Self-management for Chronic Illness: A Scoping Review on Designing Virtual Assistants for Patient-Centered Care

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Abstract

Chronic illnesses (CI) are increasing worldwide, positioning virtual assistants (VAs) as valuable tools for supporting patients in self-management. As effective self-management relies on holistic, patient-centered practices, AI is increasingly integrated into VAs to provide more personalized support. Yet, it is essential that VA design processes remain grounded in participatory approaches prioritizing patients' values, needs, and lived experiences. To assess the current state of VA design processes, we conducted a scoping review of 55 papers examining how care is framed and patients are involved. Our findings reveal AI-driven VAs prioritize reductionist approaches over holistic care with minimal patient involvement. This highlights a gap between the potential of patient-centered care technology and current implementation practices. Our contributions include (1) a mapping of care dimensions currently implemented in VAs, (2) a categorization of patient roles in the design process, and (3) design implications to expand care dimensions and patient involvement in AI-driven VAs.

CCS Concepts

• **Human-centered computing** → *HCI design and evaluation methods.*

Keywords

Design Research Methods, Health-Wellbeing, Chronic Illness, Assistive Technologies, Literature Study

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1 Introduction

Self-management is a necessary practice for maintaining a high quality of life in chronic illness, affecting more than one-third of adults annually [105, 107]. Self-management is often described as a lifelong dynamic process of self-monitoring and self-evaluation [123], which involves a perspective shift from illness to wellness [81] due to the prolonged temporal course of chronic illness where a complete cure is rarely achieved [90]. Because of this, people living with chronic illness develop rich, individualized knowledge about their own disease through routine everyday practices and adaptive strategies [53, 111, 114]. Virtual assistants (VAs), such as conversational agents and virtual medical avatars, have been designed to support patients in their self-management practices outside the clinical setting [67]. They aim to achieve this by supporting behavioral health and healthy living [71, 128], health information seeking [149, 151], and appointment, medication, and symptom tracking management [16, 54]. Given the highly individualized, contextual, and often relational (requiring ongoing assistance from informal support networks) type of care that is needed to manage chronic conditions [96, 107], VAs must be patient-centered in their approach to care [110, 150]. Patient-centered care (PCC) for chronic illness is characterized by three main aspects: (1) it seeks to support patients in developing skills and confidence to self-manage their own illness [145], (2) it holds a greater recognition of the need for holistic care [93], and (3) it asks patients directly what their preferences, needs, and values about care approaches are to understand what is most meaningful to them [33, 133]. It is critical that technologies designed to support patients are aligned with how they already care for and support themselves. Patient-centered care was found to improve health-related quality of life, symptom burden, depression, and patient activation in their health journey [104]. Without such alignment and PCC integration, technologies risk overlooking the lived realities of self-management and instead reinforce narrowly clinical or efficiency-driven models of care [132]. Despite their potential, however, it has been shown that VAs often do not deliver patient-centered care that prioritizes patient needs, values, and preferences [142].

Artificial intelligence (AI) is increasingly being incorporated into VAs to provide people living with chronic illness more hyper-personalized care, leveraging machine learning (ML) to facilitate evaluation of symptoms, personalize treatment recommendations, and foster better communication between patients and providers [4]. AI-powered VAs are on the rise in supporting people living with chronic illness [74, 91] and have shown improvements in the user experience of VAs through the delivery of these personalized interventions [73]. However, personalized medicine (PM) interventions such as these typically undermine patient-centered care, representing a more traditional and reductionist view of patients' illnesses that is incompatible with the holistic needs of people suffering from chronic illness [35]. AI integrations then introduce a new tension into VA design processes, as there is a growing need

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to explore more holistic HCI approaches in developing "human-centered AI" to increase adoption and acceptance of VAs. However, it remains unclear if AI technology is delivering patient-centered care rooted in how patients actually support themselves through daily self-management or if personalization remains largely a technical feature, prioritizing a more reductionist personalized medicine focus. We, therefore, ask: *What does patient-centered care mean and how is it enacted in the context of AI-powered virtual assistants for chronic illness?*

Recent efforts in HCI aim primarily to achieve patient-centeredness by developing clinician-facing AI technology [136], such as integrating AI into pathologists' workflows for improved decision-making [49], or automating clinical text for electronic health records [42]. While attention to provider needs can be part of the solution, true patient-centeredness requires designing AI technology from the patients' standpoint [8, 96, 140]. This can be achieved through participatory and user-centered design processes [5], where insights from patient-oriented research guide the design process [142]. This approach aligns with a larger trend in HCI toward patient-centered design that matches digital health design to the actual needs, usage, and lived experiences of people living with chronic illness [56, 65, 83, 143]. Building on this with feminist approaches to care [140, 141], we share the notion that participation is not only a methodological choice but can itself be understood as a practice of care, where patients' lived experiences and situated knowledge actively shape technological possibilities [79]. This shift moves toward interrogating how health technologies like VAs enact particular forms of care, and what patient-centeredness means in chronic illness contexts. There is a need to investigate if current HCI methodology gaps result in AI-driven virtual agents that are not patient-centric enough, prioritizing only certain aspects of care.

Therefore, in this study, we conducted a scoping review of 55 papers to explore how patient perspectives were accounted for in the design and development of virtual assistants for chronic illness self-management. In particular, we examined how patient-centeredness was enacted through the underlying concepts of care prioritized in the VAs, the associated system functionalities, and patient involvement in the design process. This review was conducted on both AI and non-AI VA systems to analyze if and how AI integrations impacted the VA design and development process.

To answer our main question on *how patient-centeredness was considered and enacted in AI and non-AI-VA design* in our review, we aim to address the following research questions:

(1) **What are the underlying dimensions of care and associated system functionalities prioritized in VA design? How do these differ when AI is integrated into VAs?**
(2) **How are people living with chronic illness participating in the VA design process for both AI and non-AI VAs?**

Our results indicate a disconnect in the design process for chronic illness self-management VAs. Despite AI integrations aimed at better meeting patients' patient-centered care (PCC) needs, which require meaningful patient involvement, design practices remain largely without such participation. Development teams often engage patients late in the process as evaluators of an already predetermined solution, replicating patterns observed in non-AI VAs. These participatory shortcomings reinforce reductionist, adherence-focused models of care at the expense of holistic and relational care dimensions that shape life with chronic illness and are necessary to enact PCC. Our findings question both the type of care foregrounded in VAs and the processes by which these care priorities are determined without substantive engagement with patients' lived experiences. These findings challenge assumptions that AI-driven technical personalization automatically equates to patient-centered care.

The scoping review makes three main contributions to HCI research and design. First, we provide a mapping of care dimensions as currently implemented in VAs, giving HCI researchers a comprehensive understanding of what care dimensions are prioritized in VA systems and highlighting key differences with AI integrations. Second, the review offers a categorization of patient roles in the VA design process, identified and classified based on their involvement in participatory design activities to shape both AI-driven and non-AI VAs. Third, we offer design implications for rethinking participatory practices that engage patients as active shapers of VA technologies and center contextual, relational care grounded in lived experience. These contributions offer guidance to VA designers and practitioners in weaving patient-centered perspectives into design and development processes, so that AI-driven assistants can more effectively foster self-management and improved quality of life for people with chronic conditions.

2 Related Work

2.1 Patient-Centeredness and Self-management in Chronic Care

Self-management is defined as the tasks that individuals must undertake to live well with chronic conditions, such as having the confidence and skills to handle medical management, role management, and emotional management [22]. It has been established that self-management strategies are a critical part of chronic condition care, resulting in improved health outcomes [122] and a higher quality of life for people affected by chronic illness [53, 107].

The individualized nature of chronic illness self-management necessitates patient-centered care (PCC), which integrates patients' perspectives on chronic disease, rendering them active partners in their healthcare journey [148]. PCC is essential because it recognizes that chronic care involves relational, psychosocial, and contextual dimensions beyond biomedical management [107, 145]. The most influential framework for patient-centered care is the biopsychosocial model, introduced by George Engel as a new scientific model to address the limitations of the biomedical paradigm [37, 38]. As the name suggests, the biopsychological model takes into account the person's biological, psychological, and social factors when engaging with and treating them. As a more holistic approach to healthcare, it views a person as a whole organism impacted by many factors, as opposed to an issue being treated as an isolated problem. People with chronic illness understand their care needs through lived experience, including how conditions fluctuate, what triggers symptoms, and how illness affects their daily routines, relationships, and sense of identity [96].

In HCI research, PCC approaches to digital health technologies have emphasized the importance of participatory design methods that center patients' lived experiences in technology development [56, 83]. HCI scholars have advocated for moving beyond efficiency-driven models of care toward technologies that align with how patients actually care for and support themselves [132]. This work follows broader trends in HCI toward more patient-centered approaches that match digital health design to the actual needs, usage, and lived experiences of people suffering from chronic illness [65].

PCC expands the concept of personalized medicine (PM), which stems from a biomedical framework and represents a more traditional, *reductionist* view of patients' illnesses [35, 135]. While PM focuses on an individual's specific biological characteristics to optimize treatment outcomes [46], PCC originates from a caring perspective and aspires to a more *holistic* view of a patient, focusing on the complex, "whole-person" [32, 89, 104]. PM approaches prioritize control over optimization of medical treatment results through precision and predictability, while PCC builds on patient agency and empowerment [35]. The tension between these approaches becomes particularly relevant in HCI when designing AI-driven health technologies, which tend to prioritize personalized medicine [17, 59, 147].

2.2 Virtual Assistants for Chronic Illness Self-management

Virtual agents (VAs), such as chatbots and medical avatars, despite the clear need for patient-centered approaches in chronic care, have not been found to deliver patient-centered care [142]. In HCI research on digital health technologies, VAs face challenges in adoption and long-term engagement, with many remaining in early-stage deployment [58]. Research has shown that health technologies such as VAs often standardize the experience of those living with chronic illness and make assumptions about care delivery that do not align with their lived realities [132]. Furthermore, a review of AI-driven assistants for chronic illness found that the majority of agents focus on diagnosis, therapy, and general conversation rather than supporting the self-management practices that patients actually engage in [125]. This misalignment reflects broader concerns in HCI about how technologies encode specific values [24] that impose hegemonic epistemologies of normative experiences [23]. In chronic illness contexts, there is a particular risk of standardizing chronic illness experiences and care through data-driven technology when their self-management actually relies on lived experiences requiring more holistic care approaches.

With AI's introduction to VAs, promising more personalized support to patients [74, 91], the risk of standardization becomes potentially more pronounced. As these personalized medicine interventions typically represent reductionist views that prioritize condition optimization over the holistic, relational, and psychosocial aspects of chronic illness management [35]. Reductionist care approaches risk reducing people to biomedical data points, contrasting with the flexible and contextual care that chronic illness self-management requires [35]. There is a need to further investigate if AI integrations into VAs manifest a shift to reductionist care for chronic illness through personalized medical interventions, and if current design processes are equipped to overcome these challenges.

2.3 Participatory Design Approaches in Health Technology

Participatory design (PD) has a well-established tradition in health technology development and, in HCI in particular, healthcare and wellbeing were found to be the most prominent areas of PD application [116]. Incorporating PD practices in the design of health technologies aligns with patient-centered care as it has been found to foster better health outcomes for people suffering from chronic illness through increased engagement and empowerment [6]. Employing these approaches has also fostered a sense of ownership among users, leading to more appropriate and user-friendly health technologies [137], and co-design specifically can significantly enhance the alignment of interventions with user needs for both psychological and physical health conditions [10].

These participatory traditions intersect with evolving philosophies of care in public health. Scholars have proposed a "fifth wave" of public health that shifts the focus of digital health technology from lifestyle choices and risk factors towards understanding persons as substantial, relational beings. This emerging paradigm recognizes that creating value for health is a complex, relational phenomenon that goes beyond traditional medical models, integrating objective measures with subjective lived experience and inter-subjective values, meanings, and beliefs [50, 64]. For health technology design, this philosophical shift challenges approaches that prioritize only behavioral optimization or clinical adherence, instead inviting participatory processes that account for care as fundamentally relational and situated in people's lived contexts.

However, despite new philosophies of care being introduced and participatory design's tradition in healthcare, the systematic application of participatory approaches in healthcare technology development remains limited. This has resulted in mismatches between technology and context of use, and is a primary reason why new medical technology fails, as identified by the WHO [106]. Furthermore, reports on how patient input is gathered and translated into design decisions in digital health development are scarce [144], making it difficult to judge the quality of design activities or understand how patient perspectives are translated into technology features. The healthcare context is uniquely complex and requires adaptive methods that account for complexity and PD approaches with vulnerable populations.

These limitations become especially pressing as healthcare technologies increasingly rely on AI-driven systems. Recent HCI research in AI-driven technologies for health has urged HCI designers and practitioners to critically examine the assumptions and normative biases embedded in ML models and to consider how these constrain other ways of knowing [156]. Participatory approaches offer a concrete route for doing this work in practice as they are often used to surface varied assumptions from multiple stakeholders within a design process [25, 154]. Yet, in a recent review on VAs for chronic illness, it was shown that very few conversational agent design processes included patients in their development [125], and that analysis of the social systems these technologies are embedded in, and their impacts on patients, are largely absent. Without such analysis, these systems risk reinforcing biases and marginalizing people impacted by chronic illness [74, 77]. Critical HCI scholars warn that tokenistic or "participation-washing" approaches can even co-opt participants, reproducing existing power asymmetries rather than challenging them [80, 131]. Drawing on feminist care ethics perspectives, we are reminded that true patient-centeredness requires ongoing involvement and staying with the messiness of shifting needs of patients [27, 141].

These methodological gaps in VA design and development processes for chronic illness self-management need to be explored further by understanding which assumptions and dimensions of care are embedded and how people with chronic illness are involved in shaping them.

3 Method

To investigate how prior work has approached the design and development of VAs for chronic illness self-management, including how care was conceptualized and how patients were involved in the process, we conducted a scoping review following the PRISMA Extension for Scoping Reviews (PRISMA-ScR) checklist [139] to ensure its quality. In this section, we detail our search strategy and data sources, the process of removing duplicates and screening for eligibility, the criteria for including and excluding articles, and our approach to data extraction and analysis.

3.1 Search Strategies

We extracted research articles from four main databases: ACM Digital Library [1], Scopus [2], Web of Science [3], and PubMed [4]. The databases were selected to capture conference proceedings and journals related to self-management of chronic diseases and assistive technology in the HCI and medical fields. Eligible papers were those written in English and with no date limitations on the searches to capture the evolution of VA design and development processes with AI integrations, and no limitations on study participant age. The search was conducted on the bibliographic databases on 2025-20-03, and the types of publications included in the search were peer-reviewed articles, conference papers, short papers, and extended abstracts.

To capture a wide range of technologies that support chronic illness self-management, the first and last author identified four key focuses for the search: *chronic illness*, *virtual assistants*, *digital health*, and *design and development processes*. Rather than limiting the scope to conversational systems only, we intentionally included a range of assistant technologies, with and without conversational capabilities. This allowed us to trace how assistive technologies were conceptualized across systems, from embodied medical avatars to machine learning powered assistants providing adaptive recommendations to patients. For example, some studies included agents represented as nurses or doctors' avatars that supported patients in making sense of their health data, while others presented assistants capable of generating tailored feedback through conversation. Additionally, both AI and non-AI assistants were included in the corpus to explore the evolution of VAs from more static assistive technology to personalized systems.

Search Category	**Search Terms**
Chronic Illness	("chronic illness" OR "chronic disease" OR "chronic condition")
Virtual assistant	("chatbot" OR "conversational agent" OR "virtual assistant" OR "digital assistant" OR "dialogue system" OR "conversational AI" OR "embodied agent" OR "avatar" OR "deepfake" OR "generative AI" OR "large language model" OR "LLM" OR "GPT" OR "generative pre-trained transformer")
Application	("digital health" OR "mHealth" OR "mobile health" OR "healthcare app" OR "app" OR "solution" OR "eHealth" OR "self-management app")
Design process	("design*" OR "develop*" OR "implement*")

Table 1: Search categories and corresponding search terms used in the scoping review.

In addition to capturing technologies themselves, the search strategy intentionally included terms related to *design* and *development* in order to surface literature that discussed how virtual assistants for chronic illness were developed (see Table 1 for the full list of search terms). Including this dimension was necessary to understand which stakeholders were involved in shaping the systems, what data informed the assistant, and how dimensions of care were conceptualized.

Across all databases, the search yielded an initial corpus of 300 papers, from September 2004 to April 2025. From ACM Digital Library, we identified 166 papers, from Scopus 86 papers, from PubMed 25 papers, and from Web of Science 23 papers.

3.2 Screening and Selection

First, 37 paper duplicates were removed from the original corpus, and papers with a citation count of zero were removed, resulting in a final screening count of 189 papers.

Figure 1 shows the final corpus selection process flow. The main author read the title, abstract, and keywords of all 189 papers to determine whether a paper fit the inclusion and exclusion criteria listed in Table 2. To reduce potential bias from single-reviewer screening, inclusion and exclusion criteria were clearly defined and collaboratively developed by the research team. Uncertain cases were discussed within the research team during the title, abstract, and full-text review.

Based on these criteria, we included 90 papers and excluded 99. Figure 1 shows the final corpus selection process flow. We proceeded with a full-text screening of the 90 publications from our search, applying the same inclusion and exclusion criteria. During this phase, we excluded an additional 35 papers, as their insights focused more on areas other than bespoke assistants, such as voice-only assistants like Google Home or Alexa for older adults [158] without providing substantial insights into the design and development process, or studies where daily lifestyle self-management is not the focus [63]. The final corpus consisted of 55 publications published between 2011 and 2025, with the most papers published in 2021 (11

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[1] ACM Digital Library: https://dl.acm.org/

[2] Scopus: https://www.scopus.com/

[3] Web of Science: https://www.webofscience.com/

[4] PubMed: https://pubmed.ncbi.nlm.nih.gov/

Inclusion Criteria
The study focuses on individuals living with a chronic illness
The study is aimed at developing a virtual assistant for patient-facing use intended to support self-management
The study discusses the goals and purpose of the virtual assistant for care delivery
The study includes a description of the design, development, or implementation process
Exclusion Criteria
The study is focused on acute conditions only
The study does not mention the development of a virtual assistant for chronic illness self-management
The study does not mention the purpose or goals of the virtual assistant for care delivery
The study is clinician-facing only
The study does not include a description of the design, development, or implementation process

Table 2: Inclusion and Exclusion criteria.

out of 55, or 22%). All reviewed papers are listed in the appendix (see Table 8).

3.3 Analysis

The screened papers were analyzed and coded utilizing Reflexive Thematic Analysis (RTA) [14, 15] over two months by the first and last author. We conducted the analysis utilizing ATLAS.ti [5], a qualitative data analysis software that efficiently sorts, structures, and categorizes large data sets, to examine how care was conceptualized, what the main functionalities of the VA were, and how patients participated in the design process for virtual assistant development. Initially, the first author analyzed 10% of the corpus to develop initial codes and then discussed them with the last author for refinement.

Familiarization The first author read all papers and extracted sentences that directly or indirectly referred to:

1. how care was framed in the introduction and throughout the paper (e.g. *"By utilizing this monitoring approach, patients' recovery and health status can be constantly monitored, thereby providing support for remote testing, medication adherence, and overall health.")* [85]
2. the functionality of each assistant that operationalizes the care concepts (e.g. *"A chatbot for instant Q&A and advice, personalized reminder systems, a data analysis module for tailored guidance, resource aggregators for health-related information, and an emotional support module to ensure a holistic approach to prevention.")* [26]
3. the role of patients in the design process (e.g. *We tested our prototype through focus group sessions and interviews. At the same time, we conducted a survey to learn more about their preferences for AUIs in apps related to chronic diseases"* [146])

Coding Following data extraction, the first author analyzed sentences to inductively generate an initial set of codes to identify key characteristics of care concepts (e.g. *Care is conceptualized as behavior change* or *"Empowerment through self-management"*), functionalities (e.g. *Health Literacy, Functionality*, and patient participation (e.g. *"Engaging patients as a first step", or "Healthy participants as patient representatives"*).

Theme generation The codes were then grouped based on their similarities to form initial themes. Following the principles of reflexive thematic analysis, we focused on finding the most salient characteristics to categorize each attribute. For care conceptualizations, we grouped the codes into seven main themes: adherence, behavior change, proaction, health literacy, relationality, autonomy, and empowerment.

Review, refinement, and classification After initial theme generation, authors iterated on these by re-examining extracted quotes and re-reading original papers to further understand the depth of patient involvement, the underlying care concepts, and functionalities of each study. Following the thematic analysis, the main care conceptualization themes were classified into two overarching care approaches, rooted in prior literature: a *reductionist care approach*, grounded in the biomedical model (e.g. optimization, adherence), and a *holistic care approach*, grounded in the patient-centered and underlying biopsychosocial model (e.g., relationality, empowerment), as detailed in Related Work. Whilst recognizing these care approaches are on a continuum rather than placed in fixed categories, we used these broad categories to classify the care concepts based on the most evident and prominent care concept as discussed in each paper. Our results reflect how the authors of the papers in the corpus prioritized these concepts.

The final themes were utilized to produce the two main contributions of mapping of care conceptualizations and functionalities in each project, and categorizing patient participation levels and the associated design activities in the VA design processes.

In addition to thematically analyzing the screened papers, additional data were captured to further characterize virtual assistant types. In a separate Excel spreadsheet, the first author collected data on: the type of VA (AI or non-AI), the AI type (NLP, ML, LLM, etc.), whether patients were involved in the process, and if so, in what role (e.g., evaluator, co-designer, initial concept generator). For a full list of the reviewed papers and data collected, see the appendix (Table 8).

4 Results

The review included 55 studies, consistent with typical scoping review corpus sizes, examining virtual assistants for chronic illness self-management. The majority of studies were conducted in the USA (n=18), followed by Switzerland (n=6), the Netherlands (n=4), and various other countries across Europe, Asia, Africa, and Australia. The chronic conditions addressed ranged widely, from diabetes (n=8) and heart failure (n=2) to hemophilia (n=1), fibromyalgia (n=1), polycystic ovary syndrome (PCOS) (n=1), and Parkinson's disease (n=1). A portion of studies (n=16) focused on general chronic illness management without targeting a specific condition, particularly in older adults. Regarding AI integration, studies were nearly evenly split between AI-powered VAs (n=25) and non-AI

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[5] ATLAS.ti: https://atlasti.com (last visited on 23/07/2025)

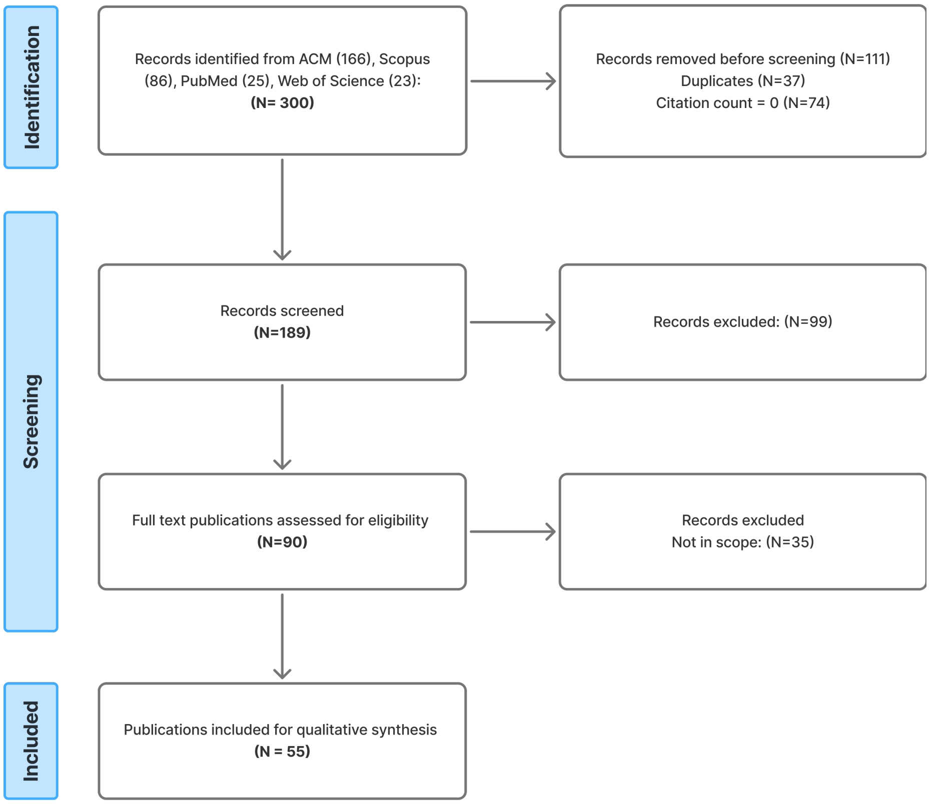

Figure 1: PRISMA-ScR Flow Chart of our Literature Selection Procedure. Under Identification, Screening, and Included, the first row of boxes shows the total records (n) identified, screened, and assessed during the main search through 4 databases, and the number (n) of records excluded based on a specific inclusion criteria or exclusion criteria. The following rows denote the total records (n) assessed for eligibility and final publications included in the analysis.

VAs (n=30). (see Table 6 and Table 7 in the Appendix for a complete list of study characteristics).

From the analysis of the studies included in the corpus, we developed a mapping of underlying care concepts framed in the VAs with their associated functionalities, and a categorization of patient involvement in the design process for virtual assistants for chronic illness self-management. This analysis was conducted as a way to assess how patient-centered care was enacted and to visualize key differences with AI integrations. In the following sections, we first describe the underlying concepts of care for chronic illness self-management as implemented in the VAs, as well as the VAs' main functionalities, to provide an overview of how care was considered in the design process. Then we will discuss how these concepts were further shaped by the types of patient participation in the process. We report these findings from both AI and non-AI VAs to examine key differences in how patient-centeredness was conceptualized and enacted.

4.1 RQ1: Underlying Dimensions of Virtual Assistant Care

The shift to patient-centered care approaches recognizes the importance of delivering holistic care rooted in self-management techniques. To examine how care was conceptualized in the VA design process, we performed a thematic analysis of how the papers discussed what kind of care their VAs would deliver and for what purpose, such as for treatment adherence or to foster deeper patient-provider relationships. Additionally, we examined what the main functionality of each VA was to further understand how the VAs operationalized different care concepts through their main functions. By thematically analyzing what kind of care the VA would deliver, we gathered the underlying dimensions of care concepts framed in the studies, which often intersect but primarily surface more dominant ones over others. Care concepts were grouped into seven main themes and, subsequently, classified under two main approaches to care in VA design, grounded in the biomedical and biopsychosocial/PCC models:

(1) A reductionist approach in which care was conceptualized as medical or clinical adherence, behavior change, and proaction or proactive care.

(2) A holistic approach in which care was conceptualized as health literacy, relationality, autonomy, and empowerment.

These approaches are not treated as mutually exclusive categories; however, in the analyzed papers, a prioritization of a primary concept over others was discussed and enacted upon through VA functionalities. In the following two sections, we detail our findings on concepts of care further, the associated VA's main functionalities, and the differences we observed when AI was integrated into systems.

4.1.1 ***Reductionist Care Approach: Underlying Concepts of Care and Functionalities.*** Our results show that a reductionist approach to care foregrounds dimensions of chronic care related to medical or clinical adherence, behavior change, and proaction. In these cases, VA functionalities were mainly recommender and predictive systems, or coaching tools that primarily emphasized compliance with treatments to ensure patients met goals set by physicians or the system itself (Table 3). We discuss these characteristics further in the following section, where we expand on reductionist approaches by describing how they manifested in VA design.

Adherence as Care. The following papers conceptualized care primarily through adherence to medication prescriptions [41, 85, 98, 118, 120] and physical exercise [69, 129]. In these papers, successful care delivery was contingent upon the ability of patients to follow pre-defined therapeutic regimens, such as exercise programs [129], treatment plans [29], therapy regimens adherence [75], lifestyle modification programs supported by AI chatbots [26]), and adherence to disease-specific education programs [87]. Adherence was often measured against the patients' actual behaviors, captured via sensor data [44], and therapeutic benchmarks or against pre-configured adherence profiles to generate recommendations [98].

To sustain adherence, systems deployed reminders such as push notifications to prompt users to take their medication [29, 120], or remind them about the need to update their self-tracked data [29, 98], and chatbot prompts to encourage continued participation on the intended therapeutic pathway.

Behavior Change as Care. Care was framed as behavior change to improve lifestyle changes [45] and positively influence disease trajectories [127] by improving self-management capabilities [87]. Behavior change goals were primarily focused on fostering healthy habits and assisting in changing attitudes towards a healthier lifestyle [75]. In fact, the majority of papers aimed to increase physical activity [28, 55, 129, 134], reduce alcohol consumption, and manage food intake [3].

To facilitate this, systems provided educational content on behavior change techniques (BCTs) [39, 134], that were not based in the actual lived experiences of patients. The tactics aimed at promoting behavioral shifts [9, 112, 129] and used goal-setting as a strategy to set and track progress toward specific health-related objectives [45, 88, 94].

Proaction as Care. Care appeared as prevention in papers where virtual assistants were designed to reduce the long-term health risks brought on by chronic illness by promoting dietary education [18] and physical activity [43]. Dao et al. (2024) developed AI chatbots to support adherence to lifestyle modification programs for diabetes prevention [26]. Preventive care was implemented through continuous monitoring and feedback tracking health statuses [20, 85].

Key Findings: Reductionist Care, Functionalities, and AI Integrations. Across the 55 studies reviewed, the majority of VAs (29/55) prioritized reductionist approaches to care over more holistic dimensions.

When examining patterns within our corpus, AI-powered VAs appeared to prioritize reductionist care more frequently (64%, 16/25) compared to non-AI VAs (43%, 13/30), which tended toward holistic care (57%, 17/30) (see Figure 2). This pattern may signal an emerging tendency in AI VA design worth further investigation.

The conceptualization of care in VA types was reflected in the choice of AI technology and associated functionalities. The main types of AI employed in reductionist care dimensions were Machine Learning (ML) to develop systems that provided personalized recommendations and treatment plans, and Natural Language Processing (NLP) to communicate educational information for behavior change or relay vital signs data from medical devices (see Table 3). These systems primarily featured one-way communication channels with patients, providing directives on maintaining homeostasis, following health coaches to prevent issues, and setting health goals to maintain good health status. The types of AIs utilized in these systems suggest a connection between the intended functionality and AI method selection under reductionist care dimensions. Collectively, these findings indicate that the majority of VAs do not focus their care around patient-centeredness, with AI-powered VAs being the primary contributors to this pattern, highlighting the need for expanded focus on holistic care approaches.

4.1.2 ***Holistic Approach to Care: Underlying Concepts of Care and Functionalities.*** The following papers adopted a more holistic approach to self-management. Through situated and contextual chronic care concepts such as relationality, health literacy, autonomy, and empowerment, these dimensions provide a more well-rounded approach to care delivery for people living with chronic illness embedded in their lived realities (Table 4).

In the following section, we describe how holistic care domains were conceptualized and operationalized in VAs by care type.

Health literacy as Care. Health literacy aimed to help patients avoid negative health outcomes by helping them understand their illness further [9, 41, 44, 72, 76]. AI was used to monitor symptoms and provide information on changes and fluctuations [157]. Furthermore, some systems supported patients in building new skills or deepening existing ones by increasing health literacy. This included promoting self-education in low- and middle-income countries [7], encouraging self-discovery of the illness and its patterns [95], and fostering more self-monitoring competencies to enable patients to notice and report health changes to providers [138].

Other studies focused on improving communication between patients and clinicians by increasing health literacy in patients. For instance, a "literacy agent" was designed to translate clinical jargon into lay language for patients [44] or to better understand provider-given instructions [11] and to learn about available treatment options to support shared decision-making [51].

Table 3: Reductionist Care: VAs' concepts of care, functionalities, and patient involvement. The table illustrates VA care concepts, functionalities, type of VA (Non-AI or AI type), and patient participation level, which will be discussed in the next section.

Care Concept(s)	Functionality	VA Type	Participation	Ref.
Adherence	Conversational agent for medical appointment reminders	Rule-based AI	Evaluation	[121]
	Recommender system and conversational agent for health data	NLP and NLG	Not involved	[98]
	Recommender system for medication management	Rule-based AI	Not involved	[120]
	Personalised treatment plans for rehabilitation	Rule-based and ML	Evaluation	[75]
	Recommender system for health goals	Non-AI	Evaluation	[29]
Adherence, Autonomy	Chatbot for symptom and medication tracking	LLM and ML	Evaluation	[118]
Adherence, Proaction	Conversational agent for medical reminders	LLM	Not involved	[26]
	Symptom monitoring	LLM	Not involved	[85]
Adherence, Health literacy, Relationality	Recommender system and conversational agent for provider plans	NLP	Evaluation	[44]
	Symptom monitoring	Non-AI	Evaluation	[41]
Adherence, Behavior Change	Exercise programs	Non-AI	Evaluation	[129]
	Conversational agent for symptom monitoring	Non-AI	Initial concept	[13]
Adherence, Behavior Change, Relationality	Conversational agent for disease education	Non-AI	Evaluation	[87]
Behavior Change	Predictive coaching system for lifestyle support	ML	Not involved	[3]
	Personalized coach for physical activity	ML	Not involved	[28]
	Personalized chatbot for healthy eating	ML	Not involved	[39]
	Conversational agent for physical activity	LLM	Not involved	[134]
	Conversational agent coach for healthy lifestyle	Non-AI	Evaluation	[55]
	Self-tracking and target setting	Non-AI	Evaluation	[88]
	Embodied conversational agent coach for rehabilitation	Non-AI	Evaluation	[127]
Behavior Change, Health literacy, Autonomy	Predictive system for disease monitoring	ML	Evaluation	[9]
Behavior Change, Health literacy, Relationality	Recommender system coach for nutrition	ML and NLP	Evaluation	[45]
Behavior Change, Autonomy	Conversational agent for education	Non-AI	Evaluation	[112]
	Health coach for nutrition	Non-AI	Evaluation	[94]
Proaction	Personalized conversational agent to prevent further chronic issues	NLP	Not involved	[20]
	Personal companion conversational agent for mental health support	NLP	Not involved	[61]
	Personalized conversational agent coach for nutrition	Non-AI	Evaluation	[18]
	Assistant to improve physical activity	Non-AI	Initial concept	[69]
	Personalized gamefied app to increase physical activity	Non-AI	Not involved	[43]

Relationality as Care. Care was framed as relational in papers where health management extended beyond the individual to include healthcare providers [72], family members [72, 130], and caregivers [126]. Patients also expected the VA to connect them with other people living with chronic illness to learn how to manage symptoms [13]. In one instance, a VA was designed to explore user perception on assistants who express the same physiological concerns as them [60].

In two cases, relationality culminated at the *community level.* O'Leary et al. (2022) explored how social influence and support networks could reduce negative health outcomes through the promotion of healthy behaviors and the sharing of health information [103]. In Kim et al. (2022), participants emphasized the need for

Table 4: Holistic Care: Virtual assistants' concepts of care, functionalities, and patient involvement. The table illustrates VA care concepts, functionalities, type of VA (Non-AI or AI type), and patient participation level, which will be discussed in the next section.

Care Concept(s)	Functionality	VA Type	Participation	Ref.
Health Literacy	Conversational agent and recommender system to explain health status	Rule-based AI	Initial concept	[76]
	Conversational agent for health related questions in low-resource language	NLP	Co-design	[7]
	Avatar agent for health counseling	Non-AI	Evaluation	[11]
	Home self-monitoring system	Non-AI	Evaluation	[138]
	Gamified apps to educate children	Non-AI	Not involved	[57]
Health literacy, Autonomy, Empowerment, Relationality	Avatar agent for illness education	Rule-based AI	Evaluation	[157]
Health literacy, Relationality	Personalised treatment risk evaluator and conversational agent	ML and LLM	Co-design	[51]
Health literacy, Autonomy, Relationality	Conversational agent health coach	Rule-based AI	Evaluation	[95]
	Conversational agent to increase shared illness understanding	Non-AI	Evaluation	[72]
Relationality	Personalised conversational agent for access to health services	LLM	Co-design	[66]
	Avatar agent for community health support	Non-AI	Co-design	[103]
Relationality, Empowerment, Adherence	Conversational agent for provider analysis	LLM	Initial concept	[97]
Relationality, Behaviour change	Goal-setting app for patient and care managers	Non-AI	Evaluation	[19]
	Gamified nutrition app for children and caregivers	Non-AI	Evaluation	[126]
	Conversational agent to support patient-provider relationship	Non-AI	Not involved	[101]
	Conversational agent to support patient-provider relationship	Non-AI	Not involved	[124]
	Personalised conversational agent interaction style	Non-AI	Initial concept	[48]
	Voice-based conversational agent with human-like physiological states	Non-AI	Not involved	[60]
	Conversational agent for tracking and reporting health data	Non-AI	Not involved	[102]
Relationality, Empowerment	Situated dashboard for family co-regulation of ADHD	Non-AI	Co-design	[130]
Autonomy	Conversational agent for healthcare questions	NLP	Not involved	[155]
	Symptom monitoring for the elderly	Non-AI	Evaluation	[1]
Autonomy, Adherence	Voice-based agent for doctor's after-visit summary and medication reminders	LLM	Co-design	[84]
Empowerment	Self-tracking of PCOS symptoms	Non-AI	Co-design	[62]
	Adaptive interface to support condition variability	Non-AI	Evaluation	[146]
	Gamified assistant to surface personal strengths	Non-AI	Co-design	[58]

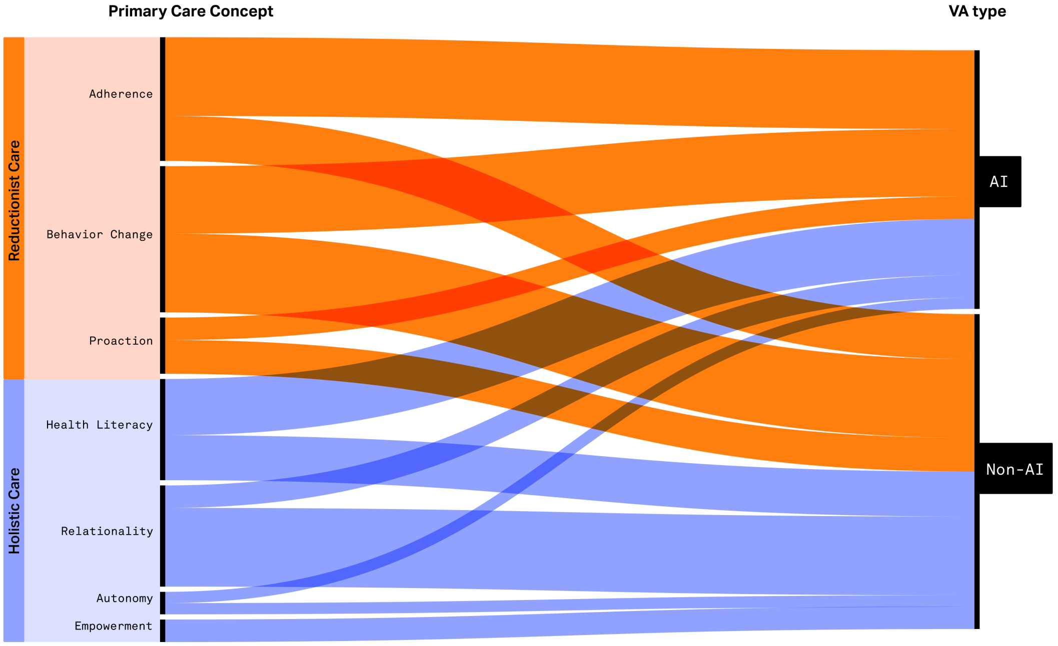

Figure 2: Primary Concepts of Care Prioritized in AI and Non-AI VAs. The figure illustrates the correlation between the primary and most dominant care concepts foregrounded in VAs and the VA type (AI or Non-AI). The size is proportionate to the number of occurrences of papers discussing either holistic or reductionist care dimensions with AI integrations (combined ML, LLM, NLP, Rule-based types) and without AI.

designing an LLM-VA that went beyond individual benefit to serve friends, families, and neighbors within African-American communities [66].

Papers were also concerned with improving, and not replacing [44, 102], the patient–provider relationship to help caregivers monitor the health status of their patients and refine therapy plans [41, 44, 72, 97], facilitate shared decision-making [44, 45], reinforce treatment adherence [51], and provide educational scaffolding for patients to better understand therapeutic options [87]. Relational care was operationalized through jointly agreed-upon therapeutic tasks [19, 101]. In two studies, conversational agents were designed and tested with different interaction styles to help foster collaboration between people managing their chronic illness and healthcare practitioners [48, 124].

Autonomy as Care. Care was also conceptualized as increasing autonomy through effective self-management. The goal was to encourage support in living an independent life at home and experience a good quality of life through daily self-management [1, 9, 84]. Autonomy in self-management would also lessen the clinicians' load by freeing them from checking patient data regularly [9]. The need for independent care outside inpatient consultations was echoed through the use of chatbots providing access to support at home [95, 155]. Autonomy provided patients with independence and accountability toward their own health condition [72, 112].

Empowerment as Care. Several studies framed care as empowering patients through their daily self-management practices [97, 146], increasing confidence in handling their conditions [87]. Jessen et al. (2018) designed a tool with patients that, rather than focusing on the deficits of managing chronic illness, was aimed at helping its users surface and use their own personal strengths in overcoming their everyday challenges [58]. Silva et al. (2024) emphasized empowering families to self-track family-level shared perspectives on health behaviors [130]. O'Leary et al. (2022) highlighted how digital health tools could enable individuals to pursue not only physical, but also spiritual health at the church community level [103]. Lastly, in an autoethnographic study, Kang et al. (2025) reported the experience with self-tracking of polycystic ovary syndrome (PCOS) symptoms to inspire more inclusive and empowering tools [62].

Key Findings: Holistic Care, Functionalities and AI Integrations. Our findings show that holistic care VAs were in the minority (26/55) compared to reductionist approaches (29/55). However, non-AI VAs tended to conceptualize care more holistically (57%, 17/30) compared to AI-powered VAs (36%, 9/25) (see Figure 2).This pattern suggests that current AI integration practices may be associated with more reductionist care concepts rather than holistic approaches. While AI-based virtual assistants represent newer technological developments and this pattern may evolve as the field matures, the current literature indicates that AI integration has not yet delivered on its promise to enhance patient-centered, holistic care, and may be trending in the opposite direction.

By examining their main functionalities, we found that holistic VAs more frequently relied on two-way conversational formats between patient and VA to provide disease education, facilitate psychosocial support, and improve patient–provider communication. This is in contrast with reductionist care functionalities in which more one-way and directive interactions were designed. To achieve the more expanded conversational nature of holistic care VAs, AI-powered VAs primarily utilized Large-Language models (LLMs) and rule-based AIs (see Table 4), contrasting with ML-powered hyper-personalized recommender systems seen in reductionist care approaches.

4.2 RQ2: Patient participation in the VA Design Process

To uncover how patient-centeredness was enacted in the design process, we analyzed how patient perspectives were considered alongside our examination of care conceptualization and associated functionalities. To achieve this, we examined patient involvement in the design and development process across virtual assistant types (AI-driven and non-AI VAs) for chronic illness self-management. This focus reflects how patient-centeredness has been framed in literature, where participation in design processes is required to ensure a patient-centered delivery aligned with patients' needs, preferences, and values [142]. We thematically analyzed the degree of patient involvement across the 55 studies and developed a categorization of this involvement into four main roles that capture the level of participation: no patient involvement, patients as evaluators, patients as co-designers, and patients involved at initial concept generation. By investigating how patients participated in the process against corresponding care dimensions and functionalities, we gained a comprehensive view of how patient-centeredness manifested in each study (see Table 3 and Table 4).

Our findings show that across all virtual assistants, the design process was not patient-centric. Most studies either did not involve patients in their development or engaged them late in the design process (see Figure 3). Very few cases engaged patients as co-designers or initial project concept generators, where patient perspectives were more deeply integrated and helped shape VA development toward a more patient-centric approach to care.

In the next sub-sections, we discuss how patient involvement manifested in the design process of non-AI VAs and AI-driven VA and their corresponding design process activities (see Table 5).

Patients as evaluators. The majority (25/55) of patients were involved in the VA design at the evaluation of a predetermined VA level. Both AI and non-AI VAs engaged patients as evaluators in activities designed to assess a VA solution rather than actively shape it with needs, values, and preferences. In fact, in *non-AI VAs*, the majority of studies (17/30) primarily took part in usability tests [1, 11, 41, 87, 88, 112, 138] and post-VA development interviews [18, 19, 29, 55, 87, 94, 126]. In certain instances, patients were tasked to evaluate specific UX features [146], and took part in semi-structured interviews to provide feedback on VA content [29] or an initial focus group to discuss a chatbot as a technology probe [94]. Finally, patients were also involved in experimental settings in single-arm feasibility studies [72], a two-arm study [127], and a randomized clinical trial [129].

In *AI-driven VAs*, activities remained largely the same as in non-AI VAs, where 32% of projects (8/25) used patients to evaluate a pre-determined AI-VA. Similar to non-AI VAs, usability tests were the most common evaluation tactic [9, 45, 75] to assess a VA. Patients were also engaged in post-VA development assessment through debrief interviews to understand their experiences with the VAs [45, 94, 95]. Additionally, in more experimental settings, people were also involved in feasibility studies to prove technical functionalities through user evaluation [44, 157].

Patients as Initial Concept Generators. Our findings show that patients were rarely engaged in a patient-centric process for VA design. In a minority of studies (5/55), patients participated to share values, needs, and preferences for VAs at the start of a project and were re-engaged to assess them after their development. This level of participation, while not a full co-design, enabled VAs to be rooted in the lived experience of patients to provide more situated self-management assistants.

In *non-AI VAs*, the initial concept generation type of participation occurred in around 10% of papers [13, 48, 69]. Patients took part in an initial focus group and followed up to assess the VA in a usability test [69] or through a survey to collect initial preferences and needs, and followed up with a usability test [13] or an experiment [48].

In *AI-VAs*, however, the initial requirement gathering was more participatory in nature, where workshops were held in two studies with the patients to gather an understanding of chronic illness self-management first, and later evaluating the AI-driven system [76, 97].

Patients as Co-designers. Across VAs, patients as co-designers from the beginning of a project until the end was rare (8/55).

In *non-AI VAs*, co-design involved initial focus groups [103], follow-up co-design workshops [58, 103, 130], and in one case in particular an autoethnographic study with a researcher suffering from the condition being designed for as a starting point [62]. Similarly, *AI-driven VAs* involved patients early in the process by understanding their needs through initial interviews [51, 66] and focus groups [7, 84]. Furthermore, in two studies, this initial requirement gathering was also followed up by co-design sessions and workshops with the patients themselves to deepen and situate the projects' understanding of chronic illness self-management [51, 66].

Centering chronic patient voices and their lived experiences resulted in deeply cultural and situated VA solutions. For instance, in *non-AI VAs*, to tailor health-related information support to the African-American population, researchers ran ten participatory design focus groups in a church because of its central role in the community. Through these interactions, participants conceptualized a "Church Connect" app to incorporate health-related, cultural, and spiritual information to foster community support [103].

In *AI-based VAs*, there were also examples of relational and cultural forms of VAs. To design an AI chatbot for hemophilia patients in Senegal, Babington-Ashaye et al.(2023) ran a focus group with local patients to create a database of 100 frequent questions on hemophilia, translated the answers into Wolof, the local language, and incorporated the content into a chatbot to test with patients. Participants mentioned using the chatbot was akin to sitting under a "palaver tree", a community space to discuss or solve problems in some African traditions [7].

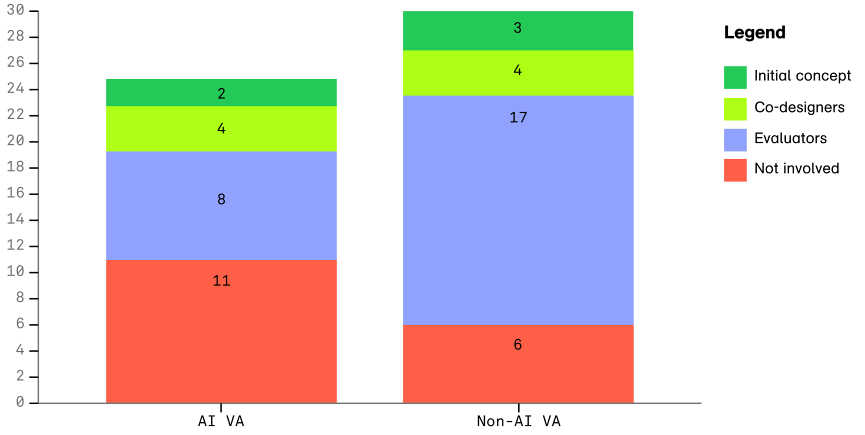

Figure 3: Patient participation in the VA design process. The figure illustrates the distribution of studies that involved or did not involve patients in varying degrees of the process.

Table 5: Categorization of patient roles defined by related design activities in the VA design process. The table illustrates the degrees to which patients participated in the design process of both VA types, AI-driven and no-AI, and corresponding paper references.

Patient Role	Related Design Activities	AI-VA	Non-AI VA
Co-designer	Interviews with patients	[51, 66, 84]	
	Focus groups	[7]	[103]
	Follow-up co-design workshops	[51, 66, 84]	[58, 103, 130]
Evaluator	Usability testing	[9, 45, 75]	[1, 11, 41, 87, 88, 112, 138]
	UX feedback session		[29, 146]
	Post-development interviews	[45, 95, 118, 121]	[18, 19, 29, 55, 87, 94, 126]
	Feasibility studies	[44, 157]	[72, 127, 129]
Initial Concept Generator	Focus group and usability test		[69]
	Initial survey and usability test		[13]
	Initial survey and follow-up experiment		[48]
	Participatory activities and evaluation	[76, 97]	

Key Findings: Patient Participation in VA Design Processes. A large group of studies (25/55) involved patients only in late-stage VA design evaluation, while the second largest group (17/55) did not involve patients at all. These results align with previous findings on VAs not being patient-centric [142]. Our review details this lack of patient-centric design further by analyzing patient roles and activities in the development process. A small number of studies (5/55) involved patients at project initiation to collect needs, preferences, and values for VA concept generation, with follow-up evaluation activities. Very few cases (8/55) involved co-design participation, where patient perspectives were deeply engaged and helped shape VA development toward more patient-centric care approaches.

Analysis by VA type revealed patterns in our corpus. AI-powered VAs showed *less patient participation* overall, with 44% (11/25) not involving patients in the design process compared to 20% (6/30) of non-AI VAs (see Figure 3). This pattern suggests that patient-centric processes have not yet been enacted in AI-VA development, despite expectations that AI integration would enhance patient-centered care.

When examining the overlap between care concepts and patient participation in AI-VAs, studies with minimal or no patient involvement prioritized adherence and behavior change, sometimes incorporating health literacy to support adherence or relationality to strengthen patient-provider relationships, for example (see Table 3). In contrast, AI systems designed with patients as co-designers or initial concept generators showcased broader, more relational care concepts (see Table 4). These studies foregrounded patients' lived illness experiences, leading to systems more contextually attuned to patient lives.

These findings suggest a connection between the depth of patient participation and the care dimensions informing VA design. When patients were involved early and substantively, systems reflected relational, social, or cultural aspects of care. Where participation was limited, care remained framed solely in terms of adherence or behavioral change, not expanding into holistic care approaches crucial for chronic illness self-management.

4.2.1 Reflections on patient involvement. In certain studies, authors critically reflected on the limitations of their patient involvement, signaling tensions between design intent and technical constraints. A few papers considered the need to develop deeper granularity in patient profiles [44, 55]. However, collecting and using sensitive patient health data posed potential privacy risks, leading to design choices that limited data collection and simplified personalization [72, 98]. This trade-off highlights an issue in current AI-driven VA design on how to reconcile patient involvement and VA personalization with data security requirements to ensure patient-centered care.

5 Discussion

In this scoping review, we analyzed the design approaches as they relate to patient participation and care framing conceptualizations in the development of virtual assistants for chronic illness self-management. We developed a mapping of care dimensions as they are prioritized in VA systems and a comprehensive categorization of patient participation in the process. Through these contributions, we highlighted key differences brought on by AI integrations in how patient-centeredness was considered and enacted in the design process. In this section, we discuss the identified methodological pitfalls in VA design and development processes and provide implications for future work.

5.1 From Technical Personalization to Patient-Centeredness

The results from our review indicate that VAs (both AI and non-AI) predominantly did not align with patient-centered care ideals for chronic illness self-management, which seeks to support self-managements skills [145], recognizes the need for holistic care [93], and involves patients in the process to understand what is most meaningful to them [33, 133]. Our findings suggest prioritization of reductionist over holistic care and show consistently low levels of meaningful patient participation. These findings align with previous research illustrating that VAs for chronic illness self-management do not align with patient-centered care (PCC) [142]. However, our work extends the knowledge in this field by providing findings on how PCC lacked in the VA design process through how care was conceptualized, and how patients were involved. Additionally, we provide new knowledge on the technical AI evolution of VAs alongside key differences in the design process observed through its integration.

5.1.1 AI Integration Lacking Patient-Centered Care. Due to the difficulty in delivering PCC through VAs for chronic illness, the main assumption underlying AI-integrated VA development has been that advanced technical capabilities would align these systems with PCC aspects by centering patients' needs and self-management practices [4]. However, our review challenges this assumption, as the observed trends suggest that AI has not made VAs more patient-centric and, in some cases, may have moved development further from PCC ideals.

While AI integrations provided personalized functionalities, such as ML recommender systems offering advice based on patients' health status [45], or LLM conversational agents coaching patients to meet health goals [26], these functionalities often did not lead to deeper enactment of PCC. In fact, PCC was operationalized mainly as technical personalization features, developed with minimal or no patient involvement in the design process. AI-integrated VAs illustrated more patient exclusion in development processes, relying instead on algorithmic approaches to deliver patient-centered experiences. Because of this, technical personalization failed to expand into the psychosocial and holistic care dimensions that characterize chronic illness management, such as relational support, empowerment through self-management, increased autonomy, and health literacy that patients consistently identify as central to their care needs [53, 96, 107, 114].

5.1.2 Algorithmic Personalization and Reductionist Care. A pattern emerged when comparing AI and non-AI systems. Although non-AI VAs also failed to meet full patient-centeredness standards, they indicated higher patient involvement than AI-driven VAs, more frequently engaging patients as evaluators and, in some cases, as co-designers and concept generators. This broader engagement corresponded with non-AI VAs leaning toward holistic care approaches, bringing them closer to genuine patient-centeredness. With AI integration, we observed a shift toward lower patient involvement and more reductionist care approaches. This pattern may point to a foundational misunderstanding about patient-centeredness in AI technology design. The assumption that technical personalization equals patient-centered care appears to have led VA design practices to conflate algorithmic sophistication with patient alignment, reinforcing technosolutionist tendencies [80, 99]. True patient-centeredness requires not just individualized outputs, but individualized processes that involve patients as authentic partners in defining problems, shaping solutions, and evaluating outcomes. We acknowledge that these patterns emerge from a research landscape in flux. AI-driven VAs represent a relatively recent development in chronic illness self-management, and the reduced patient participation we observed may reflect practical challenges associated with emerging technologies rather than fundamental incompatibilities with participatory design. As researchers, practitioners, and designers gain experience integrating AI into VA development and as methodological frameworks mature, we may see convergence toward more participatory and holistic approaches. Nevertheless, the current state of the literature suggests cause for concern as the promise of AI-driven personalization risks obscuring the need for participatory processes that engage patients as authentic partners in defining their care needs.

5.1.3 Meaningful Participation Leads to Patient-Centered Care. Recent HCI work on Participatory AI has questioned if participatory methods actually empower patients or merely extract their input, emphasizing that meaningful participation requires genuine decision-making power rather than mere consultation [12, 109]. Our review echoes this concern. Patients positioned as evaluators, typically through usability testing of pre-defined systems, had limited influence, while those engaged as co-designers were able to articulate needs, preferences, and values in ways that shaped design directions. This contrast exposes translation gaps in how patient-centered care is operationalized within HCI, where labeling a study as participatory often only includes evaluative activities that do not substantively integrate patients' lived experiences into design processes. In fact, in our review, across both AI and non-AI VAs, we observed consistent evidence that meaningful patient participation, particularly co-design, enabled more expansive and holistic care concepts, moving beyond narrow clinical metrics to encompass the full spectrum of chronic illness experience. These findings align with broader health research indicating that human-centered design and patient partnerships yield more person-centered solutions [31, 47, 82].

Beyond VA design, this pattern supports evidence from PCC that aligning with patients' self-management strategies and fostering confidence improves quality of life and reduces symptom burden [104]. Importantly, co-design also offers a pathway to anticipate and negotiate ethical concerns around AI, such as privacy and data sharing, that a few studies identified as barriers to patient participation. These challenges can become topics of discussion in co-design, allowing patients to participate in shaping how such trade-offs are addressed.

5.2 Fitting AI to Patient-Centered Care

Our review exhibits a connection between the different types of AI technology and the care concepts, functionalities, and patient participation levels that accompanied them. This suggests that the choice of AI technology itself may influence the potential for patient-centered design. When Large-language models (LLMs) VAs were designed, a broader participation spectrum was observed, where patients were either entirely excluded from their development process or included fully as co-designers. Crucially, those LLM-VAs that engaged patients as co-designers consistently resulted in more holistic care approaches and therefore more patient-centered VAs, while those that did not involve patients remained reductionist in their care delivery. This binary suggests that LLM technology can be more conducive to participatory design when designers and developers choose to pursue it. In contrast, Machine Learning-based VAs with more complex architectures appeared predominantly in reductionist care contexts, involving patients minimally as evaluators or not at all.

5.2.1 Technical Complexity as a Barrier to Co-Design. There are several factors that may explain why different AI technologies enable different levels of participation. First, complex ML systems may prioritize technical feasibility over participatory design, with development resources focused on proving algorithmic performance rather than engaging with end users meaningfully. In fact, several HCI authors have pointed out concerns over "participation washing" [131] and the co-opting of the voice of participants [12] in ML design practices. In our review, the majority of ML-based VAs did in fact involve patients mainly as evaluators or not at all. This, however, may also be due to the technical complexity of these systems creating practical barriers to co-design, as they require specialized knowledge, and the lack of proper design methodologies accounting for such complexities. Previous work has noted this difficulty in mapping the messier, contextual contributions from participants into the structured data requirements of ML systems [21]. LLMs, by contrast, may be less complex for non-technical stakeholders to understand and engage with during design processes. In HCI, LLMs have been used to engage directly with diverse users to understand their needs and perceptions in different contexts [108]. Recent work shows that their conversational and less technologically demanding nature can make AI outputs more accessible to diverse users, including those with lower technical literacy [78, 152]. Participatory workshops have even used LLMs as design materials themselves, enabling stakeholders to co-develop communication rules and interaction styles [68]. This suggests that LLMs can act not only as engines for patient-centered care but also as co-design materials that patients can directly interact with to shape how a system should respond.

For HCI practitioners designing VAs for chronic illness, this finding suggests a need to explicitly consider the participatory affordances of different technologies. The goal is not to avoid technical sophistication, but to choose technologies that enable rather than preclude patient involvement, and LLMs warrant further investigation as tools that can be built in a participatory way. The implications extend beyond individual project decisions to broader questions about how technical sophistication and participatory practices can advance together rather than in opposition.

5.3 Design Implications for Patient-Centered AI-Virtual Assistants

Our findings signal the need for continued examination of patient participation and care conceptualization in AI VA design as the field matures. The patterns we observed on low patient involvement and more reductionist care approaches in AI VAs may represent a transitional phenomenon reflecting the recent state of these technologies. As researchers and practitioners establish more robust frameworks for participatory AI design in healthcare contexts, we may see an evolution toward approaches that better integrate technical sophistication with meaningful patient participation.

To assist in this effort, we contribute the following design implications for VA researchers, designers, and development teams seeking to align VAs with patient-centered care principles. These implications are particularly relevant given the rise of AI integrations that aim to personalize healthcare experiences, yet often risk narrowing focus to individual optimization at the expense of holistic, relational approaches to chronic illness care. Our analysis reveals opportunities to leverage AI's personalizing capabilities while maintaining the needs that patient-centered care demands.

5.3.1 Rethinking Care Through Expansion Rather Than Opposition. This work extends how patient-centered care can be delivered by exploring how clinical and psychosocial approaches can inform and enrich each other rather than compete. Our findings revealed that, while VAs predominantly relied fully on reductionist or holistic approaches, some VAs with reductionist framings initially approached development holistically, e.g., aiming to improve patient-provider relationships as relational care, but ultimately defaulted to adherence strategies. Conversely, holistic care approaches often excluded clinical dimensions, potentially missing opportunities for comprehensive support. This suggests VAs tend to prioritize one form of care over another. However, prior research highlighted PCC's ability to help precision medicine, carried out mainly by AI-VAs, achieve better biomedical outcomes [35]. The aim becomes not whether to include clinical indicators, but how to embed them within broader frameworks that respect chronic illness experience complexity.

The use of clinical monitoring in VA with reductionist approaches might be reimagined within community care frameworks that chronic illness communities have already built and found meaningful [92]. Rather than positioning biological monitoring as purely individual self-management, VAs might, for instance, enable trusted care network members to monitor levels like heart rate or blood sugar and provide support during flare-ups, as suggested in recent HCI research [83]. This approach recognizes that chronically ill people are often simultaneously support givers and recipients within their communities [83], challenging the typical patient-caregiver distinction that many clinical systems assume. Such integration shows how clinical care needs can serve relational care approaches, using biomedical data not just for individual optimization but to strengthen the interdependent networks that chronically ill people rely on.

We see an opportunity to develop AI-driven VAs for chronic illness that support a well-rounded spectrum of self-management - one that recognizes when patients need data versus emotional support, when they want family involved as secondary caregivers, or how their needs shift across different condition phases. This spectrum-aware direction would mimic how chronic illness is supported in patients' lived realities, adapting to fluctuating care needs (from biomedical to holistic approaches) while maintaining patient-centeredness as an anchor throughout the development process.

5.3.2 Navigating the Technology-Participation Tension. Our findings reveal a tension in VA design that, when development begins with technical rather than experiential and relational considerations for how VAs can support people self-managing their chronic illness, designers may risk falling into technological tunnel vision. The approach to care becomes techno-centric, focusing on system performance, data collection, and model optimization rather than experiential aspects that matter most to patients. Critical HCI scholarship has cautioned against these techno-centric views of assistive technologies because they reinforce a "fix it" mentality incompatible with chronic conditions [132]. This techno-centricity is shown in our findings, where ML-based systems prioritized reductionist care (see Table 3), shifting attention away from understanding how patients actually experience their care.

Instead, co-design approaches center patients' lived experiences and holistic care needs early in the process, allowing development teams to orient toward experiential dimensions of VA interactions such as how conversations unfold, what support patients seek, and how technology can enhance rather than substitute human connection. Our findings suggest this approach leads to more holistic care conceptualizations that empower patients, inspire two-way rather than extractive interactions, and provide psychosocial support (see Table 4). The choice of AI technology can either reinforce or challenge these patterns. Complex ML architectures, with demands for specialized knowledge and data preparation, can inadvertently deepen technological tunnel vision [21, 100]. The technical sophistication required could shift focus away from sustained participatory engagement, making it difficult to maintain attention on patients' actual experiences. When patients are not adequately involved in shaping these systems, it exacerbates AI black-boxing, making technology less transparent and patients' input less meaningful [2]. This is particularly concerning in health contexts, where opaque AI systems may lack accountability when things go wrong [86], potentially threatening patient autonomy [115].

LLMs present different possibilities. Their conversational nature and lower technical barriers make them more compatible with participatory processes [78, 152]. As our findings show, they were used effectively in holistic care approaches emphasizing interactive, two-way dialogues and relational support (Table 4). This suggests LLMs can serve as flexible co-design materials, allowing patients to directly experience and shape conversational interactions during development. However, this accessibility should not substitute for deeper participatory engagement. What emerges from our review is that the technology-participation tension cannot be resolved through more sophisticated technology alone. Instead, it requires recognizing that when designers begin with technical capabilities, they inherit constraints on how deeply they can engage with patients' actual experiences of chronic illness. Starting with co-design can fundamentally shift this dynamic, positioning technology as a means to support the relational and experiential aspects of care that patients identify as meaningful.

5.3.3 Engaging Patients as a Practice of Care. In this work, we acknowledge that although ideal, traditional co-design practices engaging participants repeatedly across a design process are often unrealistic for people suffering from chronic illness. Many experience fluctuating symptoms, fatigue, and emotional burdens that limit consistent participation. The variability of ability among chronically ill individuals requires adaptive methods beyond standard protocols [83]. However, our review indicates a design process gap: while HCI researchers increasingly recognize the need for co-design with chronic illness populations, the VA development studies in our corpus minimally engaged them (see Figure 3). Researchers working with hard-to-reach populations have developed flexible approaches that accommodate resource constraints, attrition, and participation risks [36]. Recent HCI efforts have begun developing more accessible co-design practices for people managing their chronic illness with fatigue-conscious design sessions and multiple entry points [56, 65, 83]. Meaningful participation may look different for people with chronic illness, involving family caregivers, using remote methods, or creating multiple touch points rather than intensive workshops. Managing chronic conditions often overwhelms patients, making sustained engagement difficult without tailored support and non-judgmental understanding [40].

Drawing upon feminist approaches to care [140, 141], we see co-design as a practice of care beyond a methodological one. Care ethics emphasizes relational responsiveness, vulnerability, and attending to individual circumstances [113]. Co-design becomes less about efficiently gathering patient inputs and more about creating space for embracing the messiness of lived experiences and capturing shifting preferences, needs, and values [27].

Our contribution indicates how VA designers must adopt these adaptive co-design practices to truly engage people living with chronic illness as experts in their care experiences. For HCI, this means resisting reducing patients to standardized narratives [23, 24] and uncovering how VAs can adapt to various stages of chronic illness (from pre-diagnosis to treatment and beyond), which studies in the corpus rarely discuss. This adaptability is particularly crucial for elements such as goal-setting in VAs, which must be evolving and responsive to people's changing lives [34]. Critically, this includes acknowledging the emotional complexities of chronic illness [30], especially in developing AI technologies where capturing embodied and situated knowledge [52] becomes necessary to ensure these systems reflect the needs of those they are built for [70].

5.4 Limitations and Future Work

In conducting this scoping review, we adopted certain strategic decisions to provide a focused exploration of the topic; however, it also has its limitations and presents certain challenges. First, our analysis was grounded in academic papers, which provide detailed accounts of design and development processes but may not fully capture practices reported in other sources, such as grey literature, industry reports, or practitioner reflections. Future work should extend this analysis by incorporating and analyzing work undertaken in industry and in practice by VA designers to more fully capture design practices as they unfold outside academia.

Second, we relied on databases where the majority of included papers were published in English. Consequently, our findings primarily reflect Western academic discourse and may not account for perspectives, practices, or care conceptualizations emerging in other linguistic, cultural, or geopolitical contexts. Future research should aim to include work in additional languages and from diverse contexts to better understand how care, participation, and patient-centeredness are conceptualized and enacted in different sociotechnical realities and across cultures.

Third, we applied a minimum citation threshold (>0 citations) to focus on work that had begun to circulate within the research community, in line with standard practices for scoping and literature reviews [117, 119, 153]. We acknowledge this may have excluded some very recent work, yet our review was interested in capturing the effects of AI on longstanding digital health technology design processes, patient participation approaches, and care conceptualizations as reported within our review.

Lastly, we report these findings as descriptive patterns within the reviewed studies. The patterns are intended to set the stage for understanding current processes in VA design and to highlight potentially concerning trajectories for participatory research. By mapping current care conceptualizations, functionalities, and patient roles, this review offers a reference point that future work can build on to examine whether, and how, VA design shifts as AI-driven systems mature and as the field develops stronger, more consistent frameworks for patient participation in health technology design.

5.5 Conclusion

This scoping review examined how virtual assistants (VAs) for chronic illness self-management are designed and developed, showing that most systems adopt reductionist framings of care and involve patients mainly superficially, often as evaluators. AI integration frequently reinforced these tendencies by conflating technical personalization with patient-centeredness, though examples where patients were engaged as co-designers, particularly with LLM-based systems, tended to show more holistic and patient-centered approaches to care.

The review makes three main contributions to HCI research and design. First, it offers a mapping of how VAs for chronic illness are produced: who is involved, what forms of care are prioritized, and how patient-centeredness is conceptualized. Second, it provides a categorization of the domains of care conceptualized in VA design and of the chronic patient roles that define them. Finally, it contributes a set of design implications for researchers and practitioners to rethink participatory practices that engage patients as active shapers of VA technologies and to center care conceptualizations that are contextual, relational, and grounded in lived experience.

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A Appendix

Table 6: Summary of Study Characteristics (Part 1). This table summarizes the key characteristics of the included studies: target chronic condition, country, study type, functionality of the virtual assistant and AI integration type.

Ref	Chronic Condition	Country	Study Type	Functionality	VA Type
[130]	ADHD	USA	Qualitative	Situated dashboard for family co-regulation of ADHD	Non-AI
[57]	Asthma	USA	Mixed-methods	Gamified apps to educate children	Non-AI
[72]	Asthma	USA	Feasibility study	Conversational agent to increase shared illness understanding	Non-AI
[102]	Asthma	USA	Qualitative	Conversational agent for tracking and reporting health data	Non-AI
[11]	Atrial Fibrillation	USA	Mixed-methods	Avatar agent for health counseling	Non-AI
[88]	Bipolar disorder	USA	Qualitative	Self-tracking and target setting	Non-AI
[51]	Cancer	USA	Qualitative	Personalized treatment risk evaluator and conversational agent	ML and LLM
[43]	Chronic mental illness	Canada	Quantitative	Personalized gamefied app to increase physical activity	Non-AI
[19]	Chronic multi-morbidity	USA	Mixed-methods	Goal-setting app for patient and care managers	Non-AI
[48]	Chronic Obstructive Lung Disease	Switzerland	Qiantitative	Personalized conversational agent interaction style	Non-AI
[124]	Chronic Obstructive Pulmonary Disease	Switzerland	Validation study	Conversational agent to support patient-provider relationship	Non-AI
[9]	Chronic Obstructive Pulmonary Disease	United Kingdom	Conceptual study	Predictive system for disease monitoring	ML
[3]	Chronic Respiratory Conditions	Belgium	Proof of concept	Predictive coaching system for lifestyle support	ML
[55]	Comorbidities in older adults	The Netherlands	Mixed-methods	Conversational agent coach for healthy lifestyle	Non-AI
[85]	Dementia	Portugal	Validation study	Symptom monitoring	LLM
[29]	Diabetes	The Netherlands	Mixed-methods	Recommender system for health goals	Non-AI
[26]	Diabetes	Singapore	Evaluation study	Conversational agent for medical reminders	LLM
[87]	Diabetes	South Africa	Mixed-methods	Conversational agent for disease education	Non-AI
[45]	Diabetes	USA	Mixed-methods	Recommender system coach for nutrition	ML and NLP
[112]	Diabetes	Singapore	Mixed-methods	Conversational agent for education	Non-AI
[95]	Diabetes	USA	Qualitative	Conversational agent health coach	Rule-based AI
[94]	Diabetes	USA	Mixed-methods	Health coach for nutrition	Non-AI
[121]	Diabetes and Depression	Spain	Mixed-methods	Conversational agent for medical appointment reminders	Rule-based AI
[61]	Depression disorder	Malaysia	Proof of concept	Personal companion conversational agent for mental health support	NLP
[13]	Fibromyalgia	Switzerland	Mixed-methods	Conversational agent for symptom monitoring	Non-AI
[138]	Heart failure	United Kingdom	Mixed-methods	Home self-monitoring system	Non-AI
[157]	Heart failure	Australia	Randomized controlled trial	Avatar agent for illness education	Rule-based AI

Table 7: Summary of Study Characteristics (Part 2). This table continues the summary of the key characteristics of the included studies: target chronic condition, country, study type, functionality of the virtual assistant and AI integration type.

Ref	Chronic Condition	Country	Study Type	Functionality	VA Type
[7]	Hemophilia	Senegal	Mixed-methods	Conversational agent for health related questions in low-resource language	NLP
[98]	Hypertension	Italy	Mixed-methods	Recommender system and conversational agent for health data	NLP and NLG
[97]	Hypertension	Italy	Mixed-methods	Conversational agent for provider analysis	LLM
[155]	Inflammatory Bowel Diseases	USA	Feasibility study	Conversational agent for healthcare questions	NLP
[28]	Not condition-specific	The Netherlands	Proof of concept	Personalized coach for physical activity	ML
[39]	Not condition-specific	Italy	Proof of concept	Personalized chatbot for healthy eating	ML
[134]	Not condition-specific	The Netherlands	Randomized controlled trial	Conversational agent for physical activity	LLM
[20]	Not condition-specific	South Korea	Proof of concept	Personalized conversational agent to prevent further chronic issues	NLP
[18]	Not condition-specific	Switzerland	Quantitative	Personalized conversational agent coach for nutrition	Non-AI
[120]	Not condition-specific	Spain	Proof of concept	Recommender system for medication management	Rule-based AI
[69]	Not condition-specific	South Korea	Mixed-methods	Assistant to improve physical activity	Non-AI
[76]	Not condition-specific	Switzerland	Qualitative	Conversational agent and recommender system to explain health status	Rule-based AI
[66]	Not condition-specific	USA	Qualitative	Personalized conversational agent for access to health services	LLM
[103]	Not condition-specific	USA	Qualitative	Avatar agent for community health support	Non-AI
[126]	Not condition-specific	USA	Qualitative	Gamified nutrition app for children and caregivers	Non-AI
[101]	Not condition-specific	Switzerland	Quantitative	Conversational agent to support patient-provider relationship	Non-AI
[60]	Not condition-specific	South Korea	Mixed-methods	Voice-based conversational agent with human-like physiological states	Non-AI
[146]	Not condition-specific	Australia	Mixed-methods	Adaptive interface to support condition variability	Non-AI
[58]	Not condition-specific	Norway	Qualitative	Gamified assistant to surface personal strengths	Non-AI
[75]	Not condition-specific in older adults	Denmark	Conceptual study	Personalized treatment plans for rehabilitation	Rule-based and ML
[41]	Not condition-specific in older adults	Greece	Qualitative	Symptom monitoring	Non-AI
[127]	Not condition-specific in older adults	Germany	Mixed-methods	Embodied conversational agent coach for rehabilitation	Non-AI
[1]	Not condition-specific in older adults	Greece	Mixed-methods	Symptom monitoring for the elderly	Non-AI
[84]	Not condition-specific in older adults	USA	Qualitative	Voice-assisted agent for doctor's after-visit summary and medication reminders	LLM
[44]	Obesity	Switzerland	Qualitative	Recommender system and conversational agent for provider plans	NLP
[62]	Polycystic ovary syndrome	USA	Qualitative	Self-tracking of PCOS symptoms	Non-AI
[129]	Peripheral Arterial Disease	Portugal	Clinical trial	Exercise programs	Non-AI

Table 8: Corpus of studies by authors, VA type, care concepts, and patient participation.

Article Authors and Year	VA Type	Care Concepts	Patient Participation	Ref.
Jessen et al., 2018.	Non-AI	Empowerment	Co-design	[58]
O’Leary et al., 2022	Non-AI	Relationality	Co-design	[103]
Silva et al., 2024	Non-AI	Relationality, Empowerment	Co-design	[130]
Op den Akker et al., 2017	Non-AI	Adherence	Evaluation	[29]
Silva et al., 2022	Non-AI	Adherence, Behavior change	Evaluation	[129]
Mash et al., 2022	Non-AI	Adherence, Behavior change, Relationality	Evaluation	[87]
Foukarakis, 2022	Non-AI	Adherence, Health Literacy, Relationality	Evaluation	[41]
Adami et al., 2021	Non-AI	Autonomy	Evaluation	[1]
Pienkowska et al., 2023	Non-AI	Behavior change, Autonomy	Evaluation	[112]
Hurmuz et al., 2022.	Non-AI	Behavior Change	Evaluation	[55]
Matthews et al., 2015	Non-AI	Behavior Change	Evaluation	[88]
Schlieter et al., 2024	Non-AI	Behavior Change	Evaluation	[127]
Wang, Wei et al., 2024	Non-AI	Empowerment	Evaluation	[146]
Bickmore et al., 2013	Non-AI	Health Literacy	Evaluation	[11]
Triantafyllidis et al., 2015	Non-AI	Health Literacy	Evaluation	[138]
Kowatsch et al., 2021	Non-AI	Health Literacy, Relationality, Autonomy	Evaluation	[72]
Calvaresi et al., 2021	Non-AI	Proaction	Evaluation	[18]
Schaefbauer et al., 2015	Non-AI	Relationality	Evaluation	[126]
Chaudhry et al., 2022	Non-AI	Relationality, Behavioral change	Evaluation	[19]
Kim et al., 2019	Non-AI	Proaction	Initial Concept Generation	[69]
Francillette et al., 2018	Non-AI	Proaction	No Involvement	[43]
Nißen et al., 2022	Non-AI	Relationality	No Involvement	[101]
Schachner et al., 2021	Non-AI	Relationality	No Involvement	[124]
Gross et al., 2021	Non-AI	Relationality	Initial Concept Generation	[48]
Blanchard et al., 2024.	Non-AI	Adherence	Initial Concept Generation	[13]
Jayaprakash et al., 2019	Non-AI	Health literacy	No Involvement	[57]
Jung et al., 2021	Non-AI	Relationality	No Involvement	[60]
Nyapathy et al., 2019 .	Non-AI	Relationality	No Involvement	[102]
Kang et al., 2025	Non-AI	Empowerment	Co-design	[62]
Mitchell et al., 2025	Non-AI	Behavior Change	Evaluation	[94]
Zand et al., 2020	NLP	Autonomy	No Involvement	[155]
Kökciyan et al., 2019	Rule-based AI	Health literacy	Initial Concept Generation	[76]
Mahmood et al., 2025	LLM	Autonomy, Adherence	Co-design	[84]
Kim et al., 2022	LLM	Relationality	Co-design	[66]
Hao et al., 2024	ML and LLM	Health literacy, Relational	Co-design	[51]
Babington-Ashaye et al., 2023	NLP	Health literacy	Co-design	[7]
Rashik et al., 2025	LLM and ML	Adherence and Autonomy	Evaluation	[118]
Beattie et al., 2014	ML	Behavior change, Health literacy, Autonomy	Evaluation	[9]
Mitchell et al., 2021	ML and NLP	Behavior change, Health literacy, Relationality	Evaluation	[45]
Färber et al., 2023	NLP	Adherence, Health literacy, Relationality	Evaluation	[44]
Roca et al., 2021	Rule-based AI	Adherence	Evaluation	[121]
Zisis et al., 2021	Rule-based AI	Health literacy, Autonomy, Empowerment, Relational	Evaluation	[157]
Mitchell et al., 2021	Rule-based AI	Health literacy, Relational, Autonomy	Evaluation	[95]
Kyriazakos et al., 2020	Rule-based AI and ML	Adherence	Evaluation	[75]
Montagna et al., 2023	LLM	Relationality, Empowerment, Adherence	Initial Concept Generation	[97]
Dao et al., 2024	LLM	Adherence, Proaction	No Involvement	[26]
Maia et al., 2023	LLM	Adherence, Proaction	No Involvement	[85]
Op den Akker et al., 2021	ML	Behavior Change	No Involvement	[3]
Op den Akker et al., 2011	ML	Behavior Change	No Involvement	[28]
Fadhil et al., 2017	ML	Behavior Change	No Involvement	[39]
Chung et al., 2018	NLP	Proaction	No Involvement	[20]
Jusoh et al., 2024	NLP	Proaction	No Involvement	[61]
Montagna et al., 2023	NLP and NLG	Adherence	No Involvement	[98]
Roca et al., 2019	Rule-based AI	Adherence	No Involvement	[120]
Sun et al., 2024	LLM	Behavior Change	No Involvement	[134]