

Review

Digital Health Solutions for Type 2 Diabetes and Prediabetes: Systematic Review of Engagement Barriers, Facilitators, and Outcomes

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Abstract

Background: Digital health interventions, including artificial intelligence (AI)-driven solutions, offer promise for type 2 diabetes mellitus (T2DM) and prediabetes management through enhanced self-management, adherence, and personalization. However, engagement challenges and barriers, particularly among young adults and diverse populations, persist. Existing reviews emphasize clinical outcomes while neglecting engagement factors crucial to intervention success. This review highlights engagement barriers and facilitators, offering insights into improving digital health solutions for diabetes management.

Objective: The objective of this systematic literature review is to explore the barriers, facilitators, and outcomes of digital health interventions, focusing on the current state of AI applications while including partial AI and non-AI interventions, for managing and preventing T2DM and prediabetes, to inform the development of user-centered, inclusive digital health interventions for diabetes care. Unlike prior reviews, this review aims to inform the development of user-centered, inclusive digital health interventions for diabetes care, with a focus on engagement across various AI interventions and diverse populations.

Methods: A systematic search of PubMed, Scopus, CINAHL, and additional sources was conducted for studies published between January 2016 and October 2025. Eligibility criteria included English-language, peer-reviewed studies focused on digital health interventions for adults with T2DM or prediabetes, reporting engagement, barriers, facilitators, or outcomes. Data were synthesized narratively using thematic analysis, guided by self-determination theory and user-centered design. Quality appraisal was conducted using Critical Appraisal Skills Program, Mixed Methods Appraisal Tool, and AMSTAR-2 tools.

Results: From the 37 studies (14 quantitative, 3 qualitative, 7 mixed-methods, and 13 reviews), interventions comprised 19 AI-driven (eg, chatbots, ML models, and conversational agent or hybrid), 3 partially AI-driven, and 15 non-AI solutions (eg, apps and lifestyle programs), mostly from the USA (n=15). Key barriers to engagement included inadequate personalization (15/37, 41%), environmental constraints (11/37, 11%), cultural and language mismatches (14/37, 38%), and AI-specific concerns (eg, bias and privacy). Facilitators included personalized feedback (19/37, 51%), cultural tailoring (17/37, 46%), user-friendly design, and peer support. AI-driven interventions demonstrated moderate improvements in clinical outcomes (eg, lowering HbA_{1c}, weight loss, and normoglycemia conversion). However, these tools often struggled with keeping users involved and building trust. Non-AI solutions performed similarly but lacked adaptive features.

Conclusions: This review offers novel insights by synthesizing engagement barriers and facilitators across AI and non-AI intervention domains, often neglected in previous studies. It highlights the necessity for testing adaptive, culturally tailored, and user-centered AI interventions to address engagement challenges in T2DM and prediabetes management. Integrating personalization, precision, and value-based care can improve outcomes and scalability. The findings guide the creation of inclusive, AI-driven solutions aligned with self-determination theory and user-centered design principles.

Keywords: type 2 diabetes mellitus; prediabetes; digital health; artificial intelligence; machine learning; chatbots, engagement; user-centered design

Introduction

Background

Diabetes is a critical global public health concern with significant implications for individuals, health care systems, and economies. The International Diabetes Federation reported 537 million adults with diabetes in 2021, projected to increase to 783 million by 2045 [1]. Therefore, global health care spending on diabetes reached approximately US \$966 billion in 2021 [2]. Also, type 2 diabetes mellitus (T2DM) complications, including cardiovascular disease, kidney failure, and neuropathy, exacerbate health care costs, particularly in resource-constrained low-middle income countries (LMICs) [3]. Prediabetes, defined by elevated blood glucose levels below the T2DM diagnostic threshold, affected approximately 541 million adults globally in 2021, with significant increases projected by 2030 [1]. Rising obesity rates, sedentary lifestyles, and poor dietary habits worsen the impact of prediabetes [4]. However, prediabetes represents a critical window for intervention to prevent the progression to diabetes, with an estimated 70% lifetime risk of developing T2DM [5] without lifestyle or pharmacological interventions [6].

Digital health technologies have transformed chronic disease management, such as diabetes, by enhancing self-management, improving adherence, and delivering personalized interventions [7]. Furthermore, artificial intelligence (AI)-driven tools, such as chatbots and machine learning models (ML), provide real-time feedback, predictive analytics, and tailored recommendations for better lifestyle choices [8,9]. Hence, these technologies offer scalable solutions to address diabetes and prediabetes management and prevention across diverse populations [10].

While these interventions have potential benefits for individuals, digital health interventions face significant challenges. Recent studies report that high dropout rates and poor sustained engagement reduce the effectiveness of such interventions [11]. Furthermore, AI-specific challenges, such as data availability, cost considerations, AI algorithm performance, bias, and data privacy, emerge as noteworthy barriers hindering the adoption of AI applications and further complicating engagement in diverse populations [12]. Current systematic reviews of digital health interventions for T2DM and prediabetes primarily emphasize clinical outcomes, such as HbA_{1c} reduction and weight loss, which are critical, but limited attention on engagement barriers and facilitators, which are equally important for achieving these clinical outcomes [9,13,14].

Theoretical Frameworks

Self-determination theory (SDT) provides a robust framework for understanding engagement by emphasizing autonomy (eg,

user choice), competence (eg, skill-building), and relatedness (eg, social support) [15]. User-centered design (UCD) principles advocate iterative, user-driven development to ensure usability and alignment with cultural and socio-economic contexts [16]. Notably, SDT and UCD together guide the development of effective digital health interventions and will allow us to enhance their impact [17,18]. To provide a comprehensive understanding of digital health interventions for T2DM and prediabetes, this review includes both AI-driven and non-AI solutions. Non-AI interventions serve as a baseline to evaluate AI's added value in addressing engagement barriers and enhancing clinical outcomes, enabling a comparison that informs the design of future AI-driven solutions. This review aims to synthesize engagement barriers, facilitators, and outcomes of digital health interventions for T2DM and prediabetes management across diverse populations, using SDT and UCD frameworks. The specific objectives are (1) to identify barriers to engagement in these interventions, (2) to determine facilitators that enhance engagement across diverse populations, and (3) to evaluate the effectiveness of digital health interventions in achieving clinical outcomes

Methods

Study Design and Reporting Guidelines

Systematic literature reviews are usually used to collate all empirical evidence that fits pre-specified eligibility criteria in order to answer a specific research question. It uses explicit, systematic methods that are selected with a view to minimizing bias, thus providing more reliable findings [19]. This systematic literature review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [20]. We used the PRISMA checklist, which enhances the quality, reproducibility, and completeness of the review, enabling researchers to assess the validity of the methods and findings. The review protocol was developed and registered with OSF [21] to ensure methodological transparency.

Search Strategy

A comprehensive search strategy was developed for Medline (step 1) and refined through consultation with a university librarian using medical subject headings terms (step 2). Multimedia appendix A (Table S1 in [Multimedia Appendix 1](#)) represents the search strategy, combining medical subject headings terms and keywords identified with the Population, Intervention, Comparator, and Outcome framework. Then a range of electronic databases was searched, including PubMed, Scopus, and CINAHL supplemented by hand searching and reference lists. (Table S1 in [Multimedia Appendix 2](#)) lists databases searched. The search period was restricted to January 2016 through October 2025 to capture recently developed modern digital health interventions,

aligning with the rapid evolution of digital health technologies and the post-2015 surge in AI integration (eg, deep learning breakthroughs) [22,23].

The researchers collaborated to determine final papers for inclusion in review through Covidence, the Cochrane Collaboration's platform for systematic reviews. Inclusion and exclusion criteria for study selection are presented in

Textbox 1. In this paper, “Managing” refers to interventions for diagnosed T2DM (eg, self-monitoring, adherence support) [24,25] and “preventing” refers to those for prediabetes to delay onset (eg, lifestyle changes) [26,27]. These categories were applied during full-text review to ensure focus on at-risk or diagnosed adults (

Textbox 1. Inclusion and exclusion criteria for selecting studies.

Inclusion criteria

- Studies published in English in peer-reviewed journals
- Studies focused on artificial intelligence-driven or digital health interventions (eg, mobile apps, chatbots, SMS text messaging, and wearables) for type 2 diabetes mellitus (T2DM) or prediabetes management or prevention
- Studies included adults aged 18 years to 75 years with T2DM or prediabetes
- Studies reported effectiveness, engagement patterns, barriers, or facilitators
- Studies used quantitative, qualitative, mixed-methods, or review designs
- Studies published between January 2016 and October 2025

Exclusion criteria

- Non-English studies and non-peer-reviewed sources (eg, editorials and abstracts)
- Solutions without a digital component (eg, solely pharmacological)
- Studies targeting only children (<18) or older adults (>75) without broader adult data (to focus on broader adult populations, as those >75 often have unique comorbidities and digital literacy issues that require separate review)
- Studies not reporting engagement, barriers, facilitators, or relevant outcomes
- Studies exclusively on type 1 diabetes, gestational diabetes, or populations without T2DM or prediabetes. (Prediabetes populations are included in this review as they represent a critical window for prevention interventions); only populations without T2DM or prediabetes are excluded
- Studies published before January 2016.

Study Selection Process

Two reviewers independently screened titles and abstracts followed by full-text review of eligible studies, with disagreements resolved through discussion. Reference lists of included studies and relevant reviews were manually searched for additional studies. The study identification and selection process was documented in a PRISMA flow diagram for transparency. To avoid overlap from the 13 included reviews, primary studies cited within them were cross-checked against our included primaries and only unique insights from reviews were synthesized narratively.

Quality Assessment

Quality appraisal of included studies was completed by the primary researcher and verified by a second reviewer [28]. Qualitative studies, cohort studies, randomized controlled trials (RCTs), and consensus documents were assessed with the Critical Appraisal Skills Program criteria [29], selecting the appropriate checklist based on study design. Systematic reviews and meta-analyses were appraised using AMSTAR-2 [30]. Mixed-methods and developmental studies were evaluated using the Mixed Methods Appraisal Tool [31]. A scoring system calculated a percentage (number of ‘Yes’ responses divided by total relevant criteria for the study multiplied by 100) with thresholds defined as high ($\geq 80\%$), moderate (60%-79%), and low (<60%) [32]. However, studies were not excluded based on quality appraisal. Quality appraisal was primarily conducted by one reviewer with verification by a second, rather than fully independent dual review, potentially introducing minor subjectivity bias.

Data Extraction

Data were recorded using a standardized form, capturing (1) study characteristics (author, year, country, design, sample size, and demographics), (2) solution details (technology type, duration, theoretical framework, and features), (3) outcomes (categorized as: primary engagement metrics [eg, retention and adherence], secondary behavioral changes [eg, diet and physical activity], clinical [eg, HbA_{1c} and weight]), (4) barriers and facilitators, (5) quality indicators, and (6) qualitative findings on engagement.

Data Synthesis and Analysis

Due to heterogeneity in study designs, populations, and solutions, a narrative synthesis was used [33]. Quantitative data (eg, dropout rates, HbA_{1c} changes) were summarized descriptively and integrated narratively to support qualitative themes, for example, meta-analytic HbA_{1c} reductions from reviews [13] contextualized thematic barriers such as personalization lacks. A thematic analysis was conducted using an inductive approach to identify barriers and facilitators to engagement, guided by SDT and UCD principles. Themes on barriers and facilitators were derived from reported findings in included studies, using inductive coding, with reviewer interpretation guided by SDT/UCD. The process involved (1) data familiarization, (2) initial coding, (3) theme identification, (4) theme refinement, (5) theme definition, and (6) prevalence quantification. Thematic analysis was conducted by the primary researcher, with themes reviewed and refined by a second researcher. Analysis was supported by NVivo (version 20.7.0, QSR International

Pty Ltd), which was used to organize and code data. The PRISMA “qualitative synthesis” refers to the narrative thematic approach due to heterogeneity, not a meta-analysis; no quantitative analysis was feasible.

Intervention Classification

In this review, “AI-driven interventions” incorporate digital health tools that leverage AI as a core component (eg, ML models and chatbots) or as an enhancement to existing platforms (eg, mobile apps with AI features). “Partially AI-driven interventions” incorporate AI components (eg, ML for tailored messaging) alongside non-AI features (eg, manual data entry), distinguishing them from fully AI-driven interventions and non-AI interventions (eg, SMS text messaging and basic mobile apps). Reviews were classified based on the interventions they evaluate.

Ethical Considerations

This study is a systematic literature review and did not involve the collection of primary data, enrollment of human participants, or access to identifiable private information. Therefore, according to institutional and national guidelines, this work did not require Institutional Review Board or Research Ethics Board approval. All data analyzed were derived from previously published, peer-reviewed studies that had obtained their own ethics approval and informed consent as required. No new informed consent was required for this review, as no individual-level or identifiable data were collected, used, or reported. All efforts were made to ensure privacy by using only publicly available summarized findings and by not extracting or presenting any identifiable participant information from the included studies. No participants were recruited for this research and accordingly, no compensation was provided.

Results

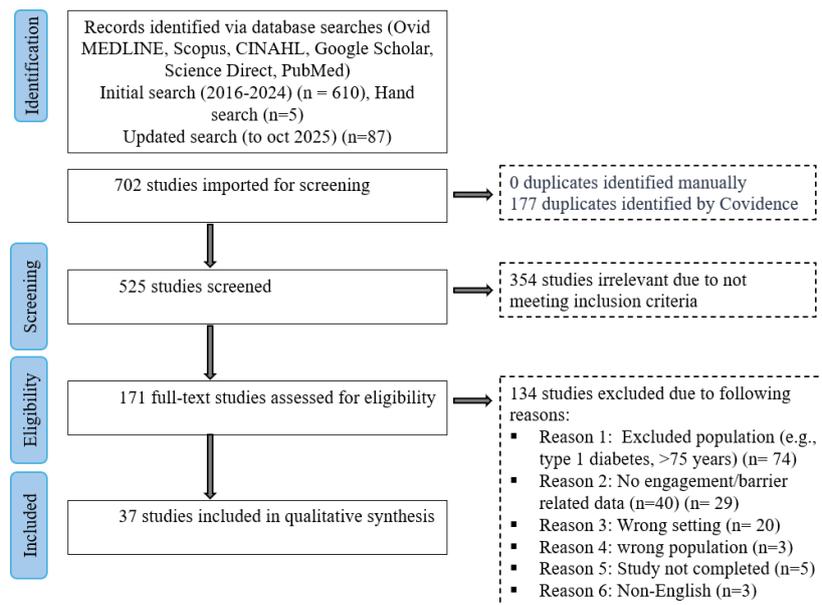
Study Characteristics

Initial search identified (January 2016 to December 2024) 615 studies and were imported into Covidence. An updated

search to October 2025 identified 87 additional records. After screening titles and abstracts, 171 full-text articles were evaluated, with 37 studies [8,9,13,14,34-66] meeting the inclusion criteria for the final narrative synthesis (). The majority of the papers were published in 2024 (n=10). The selected studies encompassed diverse populations, including Chinese Americans, Hispanics, Saudi women, and general adult populations, spanning urban and rural settings. Studies originated from various countries, with the majority from the USA/USA-affiliated studies (n=15), and included China, India, Singapore, and Saudi Arabia (Multimedia Appendix 2). Various study designs were observed, including 7 RCTs [8, 37,50,57,61,62,64], 7 systematic reviews and meta-analyses [9,13,14,47,54,56,63], 6 narrative, scoping, or other reviews [38,49,58,59,65,66], 5 observational and cohort studies [36, 51-53,55], 3 qualitative studies [44,45,60], and 7 mixed-methods studies [39-43,46,48].

Among the 37 studies [8,9,13,14,34-66], 13 are fully AI-based [8,34,35,37,39,40,44-46,50-52,60]: 7 use chatbots, large language models, or conversational agents [8,34,39, 40,44-46], 3 use ML models [37,51,60], 2 involve AI-led lifestyle interventions or digital twins [50,52], and 1 uses voice or image recognition [35]. These studies fully leverage technologies, such as chatbots, ML models (many using extreme gradient boosting), conversational agents, and voice or image recognition systems. In total, 8 studies [36, 42,43,48,53,57,61,64] are non-AI, consisting of 2 mobile apps, 4 lifestyle programs, 1 SMS text messaging-based intervention, and 1 gamified mHealth application without AI components, relying instead on traditional methods such as lifestyle interventions and conventional digital health tools. Three studies [41,55,62] are partially AI-based, combining AI features with human-led or manual components, a mobile app with tailored messaging and a provider portal, an AI-powered app with automated cues plus dietitian chat, and automated insulin titration systems. The remaining 13 studies [9,13,14, 38,47,49,54,56,58,59,63,65,66] are reviews, of which 6 focus on AI applications and 7 address non-AI or broader digital health interventions. Figure 1 details the PRISMA flowchart summary.

Figure 1. Study identification and selection process. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram.



Quality Assessment

Table S1 reports the quality appraisal scores for the 37 [8,9,13,14,34-66] studies, assessed using standardized tools, such as Critical Appraisal Skills Program, Mixed Methods Appraisal Tool, and AMSTAR-2, reflecting rigorous evaluation of methodological quality, with scores ranging from 75% to 100%. No studies were excluded based on quality, underlining the overall rigor of the included research.

Thematic Analysis

Thematic analysis was guided by self-determination theory and UCD principles. Table 1 summarizes themes, subthemes, and findings of digital health interventions.

Table 1. Themes, subthemes, and findings for digital health interventions in type 2 diabetes mellitus and prediabetes.

Theme	Summary of findings in studies
Barriers to engagement	Factors affecting user engagement and sustainable use of digital health interventions for T2DM ^a and prediabetes, impacting SDT ^b elements autonomy, competence, and relatedness. High dropout rates (6.4%-35.5% across 14/37 studies) served as a quantifiable indicator of low engagement, primarily due to low-risk perception, inadequate personalization, and lack of motivation [34].
Inadequate Personalization	Found in 15/37 studies (41%), reducing motivation due to generic content or lack of cultural sensitivity includes generic meal plans in ChatGPT responses [34], limited Chinese-specific dietary advice [35], nonindividualized calorie, targets in a formula diet RCT ^c [64], and poor demographic adaptation in ML models [51,60].
Low risk perception	Reported in 4/37 studies (11%), low perceived susceptibility reduced relevance and early adherence particularly among younger adults as users saw interventions as irrelevant [36,37].
Environmental constraints	Present in 11/37 studies (30%), regional health care system variations [38], inadequate access to advanced devices in low-income countries [39], limited smartphone/internet access [9,40], affordability challenges and poor digital literacy [41,42], and infrastructural issues in low-resource settings [57] led to reduced adoption and increased dropout, especially in rural populations [26].
Cultural and language barriers	Found in 14/37 studies (38%), include English-only interfaces [43,44], limited non-English conversational agents [45], limited localization [40] cultural mismatches in content [8,41,42] and culturally insensitive dietary recommendations [34,35] reduced engagement.
AI ^d -specific barriers	Reported in 5/37 studies (14%), include potential for fabricated information [44], limited intent recognition, nonadaptive rules-based systems [8], and inconsistent responses [46], compromising accuracy and personalization in AI-driven interventions.
Socioeconomic barriers	identified in 13/37 studies (35%) include limited smartphone access [47], low digital literacy [42], and restricted access to care [58], hindering adoption and effectiveness in resource-constrained populations.
Facilitators of engagement	Factors enhancing user engagement and adherence, supporting autonomy, competence, and relatedness (SDT) and aligning with UCD ^e principles.
Cultural and linguistic tailoring	Reported in 17/37 studies (46%), enhanced relatedness, by culturally adapted carbohydrate tracking [43], multilingual support with local accents [45], Persian food databases [41], Hispanic-focused soccer programs [36], Arabic WhatsApp peer groups [61], Chinese American web-based DPPs ^f [48] and Chinese-specific dietary recommendations [35].

Theme	Summary of findings in studies
Personalized and adaptive feedback	Found in 19/37 studies (51%), improved motivation through AI-driven adaptivity or gamification, includes use of personalized AI interactions and conversational empathy [9,14], AI-led DPP [50], personalized, adaptive or AI-powered feedback [35,51,52] and non-AI personalized communication or program choice [53].
User-friendly design	Identified in 5/37 studies (14%), include simple interfaces with no login [51], voice-based interactions [8], automated reminders [9], user-friendly WeChat mini-program [35] and multi-platform access [40], enhancing usability and engagement.
Peer support and social features	Observed in 9/37 studies (24%), include community-driven co-production [60], social support via WhatsApp [36], private Facebook groups [48], family involvement in culturally tailored DPPs [36], buddy systems in hybrid apps [37], and community features in apps [54], enhancing engagement.
Telemonitoring and real-time feedback	Found in 10/37 studies (27%), include continuous glucose monitoring and Fitbit integration [51], real-time data portals [8], real-time monitoring [67], automated alerts through AI systems [50] and cloud-based provider portals [41], built competence and accountability via real-time tracking.
Clinical and behavioral outcomes	Measurable impacts of digital health interventions on health outcomes and user behaviors, critical for evaluating effectiveness.
HbA _{1c} reduction	HbA _{1c} reduction outcomes in diabetes management include a 0.3% decrease with chatbots [9], 0.39% with mobile apps [47], 1.8% with digital twin tech [52] and 1.6% with telehealth interventions [56], improving glycemic control.
Weight loss	Weight loss outcomes in diabetes management include 1.3 kg with chatbots [14], 10.6% with app engagement [55], 7.3% at 6 months [53], up to 6.5 kg in multi-strategy DHIs ^h [56] and 5.9 kg with lifestyle interventions [64].
Normoglycemia conversion	Normoglycemia conversion outcomes in diabetes management show a 50% conversion rate with a low-carbohydrate diet intervention versus 31% with lifestyle alone [64], indicating enhanced reversal of prediabetes through technology-supported dietary strategies.
Improved physical activity	Improved physical activity outcomes in diabetes management include increased step-goal achievement with chatbots [14], enhanced VO ₂ ⁱ max and agility [36], and improved activity with app-based tracking [47].
Enhanced dietary management	Enhanced dietary management outcomes in diabetes management include improved diet with chatbots [14], 96.43% acceptable ketogenic diet responses [35], and better energy intake with lifestyle interventions [68].
Increased user engagement and adherence	Increased engagement/adherence as primary outcomes, include AI nutrition system with 96.43% valid ketogenic diet recommendations [35], culturally adapted meal adherence [43,48], improved food intake and energy management in mobile and lifestyle programs [47], 89.3% data logging with voice-based AI [8], 65% program completion [53], high chatbot acceptance [9], and 85% retention [48].

^aT2DM: type 2 diabetes mellitus.

^bSDT: self-determination theory.

^cRCT: randomized controlled trial.

^dAI: artificial intelligence.

^eUCD: User-centered design.

^fDPP: diabetes prevention program.

^gHbA_{1c}: hemoglobin A1c.

^hDHI: digital health intervention.

ⁱVO₂: volume of oxygen.

Barriers to Engagement

The thematic analysis identified key barriers such as low-risk perception, inadequate personalization, environmental constraints, cultural or language mismatches, AI-specific concerns (eg, bias, privacy), and socioeconomic barriers. Dropout rates (6.4%-35.5% across 14 studies [8,34,36,48-53,55,57,61,62,64]) served as an indicator of low engagement, primarily due to underlying causes such as inadequate personalization and motivational lacks, rather than a standalone theme. For example, declining app usage linked to repetitive content [51] and declining motivation over time [34,36], suggesting gamification as a solution, reinforced by generic features in non-AI reviews [41,56].

Declining use over time was frequently attributed to repetitive content and inadequate personalization, both of which reduced users' sense of competence and motivation. For instance [55], reported declining nBuddy app usage, while [35] noted inconsistent AI-driven dietary advice due to limited personalization. Additional studies, such as [49] and [36], highlighted similar challenges with maintaining user motivation over time [34], noted poor sustained engagement

from lack of follow-up, and [36] reported declining physical activity post-intervention. Studies suggested gamification, social incentives, and adaptive feedback as remedies to sustain interest.

Inadequate personalization, identified as a critical barrier in 15 [34,35,37,39-41,46,47,50-52,55,57,60,64] of 37 studies [8,9,13,14,34-66] (41%), weakened users' sense of competence and relevance. Static feedback, generic goal-setting, and nonadaptive content led to disengagement. Examples include generic dietary advice in nontailored chatbots [40], poor demographic adaptation in ML models [39,51], and limited personalization in traditional programs [47,69]. Although AI-driven interventions with adaptive algorithms [35,52] demonstrated improved engagement and outcomes, they still exhibited constraints in fine-grained individualization. Several studies emphasized the importance of tailoring content to user preferences, cultural context, and progress level. Examples include generic meal plans in ChatGPT (OpenAI) responses [34], limited Chinese-specific dietary advice [35], and nonindividualized calorie, targets in a formula diet RCT [64].

Low-risk perception, identified in 4 studies, [34,36,37,49] especially among younger adults, undermined intrinsic motivation and autonomy, leading to disengagement. Participants often viewed interventions as irrelevant to their immediate health needs. Several lifestyle-based, non-AI studies [34,36,49] reported decreased participation due to perceived low personal diabetes risk and lack of urgency.

Environmental constraints, noted in 11 [9,26,38-42,48,53,57,61] out of 37 studies [8,9,13,14,34-66] (30%), included socioeconomic barriers, such as limited smartphone access, and technical challenges, such as complex interfaces, affordability, and accessibility. For instance [42], highlighted technology unfamiliarity among older adults, and [48] reported navigation difficulties. Other studies, including [53] and [61], emphasized socioeconomic barriers, such as transportation or resource limitations, which further hindered engagement.

Cultural/language barriers, in 14 [8,34-36,40-45,47,48,53,61] out of 37 studies [8,9,13,14,34-66] (38%), reduced engagement in diverse populations due to noninclusive content. For example [43], reported an English-only DiaFriend app, and [40] noted an Italian-only AIDA chatbot, and [68] reported high dropout rates (not quantified) in an Arabic-only WhatsApp program, while culturally tailored interventions showed better retention, such as [48] with 15% dropout in a Chinese American web-based diabetes prevention program (DPP). These issues hinder accessibility and personalization, particularly for non-English-speaking and culturally diverse populations, reducing intervention effectiveness.

AI-specific barriers, in 5 [8,40,44-46] out of 37 studies [8,9,13,14,34-66] (14%) included potential for fabricated information [44], constrained input and miscommunication risks [45], limited intent recognition with 9% misclassification [40], and nonadaptive rules-based systems [45], compromising trust, accuracy, and personalization in AI-driven interventions. Socioeconomic barriers, in 13 [36,37,41-43,47,48,53,55,57,58,61,64] out of 37 studies [8,9,13,14,34-66] (35%), involved limited smartphone access [57], resource constraints and access issues [58], limited digital literacy and technology unfamiliarity among older adults [42], smartphone literacy requirements [41], and cost of devices and data.

Facilitators of Engagement

Engagement facilitators were identified in studies reporting high retention or engagement. Cultural tailoring, in 17 [9,14,35,36,40-43,45,48,51,54,55,58,60,61,66] out of 37 studies [8,9,13,14,34-66] (46%), enhanced relatedness through relevant content, as seen in [43] with the culturally tailored app and [36] with a Hispanic-focused program, Portuguese American carbohydrate tracking [43] and [48] with Chinese American web-based DPP (85% retention).

Personalized feedback, in 19 studies [8,9,14,34,35,37,40-42,44-46,50-53,55,57,62] (51%), sustained motivation via adaptive features or gamification. Examples include [8] with voice-based conversational AI achieving 82.9% adherence

and 89.3% data logging [50], with AI-powered adaptive interventions showing 93.4% initiation and 63.9% completion rates, and [52] with digital twin technology showing 50.7% diabetes remission rates. User-friendly design, in 5 studies [8,9,35,40,43] (14%), improved accessibility with intuitive interfaces [43], featured simple interfaces with no login requirements [8], used voice-based interactions for ease of use [40], provided multi-platform access (Telegram [Telegram Messenger LLP], website, Alexa [Amazon]), and [35] offered a user-friendly WeChat (Tencent) mini-program. Peer support, in 9 studies [36,37,48,54,55,58,60,61,66] (24%), fostered community engagement, as evidenced by [48] with a Facebook (Meta) group and [61] with WhatsApp support groups [36], with social support via WhatsApp and family involvement, and [37] with a buddy system, enhancing sustained engagement. Telemonitoring and real-time feedback (10 out of 37 [27%]) enhanced engagement via continuous glucose monitors (CGM) or Fitbit integration [51], telemonitoring with scales and pedometers [45], and cloud portals [41], enabling timely intervention adjustments and competence-building.

Clinical and Behavioral Outcomes

Thematic analysis, guided by SDT and UCD, reveals that AI-based interventions for T2D self-management foster autonomy and competence, yielding significant clinical behavioral outcomes, including HbA_{1c} reductions (0.19%-1.8%), improved diet and physical activity adherence, and weight loss (0.8%-10.6%) [9,47,55]. Culturally tailored tools and voice-based AI enhance relatedness and engagement, supporting glycemic control [8,43]. Non-AI interventions, such as lifestyle programs, contribute similarly but lack adaptive personalization, emphasizing AI's potential to address SDT-driven motivation gaps [36].

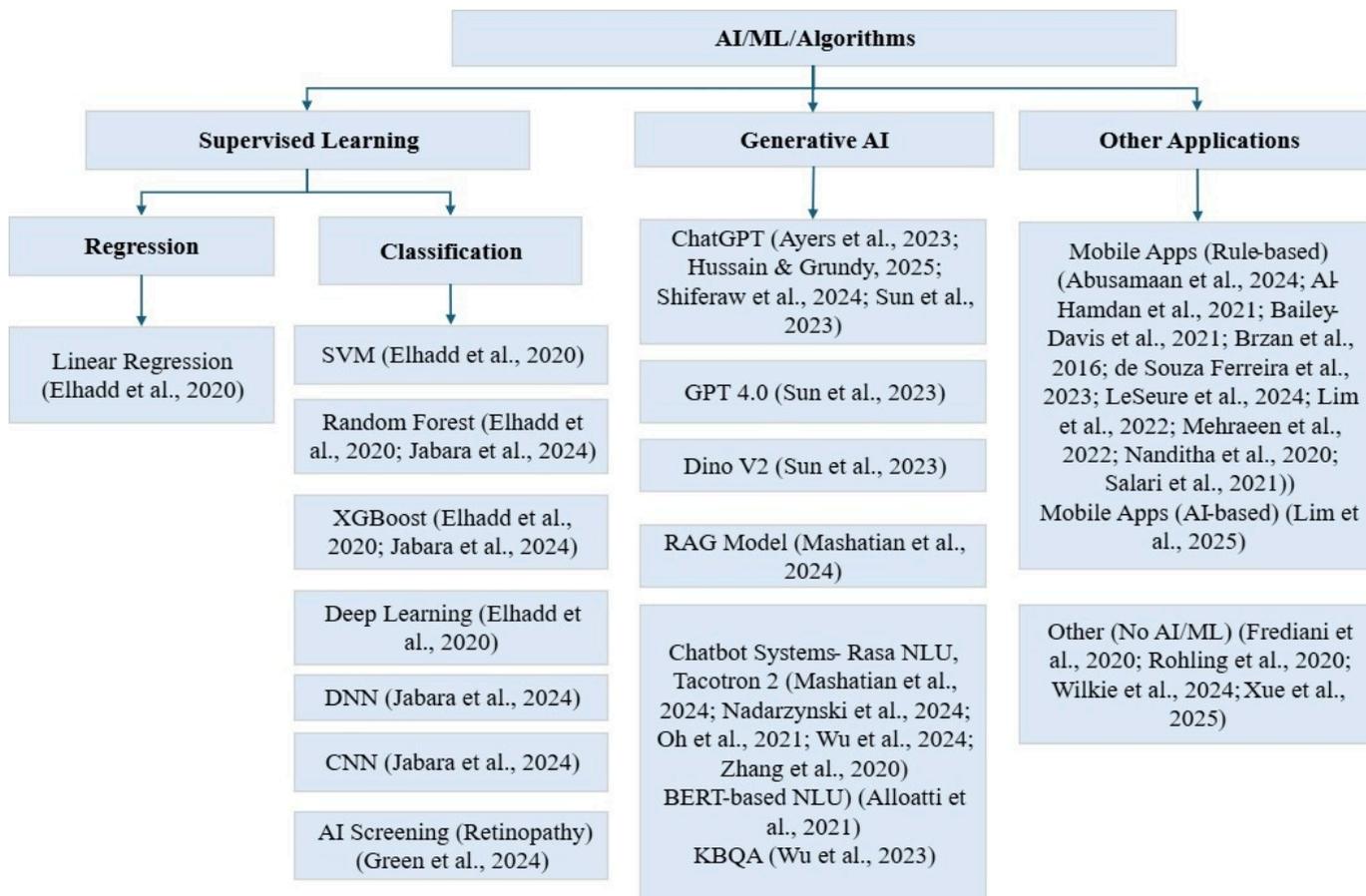
The Application of AI in Diabetes Care

The application of AI in diabetes care, as evidenced by 19 AI-based studies [8,9,14,34,35,37-40,44-46,49-52,59,60,65] among the 37 analyzed, has shown significant potential to enhance engagement and clinical outcomes through advanced methodologies (Figure 2). Quantitative results from a small subset of trials demonstrated moderate-to-high engagement (63.9%-93.4%) and relatively low dropout (6.6%-17.9%) compared with non-AI interventions [8,50,52]. For instance, an AI-powered digital twin intervention achieved a 1.8% reduction in HbA_{1c} and 4.8 kg weight loss over one year with 6.6% attrition [52], while a voice-based AI assistant for insulin titration reported 82.9% adherence and faster dose optimization relative to standard care [8]. ML models such as extreme gradient boosting achieved high accuracy in predicting glucose variability ($R^2=0.837$) [51] and enabled precise screening and complication detection using digital biomarkers from sensors, such as electrocardiograms and photoplethysmography (eg, IDx-DR, an AI-based diabetic retinopathy screening tool: 87.2% sensitivity, 90.7% specificity) [59]. Large language models (LLMs), including ChatGPT and GPT-4, delivered tailored dietary advice, with [35] reporting 74.5% accuracy on the Chinese Registered Dietitian Exam and 96.43% of ketogenic diet responses

rated acceptable or excellent, though limited by inconsistent recommendations for Chinese-specific foods. Conversational agents, such as AIDA [40], reached approximately 4000 unique users with 91% intent recognition accuracy, while AMANDA [45] offered multilingual support with a

Singaporean-accented text-to-speech feature, achieving high usability (System Usability Scale score=80.625) and positive user experience ratings (Mean Opinion Scores: 4.07 for naturalness, 3.98 for accent uniqueness, 3.88 for clarity).

Figure 2. Classification of artificial intelligence, machine learning, and algorithms in diabetes/prediabetes management. BERT representations from transformers. AI: artificial intelligence; BERT: Bidirectional Encoder; CNN: convolutional neural network; DNN: deep neural network; GPT-4: generative pre-trained transformer 4; KBOA: knowledge-based question answering; NLU: natural language understanding; RAG: retrieval-augmented generation; SVM: support vector machine; XGBoost: extreme gradient boosting [9,13,14,34-36,39-44,46,47,49,51,53-55,57-61,67,69,70].



Hybrid approaches such as the retriever-augmented generation model provided 98% accuracy in patient education for diabetes and diabetic foot care [39]. AI-driven interventions, such as the Sweetch app [67], used just-in-time adaptive interventions, improving adherence (82.9%) [8]. However, challenges included AI-specific barriers in 16% of studies, such as algorithmic bias [38,46], privacy concerns [59], and inconsistent responses [34], and alongside inadequate personalization (38% of studies) often due to generic content or lack of adaptive features [9,49,58]. Culturally tailored solutions, such as the DiaFriend app

for Portuguese Americans [43] and AI-HEALS for Chinese patients [70], mitigated some barriers but faced limitations such as incomplete backends or language restrictions. These findings highlight AI’s transformative potential in diabetes management while emphasizing the need for future large-scale, comparative, and longitudinal studies to determine their real-world effectiveness, cost-efficiency, and equity impact across diverse populations. Addressing biases, privacy, cultural adaptation, and sustained engagement challenges to optimize future implementations. Table 2 summarizes the comparison of AI-driven versus non-AI interventions.

Table 2. Comparison of artificial intelligence-driven versus non-artificial intelligence interventions.

Dimension	AI ^a	Partial-AI	Non-AI
Dropout range	6.6%-30% (n=3) [8,49,52].	6.4% (n=1) [55].	14.4%-35.5% (n=4) [53,57,61,64].
Engagement range (primary outcome)	63.9%-100% (n=4) [8,9,14,50].	Not mentioned.	65%-92% completion or retention (n=2) [48,53].
HbA ^b _{1c} reduction range	0.2%-1.8% (n=3) [9,50,52].	1%-1.2% (n=2) [55,62].	0.19%-1.6% (n=8) [13,37,47,53,56,58,61,63].

Dimension	AI ^a	Partial-AI	Non-AI
Barriers	Inadequate personalization [34,35,44,46, 51], low engagement and adherence [34,44-46,50-52], technical issues and connectivity [35,44,51], short duration and follow-up [35,44,50-52], cultural and language issues [44], and poorly defined AI taxonomy [52].	Inadequate personalization [41,55, 62], dropout and engagement issues [55,62], limited interactivity [55], cultural or language barriers [41, 55], and limited clinician time [62].	Inadequate personalization [36,42,43, 48,53,57,61,64], dropout or engagement issues [36,42,43,48,53, 57,61,64], limited interactivity [42, 43,48,53], and cultural or socioeconomic barriers [42,43,48,53, 57,61]
Facilitators	Personalized feedback and adaptive algorithms [34,35,44,46,50-52], behavioral model integration [37,50,52], remote monitoring and provider feedback [44,50-52], user-friendly design [34,35,44,46,51], culturally tailored content [44], cloud integration for provider access [51,52], structured follow-up improving adherence [8,50,52], scalable interventions [39,50,52], integration of AI and human support [52], and emphasis on scalability and precision [52]	Tailored feedback and reminders [41,55,62], automated tracking features [41,55,62], behavioral frameworks (CBT ^c , goal setting) [55,62], provider monitoring [55], educational and motivational support [41,55], cultural adaptation [41,55,62], and local food databases [55,62], real-time communication [55].	Educational content [42,43,48,53,57, 61,64], human coaching and social support [42,43,48,53,58,61], culturally appropriate design [42,43, 48,53,61], motivational reinforcement [48,53,58,61], health care professional guidance [42,48,53,58, 61], simplicity and accessibility [48, 53,58,61], integration with health care systems [42,48,53,58,61], supportive follow-up [48,53,58,61], structured educational design [13,63], emphasis on usability and accessibility [13,63], incorporation of behavioral science [13], positive patient-provider communication [13, 63], and evidence synthesis improving generalizability [63].
Clinical outcomes	HbA _{1c} reduction [50,52], weight loss [50], improved self-management and adherence [44,50,52], improved patient satisfaction [35,44], no increase in hypoglycemia [52], scalability potential [39,50,52], positive usability outcomes [35,44], and clear trends toward improved glycemic control [52]	Improved glycemic control [41,55, 62], weight loss [41,55], better engagement with mixed-mode support [55,62], improved knowledge and self-efficacy [55], feasibility demonstrated [55], and moderate-to-high user satisfaction [55].	Improved self-management [42,43, 48,53,57,61,64], enhanced knowledge and motivation [42,43,48,53,57,61, 64], weight reduction [48,53,61,64], HbA _{1c} reduction [48,53,61,64], improved patient confidence [42,43, 48,53,61], high acceptability [58], positive behavioral outcomes [42,43]. Consistent improvement in self-care outcomes [13,63] reinforced the need for personalized interventions [13] and positive health literacy and behavioral impact [63].

^aAI: artificial intelligence.

^bHbA_{1c}: hemoglobin A1c.

^cCBT: cognitive behavioral therapy.

Engagement Across Diverse Populations

Across the 37 [8,9,13,14,34-66] studies, only 8 explicitly targeted culturally or linguistically diverse populations, Portuguese Americans [43], Iranian adults [41,42], Singaporean users [45,55], Arab women [61], Hispanic men [36], and Chinese Americans [48] (Table 3). These studies collectively highlight how cultural adaptation enhances engagement and usability, though most lacked long-term quantitative evaluation. High engagement and retention were most evident in culturally grounded, community-based interventions. The Facebook-delivered DPP for Chinese Americans achieved 85% retention at one year [48], while the soccer-based Latino men's program retained 65% at 24 weeks [36]. Among Arabic-speaking women in Saudi Arabia, retention reached

100% despite cultural restrictions [61]. In contrast, prototype or design-phase studies in Iran and the US [41-43] did not measure engagement but emphasized usability and localized content. AI-enabled programs from Singapore [45,55] demonstrated high usability (system usability scale 80.6) and low dropout (6.4%), reflecting benefits of linguistic personalization and local food databases in digitally literate populations. Common barriers included low digital literacy, gender or mobility restrictions, and limited multilingual functionality, while facilitators centered on language adaptation, cultural familiarity, and social support. Overall, cultural adaptation consistently improved acceptability, but few studies measured sustained engagement, an important focus for future research.

Table 3. Population diversity and engagement metrics across studies.

Population and study IDs	Country	AI ^a type	Cultural adaptation	Engagement or retention	Key findings	Main facilitators (F) and barriers (B)
Portuguese Americans [43]	USA	Non-AI	Portuguese food and visuals	Not measured	Prototype only and expected to improve adherence	Simple interface (F) and English-only backend (B)

Population and study IDs	Country	AI ^a type	Cultural adaptation	Engagement or retention	Key findings	Main facilitators (F) and barriers (B)
Iranian [41,42]	Iran	AI or Partial-AI	Persian language, food DB ^b , and TTM ^c tailoring	Usability only (short-term)	Positive clarity or usability and no outcome data	Localized design (F) and low digital literacy (B)
Singaporean [45, 55]	Singapore	AI or Partial-AI	Multilingual TTS ^d and local food DB	SUS ^e 80.6, 6.4% dropout	High usability; engagement linked to weight loss	Personalization (F) and manual logging burden (B)
Arab women [68]	Saudi Arabia	Non-AI	Arabic-language and gender norms	100% retention	HbA _{1c} ^f reduction ($P < .001$), feasible WhatsApp delivery	Cultural tailoring (F) and mobility limits (B)
Hispanic men [36]	USA	Non-AI	Bilingual coaches and soccer	65% retention	Improved fitness, motivation, and social bonding	Peer support (F) and time and work barriers (B)
Chinese Americans [48]	USA	Non-AI	Bilingual modules	85% retention (1y)	Improved satisfaction and 2.3% weight loss	Coach support (F) and low online literacy (B)

^aAI: artificial intelligence.

^bDB: dietary behavior.

^cTTM: transtheoretical model.

^dTTS: transtheoretical stage.

^eSUS: system usability scale.

^fHbA_{1c}: hemoglobin A1c.

Discussion

Overview

This systematic review synthesized engagement barriers, facilitators, and outcomes across AI-driven, partially AI, and non-AI digital health interventions for T2DM and prediabetes. By applying SDT and UCD as interpretive frameworks, this review extends prior work that has predominantly focused on clinical outcomes [27,48]. Our findings show that the most prevalent barriers to sustained user engagement were inadequate personalization, cultural or language mismatches, socioeconomic constraints, and, in AI tools, specific concerns about bias and privacy, while the strongest facilitators were personalized and adaptive feedback and cultural tailoring. These factors, through their influence on autonomy, competence, and relatedness and usability, appear to be the primary drivers of behavioral and clinical change in digital diabetes interventions.

Main Findings

Across the 37 [8,9,13,14,34-66] included studies, digital health interventions demonstrated meaningful improvements in glycemic control, dietary behaviors, and physical activity, though sustained engagement remained a critical challenge. Inadequate personalization emerged as one of the most prevalent barriers, undermining SDT's principles of autonomy and competence and contributing to dropout. AI-based tools generally outperformed traditional digital programs when adaptivity, real-time monitoring, and tailored feedback were effectively implemented. For instance, AI-supported insulin titration and predictive analytics achieved faster glycemic improvements than standard care [5]. Interventions incorporating cultural tailoring, social support, and simplified interfaces consistently demonstrated higher engagement and completion rates. These findings

emphasize that algorithmic sophistication alone is insufficient; meaningful engagement depends on how well digital systems address users' psychological needs, contextual realities, and cultural identities.

Engagement in Diverse Populations

Engagement varied substantially across demographic, cultural, and socioeconomic groups. Young adults frequently demonstrated low perceived risk and weaker intrinsic motivation to sustain engagement, while older adults faced usability challenges and digital literacy barriers. Cultural mismatch, reported in nearly 40% of studies, led to reduced trust and relevance, particularly among minority groups.

Socioeconomic constraints such as limited smartphone access, high data costs, or inconsistent internet connectivity were especially apparent in LMIC settings. Interventions that provided multilingual content, culturally relevant dietary databases, or low-bandwidth delivery (eg, SMS text messaging-based chatbots) showed higher acceptability and engagement. These results emphasize the importance of context-aware and culturally grounded design practices when delivering digital diabetes interventions at scale.

Barriers to Engagement and Trust in AI

Several AI-specific barriers affected user trust and engagement. Algorithmic bias, arising from nonrepresentative training datasets, resulted in inaccurate risk predictions or poorly matched recommendations, particularly among ethnically diverse populations [42]. Privacy concerns were common, especially in cloud-based systems, with several users expressing discomfort about data security or opaque data handling processes [65]. Such concerns directly undermine SDT's relatedness and competence needs by diminishing the sense of transparency and credibility.

LLM-based or rule-based conversational agents occasionally produced generic, repetitive, or incorrect responses, which weakened trust and reduced perceived intervention quality. In contrast, systems that provided transparent rationales (eg, via Explainable AI), culturally adapted messaging, or adaptive learning mechanisms fostered significantly stronger engagement.

These insights highlight that strong technical performance does not guarantee user trust; trust must be actively cultivated through transparency, reliability, cultural sensitivity, and robust data governance.

Clinical and Behavioral Outcomes

Both AI-driven and non-AI digital interventions yielded positive clinical and behavioral outcomes. AI-enabled programs leveraging CGM, predictive modeling, or digital twins produced some of the largest HbA_{1c} reductions and behavioral improvements observed within the included studies [23,27]. Traditional digital interventions, such as structured online modules or SMS text messaging coaching, offered modest but consistent improvements in diet, physical activity, and self-management.

However, across all intervention types, the effectiveness of clinical outcomes was closely linked to user engagement. Interventions that successfully supported autonomy (eg, personalized goal setting), competence (eg, timely feedback), and relatedness (eg, social support) achieved higher adherence and more sustained improvements. These findings reinforce that engagement is not merely a process measure but a core determinant of intervention effectiveness.

Limitations

This review provides insights into digital health interventions for T2DM and prediabetes, but several limitations should be acknowledged. The Population, Intervention, Comparator, and Outcome-based search strategy may have missed studies using nonstandardized AI or digital health terms, and the English-only focus excluded relevant non-English or gray literature, potentially limiting the generalizability of findings to global populations. The review did not fully address informatics challenges, which are critical for scalability. Additionally, findings were not stratified by intervention type (AI-driven, partially AI-driven, vs non-AI) or by study setting and population due to limited quantitative data availability, which may restrict understanding of differences in engagement patterns and barriers across these subgroups.

The exclusion of studies targeting only children or older adults without broader adult data restricts insights into these populations, as older adults often have unique comorbidities and digital literacy challenges requiring separate evaluation. Methodological limitations of included studies, such as small sample sizes and heterogeneous designs, may affect generalizability. Quality appraisal was primarily conducted by a single reviewer and verified by a second, rather than

through fully independent dual review, which may introduce subjective bias. Additionally, the inclusion of prior systematic reviews alongside primary studies introduces potential evidential overlap. We mitigated this by extracting only novel insights from the reviews; however, a small amount of overlap in the evidence is possible. This review provides a robust foundation for understanding engagement barriers and facilitators in digital health interventions for adults with T2DM and prediabetes.

Future Directions

The results from this review point to several important areas for future research. Longitudinal trials are needed to assess the long-term impacts of AI-driven interventions, particularly in terms of sustained engagement, clinical outcomes, and cost-effectiveness across diverse populations. Future studies should also explore AI-enabled solutions that integrate real-time data, such as CGM and wearables, to offer more precise, tailored interventions that enhance motivation and adherence.

Furthermore, inclusive research is needed to explore the effectiveness of digital health interventions in LMICs and underserved populations, where cultural sensitivity and accessibility are critical. Additionally, interoperability between AI tools and existing health care systems, such as electronic health records, must be addressed to facilitate seamless data sharing and personalized care. Research should focus on the integration of AI with established health care platforms, enabling a holistic approach to patient management.

Additionally, future studies should explore low-cost, offline solutions such as SMS text messaging-based multilingual chatbots, which can help bridge digital health access gaps in LMICs. Interdisciplinary collaborations between health informatics, behavioral science, and policy experts will be crucial for evaluating the scalability and ethics of these solutions globally. Ethical considerations, including data privacy, consent, and equitable access, must also be central to future research agendas.

Conclusions

This systematic review provides important insights into the design and implementation of digital health interventions for T2DM and prediabetes management, emphasizing the need for adaptive, inclusive, and user-centered solutions. Both AI-driven and non-AI interventions have shown promise in improving clinical outcomes and engagement, though each faces unique challenges. The integration of SDT and UCD principles, alongside advances in AI technology, can lead to more personalized and equitable solutions for diabetes care. Future research must prioritize diverse populations, cultural tailoring, and advanced informatics techniques to address current barriers and optimize the potential of digital health interventions in global diabetes prevention.

Funding

No external funding was provided for this study.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Detailed search strategy.

[DOC File (Microsoft Word File), 18 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Detailed study characteristics and findings.

[DOC File (Microsoft Word File), 48 KB-Multimedia Appendix 2]

Checklist 1

PRISMA checklist.

[DOC File (Microsoft Word File), 35 KB-Checklist 1]

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Abbreviations

AI: artificial intelligence

CGM: continuous glucose monitors

DPP: diabetes prevention program

LMIC: low-middle income countries

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

RCT: randomized controlled trial

SDT: self-determination theory

T2DM: type 2 diabetes mellitus

UCD: user-centered design

Edited by Leo Quinlan; peer-reviewed by Shari Bolen, Tuan Duong; submitted 13.Jul.2025; final revised version received 29.Nov.2025; accepted 19.Dec.2025; published 12.Mar.2026

Please cite as:

Thanthrige A, Wickramasinghe N
Digital Health Solutions for Type 2 Diabetes and Prediabetes: Systematic Review of Engagement Barriers, Facilitators, and Outcomes
JMIR Diabetes 2026;11:e80582
URL: <https://diabetes.jmir.org/2026/1/e80582>
doi: [10.2196/80582](https://doi.org/10.2196/80582)

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