less attention in the medical informatics literature than other applications of AI in health, such as for image and data analysis using Machine Learning algorithms. For these reasons and to provide a comprehensive understanding of the VHA landscape in health and healthcare, a systematic review of the literature on VHA use prior to and during the COVID-19 pandemic was conducted. This review includes summaries of design, performance, and experiences with existing VHA prototypes and systems. These prototypes and systems have acted or collaborate with conveners to provide health advice and schedule appointments. In addition, they capture, communicate, analyze, and store health-related data. Ultimately, they are anticipated to improve health outcomes or the quality, efficiency, accuracy, and safety of healthcare practices. It is also considered whether and how VHA prototypes and systems guarantee safe, valid, ethical, and accountable application of AI in health and healthcare and whether these applications are expected to affect healthcare systems, practice, workforce, or education (G Curtis et al., 2021).

### 2.1. Overview of Artificial Intelligence in Healthcare

Artificial Intelligence (AI) has the potential to disrupt and transform the healthcare landscape. At the same time, AI brings new challenges, questions, and concerns, especially with regards to its ethical use in healthcare. There are many opportunities AI can help improve patient care, health systems, and health services. Applications for AI include triaging and stratifying patients, allowing specialists to focus their attention on patients at a greater risk of adverse outcomes; analysing values in medical imaging enabling the detection of malignancies; and monitoring symptoms of diseases, identifying and alerting patients to worrisome conditions. The topic of installable services refers to a 3rd party developing an analysis algorithm for deployment within the healthcare context. An example is a detection algorithm trained on population-level data. Moving the data to the algorithm would incur risk to privacy; that is, the algorithm should be moved into the healthcare organization. The algorithm is installed within the healthcare organization, and a deployment study is conducted. In contrast, a 3rd party service refers to a 3rd party hosting a service and making it available to healthcare.

AI-enabled services in healthcare are transforming the industry, and understandably, investments on this are sky-high. However, these technologies are still in their infancy and best intentions are not enough to get the implementation right. AI-based solutions can enhance the efficiency and effectiveness of healthcare delivery but can also worsen the already prevalent inequalities in healthcare systems or lead to dehumanization of care experiences. Prevention and mitigation of such unintended consequences is essential to safeguard trust, credibility, and ultimately the long-term viability of AI technologies. The infusion of AI into healthcare systems and processes raises important questions and challenges, such as robustness, accountability, and trustworthiness. These questions and challenges are part of what is called responsible AI.

### 2.2. Importance of Virtual Healthcare Assistants

Virtual healthcare assistants (VAs) can function 24/7, situated in the same sphere as potential patients, and deliver personalized attention (J. P. van Bussel et al., 2022). In addition to answering healthcare-related questions, VAs can give information about preventing diseases and healthy lifestyles, within the constraints of the healthcare professional’s guidelines. Following predictions of the ‘first encounter’ trends in the delivery of healthcare, with VAs delivering non-emergent cases and triaging the workload of healthcare professionals (HCPs) will be largely released. Global developments in Artificial Intelligence (AI) and the advent of Chatbots (CBs) made the creation of VAs possible. Besides the above-mentioned advantages, costs for both the HCPs and the patients could be lower as there would be fewer delays in scheduling appointments, shorter waiting times for the patients, and smaller traveling distances and times to reach HCP practices. High workloads and inaccessibility of HCPs can lead to reduced treatment effectiveness and increased severe disease burdens for patients. Given the above-mentioned complexity of healthcare trajectories and the accessibility of information on treatment options, patients feel overwhelmed at times. Many patients want more information than needed, especially in the early stages of treatment. Patients prefer to obtain such information preferably in a non-threatening manner, advised by a trusted source. However, the development, structuring, and maintenance of VAs in health systems seem to be hindered by a lack of knowledge.

## 3. Methodology

This literature review was originally planned as a scoping review with field expert involvement. However, scoping reviews were deemed unsuitable for this literature review. Electronic search strategies were developed through consultation with a librarian and subsequently run over five key databases of scholarly and peer-reviewed health and artificial intelligence/language processing literature: (G Curtis et al., 2021). A preliminary search was conducted across the five databases, and the results were compared to ensure substantial overlap. After filtering out duplicate results, the databases’ results were pooled and screened again to remove non-human studies, gray literature, correspondence, and non-research studies. The remaining literature was screened in reverse chronological order by year and reported on over time, focusing on the methodology, ethics and impact, data sources, and international use. Databases were then continually searched using the same keywords until saturation of discovered literature was reached. This methodology is outlined in more detail below.

“Virtual healthcare assistants” and related terms were used to capture terms used in the healthcare community (healthcare, health professional, etc., variants on “assistant”, “agent”, “helper”) and individual populations (patient, consumer, user, etc.). Inclusion criteria were that the article was peer-reviewed, written in English, and focused on the provision of health-related information and services through virtual assistants. Any articles that focused on the use of virtual assistants in healthcare but did not involve the assistant itself were excluded. Virtual assistants in healthcare that were tools used by health professionals were also excluded, focusing solely on virtual assistants for the general public.

### 3.1. Research Design

This systematic review was conducted according to the guidelines. The study was registered with the International Prospective Register of Systematic Reviews.

Eligibility Criteria  
Eligibility criteria were designed by the authors using the population, intervention, comparator, and outcome framework (population: adults; intervention: virtual health assistant; comparator: design characteristics; and outcome: user experience). Original research articles in peer-reviewed journals and full-length conference papers published between 2000-2019 were included. Studies with adult samples (aged ≥18 years) were included. Studies published in English and examining virtual health assistants providing health-related information and support, aimed at the health consumer relating to the prevention, management, or treatment of any physical or mental health condition, were included. Virtual health assistants functioning autonomously on any electronic device including web-based, mobile-related, and artificial intelligence technologies, were included. Studies comparing design characteristics between ≥2 versions of a virtual health assistant, which influence its look and feel without affecting its core content, purpose, or function, were included (for example, differing visual accents, commercial brand characteristics, or uploads), were included. Studies evaluating user experience outcomes (primary outcome) were included (for example, studies measuring self-reported evaluations indicating a more positive or negative experience, affect, or intentions to continue using the virtual assistant; and objective measures of user engagement, for example, duration of engagement, counts of visits, or frequency of use). Only quantitative data was sought from studies. Dissertations, review articles, conference abstracts, and studies with children were excluded. Similarly, virtual assistants used for training or educating medical professionals, as well as robots with a physical body, were excluded.

### 3.2. Data Collection Methods

Formal academic A review of the effectiveness of virtual assistants in health care is required. This review was reported according to the checklist. Eligibility criteria were designed using the population, intervention, comparator, and outcome framework. Population: Adults. Intervention: Virtual health assistant. Comparator: Design characteristics. Outcome: User experience.

Original research articles published in peer-reviewed journals and full-length conference papers were included. Studies with adult samples aged ≥ 18 years were included. Only studies examining virtual health assistants were included. The authors defined virtual health assistants as any virtual assistant aimed at the health consumer relating to the prevention, management, or treatment of any health condition. Virtual health assistants were included whether they functioned on a website, application, or other electronic device such as SMS or phone calls. Wizard of Oz virtual assistants were also included. Studies comparing design characteristics between ≥2 versions of a virtual health assistant were included. Design characteristics were defined as characteristics that influence the look and feel of the virtual assistant without affecting core content. Examples of design characteristics included visual cues, language style, or interaction modality. Studies evaluating user experience outcomes were included. User experience was defined as self-reported evaluations of the virtual assistant or the user’s interaction indicating a positive or negative experience, affect, intentions to continue using the virtual assistant, and objective measures of user engagement. Only quantitative data were included. Dissertations, review articles, conference abstracts, and studies with children were excluded. Virtual assistants used for training or educating medical professionals, as well as robots with a physical body, were also excluded.

### 3.3. Inclusion and Exclusion Criteria

The research used a systematic review method proposed by (G Curtis et al., 2021). The eligibility criteria were developed using the Intervention, Comparator, Population, and Outcomes framework. To be included in the review, one of the following criteria must be met: original research articles in peer-reviewed journals or full-length conference papers; studies with a sample including participants aged 18 years or above; studies describing virtual healthcare assistants; care-focused virtual assistants; virtual assistants on any electronic device; and studies comparing design characteristics between two or more versions of virtual assistants together in one group analysis. Design characteristics are defined as those that influence how the virtual assistant looks and feels without influencing its intrinsic content, purpose, or function. Studies assessing user experience outcomes were included as studies describing self-reported evaluations of virtual healthcare assistants or evaluations of interactions with virtual assistants in general. Exclusion criteria include the following: dissertations and reviews; summaries of studies; studies conducted with children aged less than 18 years; virtual assistants designed exclusively for training or educating doctors, nurses, or other health professionals; studies describing virtual health assistants with a physical body; and studies that did not include or compare users’ evaluations of those virtual health assistants. Search terms and restrictions used in the searches are shown in Table 1. There were no restrictions on language. To identify relevant quantitative studies, peer-reviewed journal articles and full-length conference papers published from January 1st, 2000, to December 31st, 2020, were searched using the PubMed, CINAHL, Psychology and Behavioural Sciences Collection, Web of Science, ScienceDirect, and IEEE databases. These databases were chosen because they cover a broad range of disciplines from which virtual healthcare assistants may emerge or be evaluated. Studies were searched using keywords and Medical Subject Headings (MESH) terms including: “virtual assistant or healthcare assistant or digital companion or conversational agent or chatbot or artificial intelligence” and “user experience or usability or satisfaction or acceptability or engagement or effectiveness or interaction.”

## 4. Literature Review

Artificial Intelligence (AI) has greatly expanded through deep learning and natural language processing, resulting in promising developments in virtual assistants (VAs). Virtual assistants are embedded in devices, providing guidance in completing tasks. In healthcare, the rise of virtual assistants has diversified delivery methods, including chatbots, IoT, smart speakers, and many other forms. This diversity has enabled public access to self-healthcare tools, reducing bounds of practicality for users and healthcare systems. However, virtual health assistants (VHAs) systems face challenges, concerning data privacy, sophistication to rightly map user need and recount to it, as well as limitations in the ability to stay relevant, engaging, and trustworthy. Reviewing the current VHA landscape can help map opportunities for future research.

The scoping exercise conducted had three objectives: (1) Describe the evidence available on the user experience of virtual health assistants; (2) Identify gaps in the literature, and outline future research directions; (3) Produce a knowledge gap map that meets objectives 1-2, and draw out implications from it. Definitions of relevant terms were formed as part of the protocol, and a systematic search of the grey and peer-reviewed literature was conducted through 38 databases. The search identified 3,963 combined results, with 938 titles and abstracts screened. Included studies examined the end-user experience with a virtual health assistant. A range of methods were employed, with most publications focused on web based virtual health assistants (G Curtis et al., 2021).

### 4.1. Current Trends in AI Healthcare Assistants

Over the last decade, the adoption of AI healthcare assistants has increased significantly, largely as a result of the COVID-19 pandemic. The AI market in healthcare is predicted to grow at a compound annual growth rate (CAGR) of over 38% in value in the coming decade. AI-based healthcare assistants are a specific form of personalized assistants that automate tasks in the healthcare industry, where each system mimics human cognition and behaviour to assist the healthcare worker. In this sector, the healthcare assistant can simulate both visual (via a virtual avatar) and speech (via a voice avatar). The speech component can automatically reply to the listener’s questions or be enabled with “Talkback” control, such that the listener is no longer limited to choosing from predefined queries. The audio/video components can assist, monitor, screen, simulate therapy, educate, and provide feedback to the patients. Recently, COVID-based healthcare assistants have been developed to answer pandemic-specific queries. Other new implementations include systems capable of monitoring eating habits, reminding patients to take medicine, and conducting risk assessment questionnaires. Chatbots utilized to monitor sleep, act as a motivational coach, and educate patients with chronic health conditions such as diabetes and hypertension have also been released (Sen Bhattacharya & Sinai Pissurlenkar, 2023).

Prior to telemedicine, a patient was required to find a physician and book an appointment, which involved switching between multiple websites to check for the relevant practitioner type, their charges, current appointments, and validity. To avoid systematic knowledge entrapment regarding the complicated healthcare ecosystem, important life-critical information must be integrated within one body, similar to general-purpose search engines. Instead of conducting extensive research, a universal healthcare assistant could be conveniently leveraged through voice queries, leading to the development of virtual healthcare agents to automate the process.

In any healthcare or general industry, decisions are made based on certainty regarding predicted outcome analytics. This is often achieved through model deployment. Within the healthcare sector, the methodology for building models must be interpreted and bias-free modeling must be ensured throughout the lifetime process of workflows and insights. The deployment team is responsible for operationalizing the decisions to ensure smooth production forecasts, without deviation from the pattern of training and test sets. The integration team ensures compatibility between clips of gluing blocks and the structure of the production systems. This includes working conditions such as techno-physical setups, guidelines, and proximity and access considerations. Compatibility must be checked continuously, and the agency must contain the capacity to dynamically scale to an AI-based, hybrid, model-operationalization and -integration healthcare assistant. Current systems using smart search web crawlers to assist the healthcare agent are incapable of addressing dynamic changes in the production environment, or identifying possible changes beforehand.

### 4.2. Case Studies and Applications

Two major national studies were identified that projected the future state of various aspects of AI applications in patient care. Released over six months apart, the two studies built on one another, with one reinforcing the other and providing a comprehensive overview of the anticipated uses of AI. However, both focused exclusively on clinical practice and did not examine potential AI applications across the entire spectrum of healthcare services. The findings regarding AI applications in clinical practice include:

Text analysis software will be widely adopted to help clinicians analyze medical documentation and free up more time for patient care. Similar methods will be adopted to analyze clinical images and make referrals more efficient. These tools have the potential to improve the work of U.S. radiologists, especially those with less than ten years of experience (Surely, 2023).

At the time of polling, the majority of U.S. clinical and administrative leaders reported using voice-enabled virtual assistants in their organization, with many using enterprise-grade AI applications. These tools will evolve to become more cognizant of the contexts and conglomerates of various patient populations.

AI chatbots will revolutionize patient screening and appointment-making. U.S. health systems that did not already have chatbots implemented them during the COVID-19 pandemic. The technology will advance further to enable more complicated dialogues, including primary care questions, prescription refills, and inquiries about test instructions. Recent event-driven AI chatbots help healthcare organizations manage overwhelming call volumes and provide personalized interactions at any time.

AI will be integrated into most electronic health records, with all clinicians reporting rapid automated documentation generation without sacrificing quality. This innovation will enable documentation to be done efficiently during patient visits and improve the accuracy of problem lists and problem-based prescribing. This is already happening among some top-tier health systems.

Real-time clinical decision support will be tightened, with most organizations reviewing and intervening in potential drug interactions. It will also evolve to guide clinicians in allocating their time during patient visits, enabling extensive auditing of referral patterns to improve health equity, and reshaping educational events using synthesized EHR data. The personalized summaries of patients’ medical histories created by AI will allow clinicians to better focus on patients.

Together, these innovations will reduce underlying clinician burnout. Other day-to-day efficiencies through technology at the patient level, including digital pre-checkin and digital postcards, will further support busy clinicians.

### 4.3. Challenges and Limitations

Despite rapid advances in artificial intelligence (AI), there are still some challenges in their application to healthcare domains. Some further research needs are discussed on both short- and long-term perspectives.

4.3.1. Sustainability Concerns Healthcare organizations worldwide have greatly invested in digital solutions in terms of financial and human resources. Providers need to ensure that the new solution can bring the desired outcome within a reasonable timeframe. Past experiences in the proliferation of AI-enabled healthcare technology have shown a tendency for underutilization of solutions post roll out, with resources ineffectively invested(Solomon Antwi Buabeng et al., 2024). There must be a thorough upfront analysis of the anticipated outcome, maturity of the technology, implementation effort, required operating resources, and necessary maintenance packages.

4.3.2. Ethical Concerns The increasing presence of AI technologies raises ethical issues in relation to a suspected lack of fairness and inclusivity in some solutions. Since VHCAs are trained based on historical data in most applications, chances are that the AI deliberates unintentional biases that were encoded in the training set. Additionally, several AI-enabled tools leverage user-generated content as input data without users’ consent for advertising and marketing purposes. For social chatbots, it is challenging to define the border between helpful and harmful advice regarding ethics and content moderation. This issue is further magnified in healthcare chatbots, which may give inappropriate medical advice to users seeking help. A recent incident illustrates the imperfection of current health chatbots that when instructed to ponder a person’s likelihood of developing cancer, four out of six trusted health chatbots recommended a precision medicine or clinical trial. The aforementioned ethical issues could also lead to reputational loss for hospitals. Health chatbots must take the precautionary principle, providing a disclaimer when giving harmful advice that additional consultation with healthcare professionals is imperative. Moreover, there must be a discussion between stakeholders, regulatory bodies, and ethical committees on the governing structure of healthcare chatbots in terms of judging whether a chatbot is reliable or not.

4.3.3. Data Concerns Healthcare systems are often worried about data security and protection. Organizations can provide better data safety. Under the current global pandemic, AI technologies capable of assessing health status remotely can be set up to reduce the risk of spreading the virus, such as early observation of pasture soundness using computer vision in a clinical environment.

## 5. Technological Framework

Artificial Intelligence (AI) is described as the simulation of human intelligence processes by machines, especially computer systems (Surely, 2023). Applications of AI include Expert Systems, Natural Language Processing, Speech Recognition and Motion Detection. Deep Learning, a subclass of Machine Learning (ML), uses networks of algorithms, inspired by the brain, to learn without explicit programming. The initial patient-facing tools involved extra actions from patients. Still, with time, patient-facing AI applications are designed focusing on Multi-modal conversational voice interfaces (C-VUI), for patient acquisition, engagement, and retention in IT and health-related industries. C-VUI can converse with patients in their own language in real-time and effects the screening instead of traditional mediators. Voice-enabled applications have become alternatives to the tiring use of keyboards, corporate facing applications, and the more involved but less ubiquitous conversational agents on mobile devices, smartphones and tablets. The integration of VUIs into traditional healthcare modalities enhanced operation speed by shortening the time to document clinical information and minimising manual data entry work.

The architectural framework for the development of a voice-based clinical VUI is proposed. Interactions slide from input/output with non-verbal modalities, through types of dialogue, contexts, and systems architectures. Procedures are outlined at allows for granularity. Systems are analysed across whole duration of engagements and states with reference to deontic operators. Principles are discussed that are accumulated from industry and academic sources and their implications for design and development. The importance of conducting formative assessment with clinical professionals, iteratively providing sufficient formality and rigour, and the possibility of generalisability across brands and types of enterprise systems are illustrated.

AI can aid applications within consumer-oriented healthcare. Large conglomerates are rolling out wearable devices so consumers are more responsible for their healthy lives. The analysis of speech recognition and synthesis, natural language processing, computer vision, and R&D reveal consumer applications of AI-based voice technologies. Applications not perceived by clinicians, such as mental health products and systems for the self-care of illness conditions, have no clinical counterpart. AI-VUI consumer applications edge into the expensive clinical IT market sectors, aiming to be the clerk behind all conversations about questions asked during appointments with GPs and clinicians.

### 5.1. AI Technologies Used

AI has been steadily incorporated into Virtual Healthcare Assistants to provide service-oriented solutions based on Automatic Speech Recognition and Natural Language Understanding. Virtual Healthcare Assistants combine Artificial Intelligence technologies and patient-facing applications in mobile health apps and web interfaces to allow patients to converse about their health 24/7. As knowledge and dialogue bases, Behavioral Health is widely studied and used in the rehabilitation of Mental Disorders, which can be facilitated with Virtual Healthcare Assistants. Popularity and efficacy growth widely led to the design and introduction of custom solutions from other sectors. Deep learning neural models are now widely available in the cloud, which has also developed libraries of pretrained models for use by non-experts.

An online survey was conducted in AI technologies in VHA Systems and academic search in relevance scientific publication databases. As a result of the literature review of the healthcare organization design and use commentary, selected technologies and algorithms are briefly discussed. The paper concludes by discussing their applicability in VHA systems and the issues in integrating and deploying them. Over the last two decades, other than sound-based Spoken Dialogue Assistants, remotely accessible chat and voice-based humanoid neuro-computers manipulated using speech for Virtual Healthcare Assistants 24/7 personal assistant, have been researched and analyzed. Successively usable web app and mobile app-based chatterbot deploys knowledge and dialog bases for domains such as Health, Culture, General, and Personal Affairs widely worldwide.

Voice-conversable Personal digital Assistants were introduced in practical applications using fixed speech codec-based telephonic services. VHA named chatbots and those that allow spontaneous Speech based textual knowledge and dialogue interfaces are also emerging rapidly to provide service-oriented solutions based on ASR and NLU. Allowing patients to consult about a symptom, over-the-counter drug recommendation, appointment services, or routine queries such as vaccination and COVID-19 questions, have designs and successful deployments in production systems.

### 5.2. Integration with Healthcare Systems

Lack of interoperability in holistically connected healthcare systems can contribute to failure. A lack of collaboration between EMR vendors and healthcare providers since the introduction of EMRs is still a challenge today. A fragmented infrastructure creates silos with no mechanism for information sharing. When data is shared, collaboration is limited to passive sharing, such as electronic referrals. Healthcare Assistants with a Virtual Assistant (VA) and Integrated Electronic Medical Records (IEMR) would enable active collaboration. A VA to answer the Health Assistant’s questions could allow the agent to proactively check in with users and ask questions based on historical entries. By integrating Workback into vendor EMRs, VAs could also present answers alongside a doctor’s chart as they enter data.

Education and engagement are essential to overcome worker anxieties about introducing AI technology. A recent survey revealed that less than one in five healthcare workers trusts general AI. Doctors worry about the loss of autonomy and integrity in the workflow. A portion of doctors fear implications for malpractice insurance rates. Those who believe they would be replaced are assets to the medication team (Fadhil, 2018). Establishing credibility and generating media celebrities aligned with operators to correct misinformation, preserve a human presence, and help staff adjust are successful strategies in tech transition history. This step is crucial in promoting stakeholder buy-in and positive perceptions of the project. A healthcare assistant’s naming can help it feel more approachable and less intimidating. Adjusting settings to speak informally and acknowledge its nature will assuage worries about misunderstanding.

VAs built on a new foundation, rather than as an add-on to existing products, would support an assortment of healthcare services. Current technology can take questions about adherence data and polity, as well as explore their roots. Foundation work in accessing lab results opens patient education about alternative treatment types, as well as clarifying treatment and drug mechanisms. A VA can improve the speed of drug prescription here—a doctor can request "Cholesterol treatment" while they browse. Similar questions could also be made to veterans, who may better describe their experience and exhibit the health benefits of new Pathways. A deeper dive would center the discussion around smoking and offer alternative treatment pathways.

Integration of the Assistant with IEMR systems would make it a real-time tool in answering team-members’ questions. Understanding natural language allows for more frequent and granular queries of the input data. In-depth lab results analyses have been implemented with this approach (Sen Bhattacharya & Sinai Pissurlenkar, 2023). Additional integrations with understandings in request and response formatting would broaden accessibility. Moreover, work in health determines medication adherence definition and establishes education plans for missed items.

## 6. User Experience

An exploration of the user experience of virtual healthcare assistants is undertaken. A systematic review of studies that explore the user experience of virtual healthcare assistants is presented, along with an exploration of the design characteristics and technical functionalities that affect user experience. Such virtual healthcare assistants may be defined as; conversational agents that interface with users to provide information, symptom checks, and health recommendations via a voice or a text interface. Design characteristics include 1) visual appearance, 2) communication style, and 3) language features. Technical functionalities include 1) interactivity, 2) multimodality, and 3) personality traits. An examination of the user experience of virtual healthcare assistants can assist in the establishment of best practice guidelines for the design of virtual healthcare assistants.

Advancements in machine learning and artificial intelligence offer promise for delivering automated, tailored, and convenient health assistance. Virtual assistants, often referred to as chatbots, conversational agents, and dialogue systems, are digital services designed to simulate human conversation and provide personalized health responses. Virtual assistance has a broad spectrum of verbal and non-verbal capabilities. They can be narrowly programmed with structured conversations to answer commonly asked user questions, or they can be open by conversing in an unlimited manner with the use of machine learning, natural language processing, and other AI-based techniques (G Curtis et al., 2021).

The user experience (UX) of a virtual health assistant (VHA) refers to the perceptions and responses of a user that are attributed to the use of or anticipated use of a VHA. The user experience varies from person to person and consists of multiple dimensions. The UX is influenced by a range of design characteristics and technical functionalities, including presentation, functionality, and interactive behavior. Factors can be classified into three design characteristics: visual appearance, communication style, and language features. Factors can be classified into three technical functionalities: interactivity, multimodality, and personality traits (J. P. van Bussel et al., 2022).

### 6.1. Patient Perspectives

The increase in cancer incidence raises an increasing need for efficient cancer care and support. While healthcare professionals (HCPs) form the backbone of cancer support, technology is expected to serve as a scalable cost-effective solution to support sufficient cancer care. VA technology can play an important role in increasing the scalability and accessibility of cancer solutions worldwide. Patients’ perspective, or more specifically their attitudes and behaviors towards this technology, has been the most neglected perspective thus far. Meaningful VA-technology acceptance research in this field is still lacking. Existing literature is scattered among various use cases, making a distinct differentiation of patient VA use cases and a broad overview of attitudes and behaviors difficult to obtain. Understanding the determinants of acceptance is indispensable for the successful adoption of this solution amongst cancer patients.

Patients are becoming increasingly interested in using VAs in general. Different attitudinal patterns toward the application of specific VAs among cancer patients are uncovered. Most patients consider it normal to use a VA to engage with care providers or receive treatment information. Patients are mostly neutral towards VA applications addressing reminders and daily reports, while they believe it would be inappropriate to confide personal concerns or feelings to a VA. Gender differences in VA use case perceptions are identified. Chatbot anxiety is generally low among patients, with female patients expressing somewhat higher anxiety levels (J. P. van Bussel et al., 2022). For precise insights into the underlying factors influencing the acceptance of general VA technology, and its use in the context of cancer, further research is suggested. However, existing systematic knowledge about these factors and potential moderators and mediators amongst cancer patients is scarce.

### 6.2. Clinician Perspectives

Main barriers to clinicians’ future use of VHCAs included concerns about patient privacy, protective legislation that encouraged professional gatekeeping in diabetes management, and the usability of the VA. Clinicians identified improvements to the realism of VHCAs’ speech and body language as the primary means to increase engagement. Concerns about patient levels of engagement, particularly the risk of a listener being distracted, were also highlighted. Future investigations should investigate attitudes toward clinical delegation to a VA and the advantages of structuring consultations in parallel rather than sequentially (J. P. van Bussel et al., 2022). The study was conducted with clinicians' perspectives on the use of VHCAs in diabetes patient education. Potential problems with patients’ acceptance and engagement due to an intermediary device (value and privacy barriers) and multisensory overload in “mixed” consultations were mentioned as important factors for mitigating future development. Even though clinic staff were committed to developing VHCAs, professional gatekeeping was seen as highly relevant, especially given the ambiguity about the VA’s role.

Attitudes toward a potential VA vary greatly among clinicians. After introducing VHCAs, research questions 1 and 2 focused on what information varied most about the concept of a VA. Clinicians’ views had a unifying theme: introducing a technology that simultaneously changes the consult structure and consult medium inevitably generates uncertainty. Subthemes illustrating the content of this uncertainty included concerns about loose ends, levels of oversight, the VA’s knowledge and manner, and potential for clinical delegation. After examining privacy concerns discussed in 1B, it was concluded that clinics vary widely in the perceived relevance of potential barriers to the implementation of VHCAs in diabetes patient education. Addressing these gaps in knowledge may facilitate the consideration of future improvements for VHCAs in working diabetes care.

## 7. Ethical Considerations

Ethical considerations regarding AI and healthcare involve both the challenges and positive implications generated by AI taking the place of a human being capable of expressing empathy. Furthermore, discussions arise surrounding the opportunities and accompanying challenges brought about by the new AI-regulated arena. Lastly, the interplay, limit, and advantages of the use of human and numerous artificial intelligences are neither rare nor trivial.

Potential ethical dilemmas must be addressed. Topics of discussion encompass the very first ethical, legal, social issues regarding machine learning implementation, the necessity and feasibility of precise regulation in the healthcare landscape, and guidelines for the responsible use of predictive clinical AI models. Major areas of discussion include the issue of explicability as one of the basic themes of AI ethics, moral considerations that would impact patient autonomy, the role of the public in AI governance, and the ethical issue of algorithmic bias in healthcare (Maccaro et al., 2024).

Considerable attention has focused on social and ethical aspects of the use of AI technologies in the healthcare domain. Research unveils the intricacies of the intersection of ethics and AI by revealing the variety of perspectives through which ethical dilemmas can be articulated. Several ethical questions include socio-cultural enablers and challenges in planning algorithm implementation, the role of the algorithm's purpose in determining acceptability, and the nature and degree of trust to be established among the patients, healthcare specialists, and algorithms. Unavoidably, a few topics of discussion recur. What ethical concerns are being raised? Are they new or not? What ethical framework is framing the discussion? Are the provide AI algorithms more or less unobtrusive than the human ones? Research reveals the multiple facets through which AI ethics is perceived and analyzed. Questions arise relating to discriminatory features, negative unintended consequences, accountability measures, interactions with human agents, social consequences, and data issues.

### 7.1. Data Privacy and Security

Patient privacy and safety are essential to achieving the full potential of AI in virtual assistants. Generally, privacy can be guaranteed by restricted access to personal information. However, it is a well-known fact that the most efficacious AI-based systems require vast amounts of data to train the algorithms. In the specific case of healthcare systems, information trained models can leave traces that could jeopardize a patient’s privacy, as many entities can use the models as a “side-channel”(Tetteh, 2024). Furthermore, additional patient data is required to evaluate how well users perceived the virtual assistant’s device. Different safety aspects such as safety purpose, safety of case and procedure, security, test and piloting, and monitoring and maintaining the product update lifespan must be addressed. In terms of safety of care, AI systems tend to be black boxes and there are concerns that patients can receive harmful care without understanding why or how the decision was made. Outside of healthcare, concerns about the lack of transparency around how systems operate have come to prominence with the rise of AI tools and various decision-making algorithms used in different sectors. This raises a myriad of questions about whether safety is compromised when you do not fully understand the inner workings of the model or whether there is a benchmark or process to ascertain that the AI system is trustworthy. In light of their limitations, legal implications and risk mitigation strategies of Conversational Generated Transformers are highlighted. Lawsuits are expected and could put pressure on organizations to provide greater transparency in the AI processing chain, as there may be liability on both users and developers at many levels (Oliva et al., 2022).

Most of the issues previously reported on safety and security could lead to both public and governmental perception of AI virtual healthcare assistants. The responsibilities of stakeholders involved in the development and implementation of AI systems in healthcare could be deemed a noteworthy topic among the broader conversations of AI ethics and regulation. While some parties hold greater responsibilities, it may also be argued that collective ownership of AI safety and compliance of stakeholders involved in AI virtual healthcare assistants is pivotal to better explore their opportunities.

### 7.2. Bias and Fairness in AI

Recent years have seen an increase in the adoption of artificial intelligence (AI) systems utilizing deep neural networks for many medical tasks. AI systems capable of automated diagnosis in biomedical practice have been developed, several diagnostic capabilities of which have been shown to match those of domain experts in different specialties. Although there have been remarkable achievements, concerns about the fairness and bias of AI models in biomedicine are also abundant (Yang et al., 2024). Bias in healthcare refers to systematic error in the estimates of the effectiveness or other parameters of interest due to flaws in the study’s design, conduct, or analysis. This type of error can be introduced at any point in the research (e.g., design, choice of study population, execution, statistical analysis), bias the study results, and make it difficult to accurately interpret the study findings. More generally, unfairness refers to decision-making processes that contain systematic errors or disparities, in that cast a decision disproportionately affecting a subclass of their population (e.g., different populations with different race in prediction tasks). In contrast, fairness means eradicating those biases so that those decisions are equitable. There are many definitions of fairness in the context of machine learning, one of which is demographic parity (i.e., equal opportunity), which requires the probability of positive predicted labels to be the same across different sub-groups.

In biomedicine, the criteria for making subgroups can take demographic information into consideration (e.g., race, sex, or age) or subgroup at the other level (e.g., different imaging modalities, scan/disease severity). A subset of tasks that automatically make predictions in healthcare, such as predicting in-hospital mortality and disease progressions, may be consequential. Consequently, notably unequal behavior of algorithms toward different population sub-groups may violate the principles of bioethics. For instance, when it comes to predicting in-hospital mortality, the group of patients under 55 years old was predicted to live well beyond what it should have been, indicating significantly and systemically lower performance. Moreover, AI models that predict healthcare-related information have been shown to predict protected information from the images of scans.

## 8. Regulatory Framework

Artificial intelligence (AI) technologies have the potential to significantly improve health outcomes. AI tools can analyze clinical data to detect diseases early, improve safety, and help allocate medical resources more efficiently. While there are numerous solutions using AI technologies in healthcare, many have not been approved by local regulatory agencies, creating a rapidly evolving scenario where health professionals have no benchmark to assess how safe these tools are (Mennella et al., 2024). Integrating AI technologies in healthcare systems raises various ethical challenges, uncertainty, and accountability about these systems. Various countries and international organizations are working on regulatory and institutional frameworks to address this issue. Nevertheless, how to use these guidelines at the local level, how to ensure compliance with AI systems, and how to deal with regression scenarios remain open questions. This research explores the ethical and regulatory challenges posed by the introduction of AI technologies in healthcare.

AI tools have been proposed that rely on a sensitive intersection of regulations concerning health data, medical devices, safety, and product liability. Health data regulation was written at a time when healthcare records were exclusively paper-based, so it would require significant reviews to ensure compliance of AI systems working on medical image regulation. Since the advent of the first safety regulations of medical devices, research has moved from purely computerized systems to hybrid systems that include AI components or pure AI systems that perform risk-critical tasks. Many AI tools working in healthcare are not medical devices as defined and regulated by the FDA and similar institutions, as they do not bear directly any risk to patients. AI tools might have a crucial role in creating biased datasets that led to faulty models. Furthermore, the new generation of health applications is capable of generating data that is proprietary and harmful in itself, creating transparency and accountability issues concerning its use.

### 8.1. Current Regulations

In the healthcare field, the increasing offer of Artificial Intelligence (AI)-based applications drives concern about their regulation and governance. The technology applied to healthcare, especially with regard to the fostering of big data and numerous publicly available databases, has opened a new age of possibilities. Aged care robots, assistive robots in general, and telecare platforms are becoming daily opportunities (Mennella et al., 2024). Such technology is considered vital for the success of the integration between health and care services needed for ensuring universal health coverage at a personal and national scale.

The World Health Organization has dedicated reports to this very important topic, which combines ethics, privacy, and technology. Frameworks and schemes for technology regulation and validation in healthcare settings are still lacking in many countries, although ethics guidelines are increasing. Some key points would need to be taken into consideration. The technology is likely to be tested in simulation environments before being introduced extensively in healthcare settings. Simulations would also be useful for the development of possible benchmarks for technical aspects assessment. Beyond technical safety checking, there are some fields that deserve attention, including calibrating the interaction with the users in realistic settings.

Artificial Intelligence (AI) for supporting healthcare services has never been necessitated as much as by the recent global pandemic. In this regard, the state-of-the-art in AI-enabled Chatbots in healthcare proposed during the last few years was reviewed (Sen Bhattacharya & Sinai Pissurlenkar, 2023). AI-enabled technology was the focus of this study because of its potential for enhancing the quality of human-machine interaction via Chatbots, reducing dependence on human-human interaction and saving man-hours. Reported Chatbots included smart health assistants, telehealth support assistants, conversational agents, symptom checkers, and wearable devices. Although extensive work has been done on AI-enabled technology, there is a handful of Chatbots that are being used for patient support, while there are others that are in the clinical trial phases.

### 8.2. Future Directions

Candidate languages are Chinese, English, French, German, Japanese, Korean, Malay, Thai, and Spanish. There are unprecedented advances in deep learning and its applications, including healthcare. Although VHCAs are not a new technology per se, combining voice control and deep learning enables the use of VHCAs in a wide array of real-life health-care applications. As the interplay between individual and population-based treatment and intervention becomes continuously more complex—and health care systems, medical technologies, and data become smarter—the pent-up downstream demand for VHCAs across multiple stakeholders could soon be unleashed. There is room for VHCAs to develop and become an effective tool for the patient and healthcare professional. Regulations need to be in agreement with the rights of patients and, more generally, consumers. A privacy regulation paradigm, such as GDPR, that puts the personal data processing rights on the individual patient should be considered. During the design process, healthcare practices and healthcare providers should work hand in hand with nursing and medical professionals. Research shows that voice-controlled VHCAs should be easy to use and integrate into existing systems. They should be implemented on platforms where users are already familiar with. The introduction of these technologies should be gradual, starting with low-complexity tasks and possibly involving an education program. Another line of future research should assess how VHCAs can complement conventional treatment in human-CGI interactions (Ermolina & Tiberius, 2021). With the rapid development of generative deep learning algorithms, VHCAs promise to become better conversational agents in terms of understanding and emulating the user’s language. There are many unanswered ethical questions regarding intentional deception, the user-vs-user power balance, and the VCHA’s emotions.

## 9. Implementation Strategies

Implementing VAs requires a lot of attention, as the situation is more complex than expected from a transactional perspective. Results have revealed important topics to consider. Health systems must find a healthy compromise between innovation and (safety) regulation. There is a widespread shortage of health professionals, who obviously should be involved in implementation strategies, but this raises the question of how to organize their active participation in the diverse processes involved. In this regard, evaluation at each lower stage is important to reach the next stage. However, this can sometimes be at the expense of efficiency and may go against current focus on timely access to care. Limited commercial interest often results in underinvestment in affordable products. These all require large-scale and collective procedures. Therefore, the cooperation of government and industry is essential so that early involvement of designers is built into the process, reducing the risk of failure at later stages.

AI technologies are still fragile and limited to specific tasks. Any remedial intervention must be software-based and targeted at inappropriate selection criteria. This requires constant human checking to avoid incorrect decisions. It is expected that all these considerations will slow down adoption of (potentially) productive technologies in otherwise speed-driven sectors such as healthcare. Nevertheless, health authorities must exercises their ultimate (and collective) power as it can be expected that the minutiae of implementation will now multiply, requiring top-down enforcement. Finally, there may be long-term health implications of slow implementation as that implies delayed speedup in productivity (J. P. van Bussel et al., 2022).

### 9.1. Best Practices

A user-centered design approach that includes an iterative development process and co-design with end-users and relevant stakeholders can support the design of VAs with a more engaged user experience (G Curtis et al., 2021). Design recommendations relating to both choice and optimization of visual appearances can be provided. The study provides an overview of VAs for health; a user-centered design process is illustrated with an example, demonstrating how the design was informed by both psychological theories and user studies examining choice of design attributes. Empirical studies examining design optimization relative to user engagement are briefly summarized and implications for practice and research considered. Virtual health assistants (VHAs) are computer software programs that can coach, inform, connect with, and remind users regarding health-related activities. The potential for technology-mediated convenience services to automate a wide range of tasks, from simple reminders of upcoming appointments to complex customized service delivery tailored to an individual’s needs has been modernized through enhancements in cloud-based infrastructure, machine learning techniques, and powerful data visualization tools. Users can now demand rich and customized services at their convenience with minimal additional effort. Virtual assistants (VAs) refer to technologies based on a dialogue system designed to simulate a human conversation and assist with a wide range of tasks (social, work or health) through either voice or text dialogues. Today, VAs are built into and can complement many technology-based applications. They can also function or be used as stand-alone apps and are increasingly being designed for health. Health applications of VAs continue to proliferate in this context. Since health is ubiquitous in everyday life, the prevalence and scope of health virtual assistants (VHGs) such as human-like avatars delivering cognitive behavior therapy for depression and anxiety, diet, and physical activity promotion are notable examples. A myriad of VHGs are also available to carry out daily health tasks such as medication management and scheduling routine appointments remotely. Associated with a plethora of health VAs is a diversity of science, design, and user experience issues (UIs) relevant to education, research, and practice. Users’ VHs interactions are influenced by many dimensions of user experience, including perceptions, feelings, thoughts, actions, and well-being states resulting from use. User experiences are determined by the design and performance of the technology and the user and context interaction. There is an urgent need to examine (1) how user experience of health VAs can be optimized to support personalized health tasks; (2) how limitation in user experience can undermine effectiveness and harms of health VAs; and (3) how user experience design can promote the sustainable competitive advantage and business model of health VAs.

### 9.2. Scalability and Sustainability

Almost half of the included VHCAs and the majority of the studies reported on an implementation in clinical practice of the developed VHCA or on plans to do so or piloting it within the healthcare settings. Consideration of the scalability and sustainability at the planning stages is recommended within academic and research health institutions’ or other funding organizations’ requirements (Bevilacqua et al., 2020). This sustainability paragraph could only be answered affirmatively by one out of five including VHCAs and without the knowledge of the data. The absence of evaluation did not appear to have a negative impact on the implementation of a VHCA in clinical practice. The absence of evaluation did result in fewer studies and the current affordance of a VHCA. Subsequently, a VHCA addressing a specific clinical purpose was best positioned for implementation in clinical practice. Sustainability was frequently used as an argument to choose to address a specific clinical implementation goal(Abigail Mba Dabuoh et al., 2024). However, these VHCAs had not been implemented in clinical practice yet and their scalability and sustainability had not been tested in the healthcare setting either. Currently, the long-term scalability and sustainability of a VHCA in clinical practice appears to depend on the quality of the VHCA and on factual scalability and sustainability. Little consideration and testing of health technology scalability and sustainability and knowledge of the data appear to be common and preoccupying according to the fast-growing field of VHCAs to address mental health and related disorders in need.

Further and more extensive efforts in providing scientific evidence on the scalability and sustainability of a VHCA in health care would be welcomed. An implementation plan with considerations of scalability and sustainability is of high importance in turn for the possibility of obtaining funding of its own project. Recommendations for the implementation of VHCAs in health care could be further extended to include planning for scalability and sustainability and active and long-term efforts in generating the needed data. Within this, the recommendation of VHCAs design and content to include considerations for scalability and sustainability should also be included.

## 10. Evaluation of Effectiveness

Virtual healthcare assistants (VHAs) have been developed for various healthcare purposes and profiled as new communication conduits between patients and healthcare systems. In an effort to assist the development and evaluation of VHAs, the literature has been systematically reviewed for relevant user experience attributes. 48 articles were found after detailed screening of 6879 articles, which present 45 unique studies. The VHAs used in the research were categorized into 8 health domains, and the 27 examined characteristics were classified into 5 categories. The 140 outcome variables were categorized into nine categories. The findings provide a strong motivation to build a database of previous studies and guidances for future VHA designs (G Curtis et al., 2021).

Telehealth has developed rapidly during the COVID-19 pandemic. Beyond video conferencing, chatbots and VA-like interfaces have also assisted patient assessment, symptom monitoring and other healthcare services. Being programs or systems which use textual or vocal input outputs to facilitate reader understanding and assist tasks, using AI and ML technologies, all of them belong to the general category of VHAs. They can efficiently gather real-time patient information and by adopting machine learning technologies, analyze large amounts of patient data to improve triage decision-making. Meanwhile, the rapid development of mobile technologies has also encouraged the replacement of some traditional in-person medical and health assistances. People have rapidly shifted health inquiries behaviors towards search engines, websites and mobile apps. To assist the design of VHAs including different UIs, it is crucial to inform researchers and practitioners about existing literature by systematically reviewing and assessing it. Based on a systematic scoping review, user experience attributes of VHAs related to software architecture complexity, AI/ML algorithm intelligence level, input physiological measurement level, and also user’s entitlement of customization, views on privacy and health literacy remain rarely studied.

### 10.1. Metrics for Success

For many applications and environments, including healthcare, it is important to measure the success of AI systems. Despite a growing number of health AI technologies for various use-cases, only a limited amount of attempts have been published in scientific literature on how to measure their effectiveness in healthcare environments. This is unfortunate, as measurement is necessary to demonstrate success or failure, and learn from experiences. The need for practical approaches for healthcare organizations is dire, especially since many of them are required to report key performance indicators to regulatory organizations.

To find the quality metrics for measuring the success of new AI technologies, health AI use cases were analyzed from scientific literature in terms of how their effectiveness was previously quantified. The emphasis was placed on healthcare environments where available data for measuring success was scarce, and where the successful implementation and presence of such systems is vital for the future of healthcare, such as healthcare chatbots. The knowledge uncovered from this literature search is synthesized to quality metrics that may be applied to future system developments. The emergent metrics were categorized along multiple dimensions of the systems’ functionality, preparation, performance, integration, and outcome. Each metric was characterized in terms of how it contributes to achieving quality measure scores. Furthermore, suggestions for other relevant metrics were made.

110 healthcare AI applications were found. The largest share of applications is found in the field of treatment and intervention, followed by screening and diagnosis. The large outline of healthcare purposes shows algorithm agnostic applications in broad conditions. Knowledge-bases and augment accuracy were most frequently cited. Mentioning outcomes included indicators of use and limitations, organizational impact, and else.

### 10.2. Impact on Healthcare Outcomes

Artificial Intelligence (AI) has emerged as a transformative tool across various industries, with healthcare being one of its most significant beneficiaries. The evolution of AI in healthcare, primarily spurred by Big Data, the Internet of Things, and cloud computing, has evoked public interest, debates, excitement, and concern on a global level. Automated applications analyzing health-related personal data have been growing at a striking rate, including, but not limited to, VirtHAs. Used interchangeably with digital health assistants or virtual assistants, VirtHAs have become increasingly adopted in virtual patient engagement and care. This paradigm shift is widely considered beneficial yet troublesome (G Curtis et al., 2021). Despite the growing literature examining design characteristics and user engagement of VirtHAs across health domains, evidence on the robust or conflicting impact on healthcare outcomes is scarce. Thus, this systematic review aims to offer insights into the efficacy of VirtHAs on healthcare outcomes across health contexts.

A systematic review is conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Literature is systematically searched from five electronic databases. Peer-reviewed journal articles published in English since January 2010 are included if the virtual agent is the main component of an intervention to improve any healthcare outcomes. The quality of the studies is assessed using the Mixed Methods Appraisal Tool (MMAT). 2241 records are identified after removing duplicates. Potentially relevant articles are screened against the eligibility criteria. NLP software is adopted to cluster and prioritize citation intention extraction tasks. Full texts are reviewed for eligibility, with a total of 80 articles passing the full-text review. The quality of included studies is assessed, resulting in 39 studies in the final data synthesis. A customized knowledge mapping tool is developed to visualize the involvement of different health domains and VirtHAs in each included study—for health topics, 39 studies are found targeting mental health, 16 studies targeting chronic health condition treatment or management, and others. A holistic understanding of VirtHAs and their impact on healthcare outcomes is obtained for scientific, clinical, and public stakeholders.

## 11. Future Directions

Before attempting to answer these questions, a few remarks are due concerning the circumstances of conducting the research and its limitations. Due to the general decline in privacy in the digital age and political reasons at the individual level, acquiring personal information has become more difficult. Various powerful software solutions are available to extract publicly available information about VHCAs. However, the research team refrained from doing that for ethical reasons. Notably, even the most powerful tools take time to develop and require technical expertise. Thus, it would be convenient for companies and researchers to collect information about VHCAs that had not been implemented and were not yet publicly available without relying on elaborate prototypes in a short time.

Another significant limitation of the research stems from the difficulty of convincing the developers to disclose the details of already operating VHCAs in the database. This required research participants from the developers’ perspective to share information that they were not obliged to share. In return and as an incentive, only the information about the VHCAs that could be disclosed was provided, while the publications presenting the detailed methodology were strictly enforced with the confidentiality of the codebases. Therefore, it has to be noted that although VHCAs are available for public use and their modes and settings can be shared in the literature, their public disclosures have not been subject to systematic scholarly scrutiny due to the general decline in digital privacy and the aforementioned ethical concerns. However, this also raises the question of whether the human characteristics of the VHCAs should be disclosed. As strict regulations have emerged to comply with the ethical usage of AI and the usage of deepfake technologies, some governmental founding entities and research institutions in the field have started to test the ethics of employing technology-source VHCAs in research.

### 11.1. Innovations in AI Healthcare Assistants

Recent remarkable advancements in artificial intelligence (AI) show great potential for improving healthcare delivery and specialists’ productivity. In addition to commercial implementations of AI in healthcare, a swathe of academic work on AI-based healthcare assistants has appeared in recent years. A handful of systematic reviews that offer detailed summaries of a subset of related advances, such as expert systems, automated medical instruments, and diagnostic recommendation engines, have provided a solid foundation for new research in the field. Nevertheless, despite large bodies of work investigating user interfaces for healthcare systems, the lack of AI healthcare assistants that converse with users of the system remains an open problem.

Converse AI healthcare assistants take natural language questions and retrieve answers from a knowledge base consisting of source documents. Nonetheless, developments in this direction for application domains beyond web search have been scarce. Following successful large language models and the emergence of intelligent agents in commercial use, there is a need to scan the landscape of innovations in healthcare assistants. Many implemented products and developments therein have not been documented in the academic literature yet. Such a review would offer a timely overview of potential directions for academia to address fundamental research challenges relevant to healthcare assistants. One avenue of research is improving the ability of the current officers to navigate documents and extract accurately supported answers.

With the utmost discussion of information retrieval, natural language processing, and monitoring and maintaining reliability across knowledge domains, exploratory innovation in combining real-time data sources and cross-domain reasoning is needed. On the innovation side, systems that apply state-of-the-art AI methods in new ways are rare, and the review might lead to identifying products that operate outside the common thematic of healthcare coverage at certain levels. Another actively developed design space is on the options of embedding assistants across different applications, devices, and communication channels, which could guide healthcare stakeholders in adopting and integrating new services into the day-to-day operations.

### 11.2. Potential Research Areas

Innovations in the Virtual Healthcare Assistants field. Despite health AI compliance and privacy legislation enforcement, social aspects of AI-based virtual healthcare assistants in the healthcare area were neglected. Research for the cognizance of the general population about AI health benefits, especially in low- and mid-income countries, is needed (Surely, 2023). More public access forums, seminars, and webinars on trust and use of these systems should be organized by health services. Virtual healthcare assistants operating on a pre-defined protocol rules and making decision tree-driven queries obtain less trust by users than those capable of elaborated speech. Technology acceptance models for VHCAs should be upgraded to capture both Turing tests and human characteristics of the interaction agents. Care bots’ credibility issue, their evaluation from users’ perspective, and economic aVHCAs’ effect on the closure of hospitals/clinics and other service facilities were neglected. Transparency in AI health decision-making respect to exceptions, mistakes, and biases should be investigated more since distrust in AI may never be overcome. Differentiated trust of VHCAs’ smart agents due to ethical issues connected with elder care and usage of one speech agent across platforms and devices should also be taken into consideration. The role of scoreboards, discussions, and announcements in the development of trustworthy with transparency techniques and the quality of care delivered by social VHCAs smaller than four weeks should be investigated more.

Innovations in the health area of the examined virtual healthcare assistants fields. Trust-building pathways of health AI and the role of creativity and appearance of sounding voices on chatbots’ believability by echo chamber design and advertisement filtering are need to be uncovered. Smart health operation implementation cooperation with telemedicine use, robotic enhancements, and influencing users’ sedan chairs was neglected (A. Younis et al., 2024). The adoption of VHCAs in urban enlightened areas and the guarantee of some functionality like care bots education were reported to give side effects in one’s health and well-being. Since there was a lack of human agents’ characteristics’ understanding of users’ perceptions in the doctor-patient interaction sphere, the role of care bot character generation type and interactants’ health change assessment/ complaint dismissal play should be investigated more. Notifications’ assessment on the recommended time of day short messages conveying nature health tips and general well-being monitoring via health detection and alarm detection were ignored. Creation of smarter smartphone AIVHAs concerning multimodal vigilance were need to be performed. In addition, telenursing development beyond teleconsultations and biomedical signal analysis in other areas of virtual healthcare assistants’ employment were needed. Advances in sensors’ and classifiers’ miniaturization, and in neural networks’ parallelism causing extensive drones’ and sensors’ technology proliferation noticed general vibrancy in this regard and affordable telepathology introduction were neglected.

## 12. Conclusion

The findings from this study aimed at gathering information on existing AI-enabled chatbots (Vs) in the healthcare domain illustrate the extent of the growth in this new sector of knowledge service. The healthcare Vs found varied significantly across access modes, target users, target demographics, institutions/entities behind them, healthcare sectors (physical/mental), and functional services. Vs targeted both the physical healthcare and mental healthcare sectors were found. However, Vs for physical healthcare appeared to be more varied than Vs for mental healthcare. In addition to targeted healthcare sector-wise breakdown presented in the findings section, it would be insightful to have an analysis of Vs with respect to individual functional services under these two healthcare domains. There has been a tremendous increase in the number of chatbots developed for varied functional services ranging from healthcare information to triaging symptoms and booking vaccinations (Sen Bhattacharya & Sinai Pissurlenkar, 2023). This reflects on the viability and popularity of this automated service. Research on chatbot technology and its applications in varied domains has been enabled by this increased interest. However, there has been a dearth of such systematic reviews in identifying the development progress of chatbots in healthcare services and their variety based on a range of attributes. Chatbots have gained widespread attention, especially in the healthcare domain. Since successful adoption of this technology primarily relies on understanding the user evaluation and satisfaction of the service, further research capturing and analysing user perspectives is necessary. This could include gathering information on the background and role of the end-user; the Vs aspects including automation accuracy, service and health information quality, and user satisfaction with the chatbot.

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