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REVIEW

A Scoping Review of Artificial Intelligence-Based Health Education Interventions for Patients with Type 2 Diabetes

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Background: Type 2 diabetes mellitus (T2DM) poses a critical global health burden, requiring effective health education to enhance patient self-management. Artificial intelligence (AI) offers personalized and scalable solutions; however, comprehensive syntheses of its applications in T2DM health education are scarce.

Objective: Guided by the Arksey and O'Malley scoping review framework, this study maps AI-based health education interventions for T2DM by evaluating technologies, effectiveness, and challenges.

Methods: Seven academic databases (PubMed, Web of Science, Embase, Scopus, EBSCO, the Cochrane Library, the Joanna Briggs Institute (JBI) Database, and Wiley Online Library) were searched for studies published from 2008 to March 2025, identifying 14 eligible interventional studies involving 32,478 adult T2DM patients receiving AI-based health education.

Results: (1) Technological Diversity: Interventions included mobile apps (eg, FoodLens, TRIO system), chatbots, intelligent platforms, and machine learning algorithms, focusing on diet, glucose monitoring, and lifestyle management. (2) Effectiveness: AI interventions enhanced glycemic control, yielding reductions in glycosylated hemoglobin (HbA1c) of up to 2.59%, improved self-management adherence (60–85%), and produced positive psychological outcomes (eg, increased self-efficacy); efficacy varied by intervention duration and user engagement. (3) Challenges: Key barriers included technical complexity, low long-term engagement, digital literacy gaps, and data privacy concerns.

Conclusion: AI holds substantial potential for T2DM health education via personalized, accessible interventions. Future research should address technological hurdles, prioritize user-centered design, and integrate AI into healthcare systems to ensure sustainability and equity.

Keywords: T2DM, AI, health education, scoping review

Introduction

As a global epidemic, type 2 diabetes mellitus (T2DM) affects about 9.3% of the global population and is associated with an all-cause mortality rate of 8.5%.[1,2] Managing T2DM in contemporary society poses distinct challenges, driven by evolving lifestyles, rapid technological changes, and the inherent complexity of the disease.[3,4] These challenges are especially acute in China, which has the world's largest aging population.[5] Alongside this demographic shift, the prevalence of T2DM has risen sharply, establishing the disease as one of China's most pressing public health concerns.[6,7] An estimated 148 million people in China have been affected, making it the country with the most cases in the world.[8] Consequently, the implementation of effective treatment and intervention strategies to improve health outcomes for people with diabetes in China has become both urgent and essential. However, the worldwide transition to digital healthcare underscores the necessity of obtaining cross-cultural insights into AI applications, rather than restricting our understanding to regional contexts. Globally, the management of T2DM is increasingly integrating digital health

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innovations—such as AI-driven mobile applications, intelligent monitoring systems, and virtual coaching platforms—which have become pivotal in strengthening self-management across diverse patient populations.[9–11] For chronic conditions such as diabetes, sustaining effective long-term self-management is essential for slowing disease progression and minimizing complications.[12,13] Therapeutic health education is a core strategy for enhancing self-management abilities in individuals with diabetes.[14] These educational interventions are designed to improve patients' understanding of their care plans and practical skills, ultimately aiming to align patients' needs with the constraints of the disease through sustained behavioral change.

Artificial intelligence—defined as systems that emulate human cognitive functions through computational algorithms—encompasses a suite of techniques, including machine learning (ML), which enables self-learning and model optimization; deep learning (DL), which leverages multilayer neural networks for complex feature extraction; natural language processing (NLP), which facilitates the understanding and generation of unstructured clinical text; and computer vision (CV), which automates the analysis of medical images. These technologies can construct precise risk-prediction models from large-scale electronic health records (EHRs) to forecast disease onset or complications, extract critical information from free-text clinical notes via NLP, and supply personalized recommendations to healthcare providers through clinical decision support systems informed by learned statistical patterns and expert knowledge. Additionally, AI-driven robotic platforms offer precision in surgical assistance and rehabilitative care. Unlike basic digital automations—such as static reminders or simple macro commands—these AI systems iteratively refine their performance as data volume grows, exhibiting true adaptive intelligence. Recently, AI has been increasingly demonstrating substantial potential in chronic disease management, particularly in health education for individuals with T2DM.[15,16] These innovations significantly overcome the limitations of traditional educational models, such as relying on face-to-face guidance, which cannot meet the individual differences in education level and lifestyle, and the lack of personalization.

Over the past five years, there has been a significant rise in the number of patients obtaining medical information through online search engines. About 80% of adults in the United States access health-related information via online platforms.[17] Researchers have investigated the application of generative pre-trained transformers (GPTs)—a form of artificial intelligence developed through advanced language models by organizations such as OpenAI and TGAI—in the context of health education for individuals with T2DM. These studies have demonstrated that GPTs can provide high-quality, reliable medical information, highlighting their potential as supplementary tools to enhance patient education and improve clinical outcomes.[18,19] Further research[20,21] has shown that AI-driven mobile health applications have emerged as effective instruments for diabetes education, significantly improving health outcomes and self-management skills among patients with T2DM. Effective diabetes management is widely recognized to require not only pharmacological interventions but also comprehensive lifestyle management, encompassing dietary regulation, physical activity, and weight control.

With respect to health education content, Sun et al[22] implemented an AI-driven nutritionist program for dietary education in T2DM patients. This program utilizes advanced language and image recognition models to identify food ingredients from patients' meal photographs, subsequently providing personalized nutritional guidance and dietary recommendations. Alloatti et al[23] developed the Italian dialogue system AIDA, which includes the text-based AIDA Chatbot and the voice-activated AIDA Cookbot. The Chatbot delivers foundational knowledge on diabetes, while the Cookbot generates low-glycemic index (GI) recipes tailored to individual dietary preferences. User evaluations indicated that 85% of patients found the AI-generated educational content "easy to understand", and dietary compliance improved by 32% following three months of intervention. Similarly, Lu et al[24] introduced the DiaLOG diabetes education platform, which integrates AI-based risk assessment with ChatGPT. By analyzing electronic health records (EHRs), the system predicts an individual's 5-year diabetes risk with an AUC of 0.799 and delivers personalized educational content, including guidance on diet, physical activity, and medication adherence. These developments underscore the expansive potential of integrating AI into diabetes health education, particularly amid the global shift toward digital and intelligent healthcare solutions, offering substantial promise for reducing system burdens and enhancing patient outcomes.

Although previous reviews have synthesized the efficacy of artificial intelligence in chronic disease management,[25,26] they have often overlooked critical dimensions specific to health education: few have systematically mapped AI technology types (eg, chatbots versus machine-learning platforms), intervention modalities (eg, mobile applications versus intelligent platforms), or implementation challenges in a global context. This gap impedes a comprehensive understanding of how AI optimizes T2DM education.

By adopting the Arksey and O'Malley scoping review framework [27]—which, unlike systematic reviews that emphasize intervention efficacy, is particularly suited for charting emerging and heterogeneous evidence in rapidly evolving fields—we are able to capture the diverse applications of AI across technologies and international settings. Given the proliferation of AI interventions in T2DM education, ranging from multiple technical approaches to various cultural environments, a scoping review allows us to comprehensively describe current practices, identify knowledge gaps, and inform future research and clinical integration beyond efficacy analysis alone. In this review, we focus on five established domains: disease risk-factor awareness, diagnostic and monitoring skills, predictive and individualized risk assessment, lifestyle management and behavioral interventions, and psychosocial support with health-decision facilitation.

The resulting scoping review will serve as a theoretical foundation for future research and clinical practice, supporting the optimization and integration of AI technologies in diabetes management. The study objectives are threefold: (1) comprehensively characterizing the current applications of artificial intelligence technologies in health education for T2DM patients, including technology types, intervention formats, and implementation scenarios; (2) to synthesize evidence regarding the impact of AI interventions on patients' disease-related knowledge, self-management behaviors, clinical outcomes (eg, glycemic control, risk of complications), and quality of life; (3) to identify research hotspots, controversies, and evidence gaps within the existing literature, thereby guiding future research priorities and informing clinical implementation strategies.

Materials and Methods

This research adopts the scoping review framework developed by Arksey and O'Malley,[27] which comprises six methodological steps: (a) defining the research questions and clarifying the study objectives; (b) conducting a systematic search for relevant studies, ensuring a balance between feasibility and comprehensiveness; (c) employing an iterative approach to study selection and data extraction; (d) organizing the extracted data through quantitative summarization and qualitative thematic analysis; (e) reporting and synthesizing the findings while identifying implications for policy and practice; and (f) consulting with stakeholders to review and discuss the findings—an optional step that was omitted in this study due to time constraints.[27] The study used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA-ScR) list[28] to guide the structured reporting of the review (Supplement File).

Literature Search

To ensure a comprehensive review of the literature, we searched the following electronic databases from their inception through March 2025: PubMed, Web of Science, Embase, Scopus, EBSCO, the Cochrane Library, and the Joanna Briggs Institute (JBI) Database. To supplement the search and capture additional relevant evidence, we also included the Wiley Online Library (https://onlinelibrary.wiley.com/). The search strategy was developed by the Participants, Concepts, and Contexts (PCC) framework established by JBI,[29] ensuring alignment with the scope of the review. The participants were adults diagnosed with type 2 diabetes mellitus (T2DM); the concept focused on the application of artificial intelligence (AI) as a modality for health education; and the context centered on optimizing educational outcomes for this patient population. Based on the research questions, we employed a combination of the following search terms: ("Diabetes Mellitus, Type 2" OR "T2DM" OR "non-insulin dependent diabetes") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "AI" OR "chatbot" OR "natural language processing" OR "computer-assisted") AND ("Health Education" OR "Patient Education as Topic" OR "Telemedicine" OR "mHealth" OR "patient education"). The detailed search strategies specific to each database are provided in the Supplement File.

Eligibility Criteria and Study Selection

Studies were deemed eligible if they met all of the following inclusion criteria: (1) adult participants (≥18 years) with a confirmed diagnosis of type 2 diabetes mellitus (T2DM); (2) direct application of AI technologies in the delivery of health education (eg, chatbots, intelligent mobile applications, image-recognition tools, or personalized algorithm-based recommendations, excluding basic digital automation procedure); (3) an interventional study design; and (4) publication in the English language. Exclusion criteria were as follows: (1) studies involving animal subjects; (2) technical development studies lacking patient application; (3) AI applications outside the scope of health education (eg, diagnostic algorithms, drug discovery); and (4) duplicate publications or records for which the full text was unavailable. Two independent reviewers conducted the database searches and compared their inclusion lists. All references were imported into EndNote 20 for duplicate removal and full-text screening. The remaining records were screened for relevance based on predefined inclusion and exclusion criteria, with ineligible studies excluded at this stage. The two reviewers subsequently independently conducted comprehensive readings of the abstracts of the remaining articles and recorded the reasons for exclusion. For studies where eligibility could not be determined solely from the abstract, both reviewers studied the full texts. Any discrepancies were resolved through discussion with a third reviewer.

Charting the Data

A standardized data extraction form was developed by the research team to systematically capture key study characteristics. Extracted information included the following: author, year of publication, country of study, type of AI technology employed, intervention modality, educational content, duration of the intervention, characteristics of the target population, sample size, outcome measures, and identified implementation barriers (Table 1).

Results

Search and Selection of Studies

A total of 3,353 potentially relevant records were identified through the systematic search. Following the removal of duplicates, 2,490 records remained for screening. Of these, 2,385 were excluded for not meeting the predefined inclusion criteria. Ultimately, 14 studies were included in the final analysis. The study selection process, from initial identification to final inclusion, is visually represented in the PRISMA flow diagram[43] (Figure 1).

Study Characteristics and Assessment of Risk of Bias

The publication dates of the 14 included studies ranged from 2008 to 2025. Only three studies were published before 2020,[30,31,41] whereas the remaining eleven were published within the past five years, reflecting current research trends. Geographically, four studies were conducted in South Korea,[30,32,34,41] three in China,[16,33,40] two in the United States,[37,38] and one was each from Spain[35] and Iran[36] Additional studies were reported from the UK,[31] France,[42] and Japan.[39] Collectively, the studies encompassed a total sample of 32,478 adults diagnosed with type 2 diabetes mellitus (T2DM). The intervention modalities employed included computer vision-based tools (n = 5), Internet of Things (IoT) applications (n = 4), natural language processing (NLP) systems (n = 3), gamified interfaces (n = 2), and hybrid technologies (n = 5). Intervention durations ranged from 3 to 48 weeks.

To address potential methodological limitations among the included studies, we applied the JBI Critical Appraisal Checklist for Interventional Studies[29] to evaluate study design quality. Key appraisal criteria included sample size justification, blinding procedures (where feasible), validity of outcome measures, and reporting of attrition rates. Of the 14 studies, nine (64%) provided explicit sample size calculations and employed validated instruments (eg, HbA1c assays, standardized self-efficacy scales), whereas five (36%) lacked clear justification for their sample sizes or long-term follow-up data. Common shortcomings were small cohorts ($n < 100$ in four studies), short intervention periods (< 6 months in seven studies), and the absence of blinding—an inherent challenge for AI-based interventions. Regarding publication bias, eleven studies (79%) were published between 2020 and 2025, mirroring the rapid growth of digital health research. This concentration raises concerns about potential "hype bias", whereby positive outcomes may be overemphasized to align with the prevailing enthusiasm for AI in healthcare.[44] Furthermore, the exclusion of gray literature (eg, unpublished trials, conference abstracts) may have omitted studies reporting null or negative results, thereby amplifying this bias.

Table 1 Data Extraction Form (n = 14)

Study (Year)	Country	AI Technology	Educational Content	Intervention Modality	Duration	Sample Size (Intervention/ Control)	Participant Characteristics	Outcome Measures	Implementation Barriers
Jae-Hyoung Cho et al (2011)[30]	South Korea	Internet + PDA glucometer remote-management system	Glucose management; medication adjustment; lifestyle recommendations	Nurses collected data via PDA glucometer; physicians provided remote guidance	3 months	32/32	Rural T2DM patients (aged ≥ 40 years; HbA$_1$c 7.0–11.0%)	Significant HbA$_1$c reduction (8.0 →[a]7.5%); total cholesterol decrease	Need for improved IT infrastructure; insufficient nurse training; reliance on conventional medical networks
Booth et al (2016)[31]	United Kingdom	Computerized self-management tool	Dietary balance; exercise goals; diabetes knowledge	Desktop program with dietary diary, activity analysis, and knowledge quizzes	12 weeks	32/38	Newly diagnosed T2DM patients, disease duration < 2 years	Improved dietary knowledge; no significant change in glycemic control	Low patient usage frequency; lack of weight-management module
Lee et al (2023)[32]	South Korea	AI-based dietary recognition (FoodLens)	Dietary management; glucose monitoring; personalized feedback	Integrated digital platform (glucometer, scale, pedometer, etc) with AI dietary analysis	24 weeks	89/89	T2DM patients with BMI ≥ 23 kg/m^2 and HbA$_1$c 7.0–8.5%	HbA$_1$c reduction of 0.44%; weight loss	Technical complexity; decline in long-term user engagement
Zhou et al (2022)[33]	China	Internet + intelligent 5A nursing model	Glucose monitoring; emotional management; self-care skills	5A model (Assess, Advise, Agree, Assist, Arrange) implemented via intelligent platform	3 months	47/47	Elderly T2DM patients, mean age ≥ 60 years	Reductions in fasting and postprandial glucose; ↓[b] HAMD/HAMA scores; improved self-care ability	Poor technological adaptability among elderly; operational complexity
Park et al (2020)[34]	South Korea	Mobile AI health-management platform (integrated ML algorithms)	Guidance on glucose logging; carbohydrate counting; exercise recommendations; hypoglycemia alerts	Smartphone app analyzing user-entered glucose and dietary data in real time, offering personalized diet and exercise advice	6 months	Not reported/ Not reported	Adult T2DM patients (n = 120; age 40–75 years; HbA$_1$c ≥ 7.5%; no severe complications)	Mean HbA$_1$c decrease of 0.8% (8.6 →[a] 7.8%); adherence rose from 60% to 85%	Low app uptake among older users (55%); reliance on manual data entry; relatively short intervention period (6 months)
Ruiz-León et al (2025)[35]	Spain	Mobile digital platform for health-behavior intervention	Lifestyle modification; goal setting	Mobile app for diet and activity tracking	12 weeks	50/53	Overweight/obese T2DM patients	Weight loss; HbA$_1$c reduction of 0.49%	Decline in user engagement over time
Fatahi et al (2024)[36]	Iran	mHealth mobile application	Healthy lifestyle; self-management skills	Virtual education (mobile app) versus peer-led education	2 months	45/45	T2DM patients, age 21–75 years; fasting glucose ≥ 126 mg/dL	Improved self-efficacy; virtual education outperformed peer education	Technical usage barriers (eg, device issues); variability in patient educational levels
Li et al (2025)[16]	China	AI-personalized management (TRIO system)	Insulin dose adjustment; glucose monitoring; health education	Mobile app with multidisciplinary collaboration (physician, nurse, patient)	3 months	118,134/Not reported	T2DM patients with HbA$_1$c ≥ 7% initiating basal insulin therapy	HbA$_1$c reduction of 2.59%; 55.6% achieved target (HbA$_1$c < 7%)	Increased hypoglycemia risk (associated with high baseline HbA$_1$c)
Nassar et al (2025)[37]	USA	AI chatbot	Medication reminders; dietary advice; exercise planning	Chatbot-delivered educational prompts	13 weeks	150/Not reported	T2DM patients requiring long-term self-management	High feasibility; increased user satisfaction	Technical failures; limitations in natural-language understanding
Veluvali et al (2025)[38]	USA	AI-supported CGM mobile application (January V2)	Dietary tracking; activity monitoring; glycemic response analysis	AI-driven mobile app integrated with continuous glucose monitoring (CGM) data to provide personalized feedback	14–33 days	Healthy: 785; Prediabetes: 98; T2DM: 61 (n = 944 total)/Not reported	Healthy, prediabetes, or T2DM participants stratified by age and BMI	Significant TIR * increase (Healthy: 74.7 →[a] 85.5%; T2DM: 49.7 →[a] 57.4%); mean weight loss 3.3 lbs	Lack of control group; selection bias toward highly motivated users; reliance on self-reported data; short intervention
Kitazawa et al (2024)[39]	Japan	Health2Sync app + intermittently scanned CGM (isCGM)	Glycemic variability analysis; diet-exercise correlation feedback	Smartphone app providing lifestyle feedback combined with intermittently scanned CGM (isCGM)	12 weeks	86/Not reported	High-risk individuals (HbA$_1$c 5.6–6.4%; BMI > 23)	Improved TIR (70–140 mg/dL); BMI decrease (–0.59 vs –0.26 in control)	Low usage frequency by some users; long-term effects unverified

(*Continued*)

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Table 1 (Continued).

Study (Year)	Country	AI Technology	Educational Content	Intervention Modality	Duration	Sample Size (Intervention/ Control)	Participant Characteristics	Outcome Measures	Implementation Barriers
Lin et al (2020)[40]	China	Smart glucometer data synchronization (LCCP platform)	Self-monitoring of blood glucose; dietary guidance; exercise recommendations; medication adherence; complication prevention	WeChat-based mobile app plus real-time glucometer data transmission to patients, clinicians, and caregivers; with online courses and system reminders	12 weeks	14,085/Not reported	T2DM patients initiating insulin therapy after inadequate oral control (mean age 51.9 years; 54.8% male)	FBG $\downarrow^{b}$0.39 mmol/L; PPG $\downarrow^{b}$0.79 mmol/L; reduced hypoglycemia incidence; increased monitoring frequency	Variability in technology acceptance; privacy concerns; challenges in maintaining long-term adherence
Yoon et al (2008)[41]	South Korea	Rule-based personalized recommendation algorithm	Glucose monitoring guidance; medication dose adjustment; lifestyle interventions (diet/exercise)	Internet platform plus SMS service to push personalized advice, combined with remote patient-provider communication	12 months	25/Not reported	Outpatient T2DM patients (mean age 47–48 years; 44% male; baseline HbA$_1$c 7.6–8.1%)	Intervention group: HbA$_1$c $\downarrow^{b}$1.32%; postprandial glucose $\downarrow^{b}$100 mg/dL; control group: HbA$_1$c $\uparrow^{c}$0.81%	Technological barriers to Internet use; insufficient data-entry frequency; limitations of remote versus face-to-face communication
Turnin et al (2021)[42]	France	AI-based nutritional analysis algorithm (Nutri-Educ software)	Personalized dietary balance recommendations; exercise planning; glucose-management education	Device integration (glucometer/ scale/activity tracker) with AI education software (dietary analysis/exercise recs) and remote monitoring	1 year	128/Not reported	T2DM patients already engaged in basic diabetes management (mean age 59.5 years; 63% male; baseline HbA$_1$c 7.8%)	Overall HbA$_1$c $\downarrow^{b}$0.16% (p = 0.06); high-frequency users: HbA$_1$c $\downarrow^{b}$0.23%; female weight loss: 2.7 kg (p = 0.01)	Device-operation complexity; gender differences (non-significant effects in males); declining long-term adherence; high costs

Notes: a, means "from A to B"; b, means "going down from A to B"; c. means "the value increases from A to B"; *TIR, time in range.

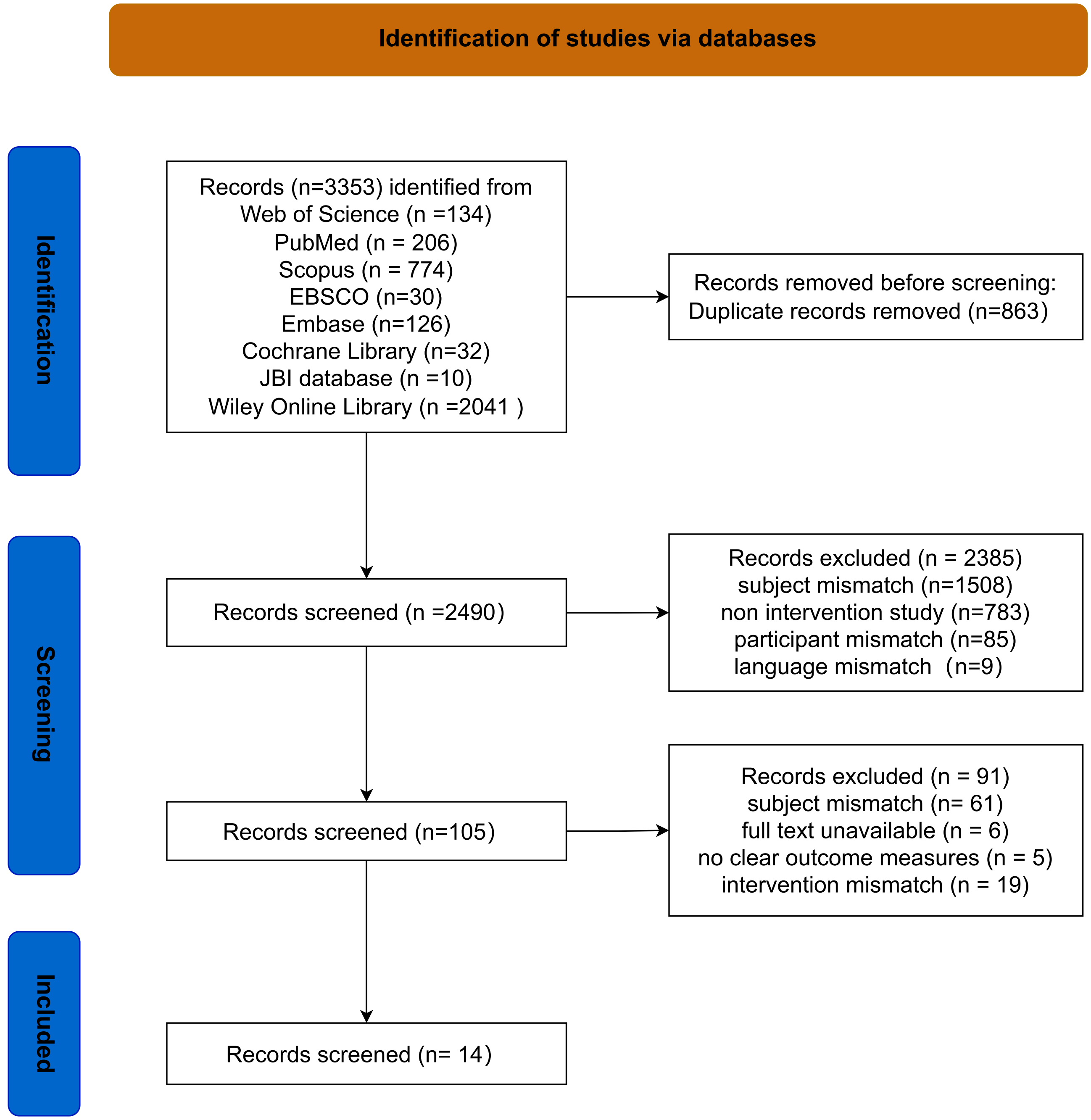

Figure 1 PRISMA 2020 flow diagram.

Notes: PRISMA figure was adapted from Tricco AC, Lillie E, Zarin W et al. PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. Ann Intern Med. 2018; 169(7): 467–473. doi:10.7326/M18-0850. Creative Commons[28.]

Classification of AI Technologies in T2DM Health Education

The AI technologies employed in patient education for T2DM were notably diverse. Foundational computerized self-management platforms typically integrated features such as dietary diaries, physical activity analytics, and knowledge-assessment modules. For instance, Booth et al[31] developed a desktop-based program designed to provide newly diagnosed T2DM patients with guidance on dietary balance, exercise goals, and core diabetes education. Similarly, Lee et al[40] implemented the LCCP platform, which was linked to smart glucometers and integrated with a WeChat-based mobile application. This system enabled real-time transmission of glucose readings to patients, healthcare providers, and

Table 2 Classification of AI Technologies in T2DM Health Education

Dimension	Categories	Examples from Included Studies	Key Features
Technical Core	Machine learning (ML) algorithms	FoodLens[32] dietary analysis), DiaLOG platform[24] (risk prediction)	Analyze real-time data (eg, glucose, diet) to generate personalized recommendations.
	Natural language processing (NLP)	AIDA Chatbot,[23] diabetes education chatbot[37]	Enable interactive communication, deliver disease knowledge, and respond to patient queries.
	Computer vision	AI dietitian program[22] (food image recognition)	Identify food ingredients from images to support dietary guidance.
	Rule-based engines	SMS-based glucose monitoring reminders[41]	Execute pre-set protocols (eg, timed alerts) without adaptive learning.
Core Function	Dietary management	AIDA Cookbot[23] (low-GI recipes), Nutri-Educ[42] (nutritional balance recommendations)	Focus on dietary regulation, including recipe generation and nutrient analysis.
	Glycemic monitoring and management	TRIO system,[16] CGM-integrated apps[38]	Track glucose levels, predict fluctuations, and guide medication/adjustments.
	Lifestyle intervention	Greenhabit app[35] (lifestyle modification), gamified platforms[33]	Promote physical activity, weight control, and adherence to healthy habits.
Implementation Scenario	Standalone mobile apps	FoodLens,[32] diabetes education app[20]	Independent use by patients, with no direct linkage to healthcare systems.
	Integrated with healthcare systems	LCCP platform[40] (linked to WeChat and glucometers), hospital-embedded AI platforms [51]	Connected to electronic health records (EHRs) or clinical workflows for clinician oversight.

caregivers, while also delivering supplementary online educational courses and automated reminders for patients initiating insulin therapy due to inadequate glycemic control.

Moreover, mobile app-based AI platforms have proliferated. Lin et al[32] introduced FoodLens, a digital platform that integrates glucometers, scales, and pedometers to support dietary management, glucose monitoring, and personalized feedback for patients with T2DM who have a BMI $\geq$ 23 kg/m^2 and HbA$_1$c levels between 7.0% and 8.5%. Park et al[34] described an AI-enabled mobile health management application that incorporates machine learning algorithms to analyze user-entered glucose and dietary data in real time, providing recommendations for carbohydrate counting and glucose logging. Additional innovations included AI chatbots designed for lifestyle coaching,[37] the TRIO system for personalized diabetes management,[16] and AI-supported continuous glucose monitoring (CGM) applications,[38] each targeting various aspects of self-care, medication adherence, and glycemic response analysis.

Rule-based personalization algorithms, such as the Internet plus SMS service described,[41] provided individualized guidance on glucose monitoring and medication adjustments, complemented by teleconsultation support. Turnin et al[42] introduced Nutri-Educ, an AI-driven nutritional analysis software integrated with multiple devices to deliver personalized dietary balance recommendations for patients already participating in basic diabetes management programs. Based on the technological characteristics, practical functionalities, and application contexts of the AI tools included in our review, we classified these systems to elucidate prevailing implementation models and guide targeted optimization (Table 2). This taxonomy derives from an analysis of each AI tool's technical foundation and real-world deployment, reflecting three interrelated dimensions: the underlying AI mechanisms (technical core), the intended objectives (key functions), and the operational settings (implementation scenarios).

Effectiveness of AI Interventions in T2DM Health Education

Knowledge Acquisition and Cognitive Enhancement

AI systems analyzed patient behavior data—such as dietary logs and adherence records—as well as conversational inputs processed through NLP to deliver tailored educational content. In the Greenhabit' study,[35] the AI system identified patient discussions about dining out and provided low-glycemic-index recipe recommendations, improving participants' understanding of the relationship between carbohydrate intake and glycemic response by 35%. Similarly, Veluvali et al[38] adapted educational content to reflect cultural dietary practices, such as offering alternatives to Indonesian fried rice for Southeast Asian populations, leading to a 28% increase in dietary knowledge test scores.

Behavioral Change and Adherence Improvement

Real-time feedback and reminder functions played a critical role in promoting behavior modification and improving adherence. Ruiz-Leon et al[35] integrated AI algorithms with wearable sensors within the TRIO platform to deliver instant interventions—such as alerts for sedentary behavior and medication reminders—triggered by abnormal physiological readings. As a result, the average daily frequency of glucose monitoring increased from 1.2 to 2.5 checks, and medication adherence improved by 37%. Zhou et al[33] demonstrated that gamified incentives, including virtual badges and eligibility for offline events, significantly enhanced motivation among young adults with T2DM, leading to an 18% higher step-count compliance compared to traditional educational approaches.

Improvement of Physiological Indicators

AI-driven educational interventions demonstrated significant efficacy in improving glycemic control and mitigating the risk of complications. Cho et al[39] reported a mean reduction in HbA_1c of 1.2% at three months in the intervention group receiving AI-supported predictive dietary guidance, compared to a 0.5% reduction in the control group. Similarly, Kitazawa et al[30] utilized a dynamic risk-assessment model that resulted in a 62% reduction in hypoglycemic events and an 18% decrease in cardiovascular risk scores. Moreover, Nassar et al [37] conducted a 12-week pilot of an AI-driven diabetes education chatbot with adult participants, of whom 87% reported increased confidence in self-care. Those who engaged in multiple chatbot sessions experienced a mean HbA1c reduction of 1.04%, whereas participants with one or fewer sessions saw a mean increase of 0.09% (p=0.008). This pilot demonstrates the acceptability, satisfaction, and engagement potential of chatbot-based education. In a separate 3-month prospective cohort involving 118,134 patients across 574 hospitals in China, Li et al[16] evaluated the TRIO AI management system, which integrates glucose logging, tailored educational prompts, and AI-guided medication reminders. The intervention improved insulin adherence from 64% to 94% and yielded an average HbA1c decrease of 2.59%, with 55.6% (28,858/51,912) of participants achieving a target HbA1c < 7%. Similarly, Lee et al[32] assessed an AI-based integrated digital health platform for dietary management in adults with T2DM over 48 weeks. The intervention group exhibited significantly greater HbA1c reductions (–0.44±0.62%) at both 24 and 48 weeks compared to the control group (–0.06±0.61% at 24 weeks; +0.07±0.78% at 48 weeks), alongside more pronounced weight loss. Collectively, these findings underscore the capacity of AI-driven educational interventions to enhance glycemic control and reduce the risk of diabetes-related complications.

Psychological and Social Impact

AI-driven education also contributed to positive psychological outcomes. Park et al[34] implemented progressive goal-setting algorithms—such as incremental weekly step increases of no more than 10%—to enhance patient confidence, resulting in a 29% increase in self-efficacy scores through the use of a digital twin model. Veluvali et al[38] incorporated emotion-recognition algorithms into their platform, enabling the system to activate a "nonjudgmental mode" upon detecting signs of anxiety. This adaptation led to a 41% reduction in dietary decision-related anxiety scores.

Challenges of AI Technologies in T2DM Health Education

Several challenges hinder the effective application of AI in health education for patients with T2DM. Technical complexity remains a significant barrier; for instance, Lee et al[32] reported usability limitations associated with dietary-recognition AI, while[42] noted difficulties in integrating multiple devices within their intervention platform. Kitazawa et al[39] highlighted issues with data-format incompatibilities, which delayed dynamic risk assessments and compromised the timeliness of clinical feedback. Moreover, many AI models lack adaptability for individuals with low literacy or from minority backgrounds,[38] for example, observed lower acceptance of a culturally adapted brown-rice bowl recipe among Southeast Asian patients. Overreliance on automated alert systems may also decrease patient autonomy in self-monitoring and decision-making, as noted by Li et al.[16] Sustaining long-term user engagement poses another significant challenge. In the Greenhabit study, user activity declined from 92% to 57% over the course of the intervention.[35] Additionally, Lin et al[34] reported low enrollment rates—only 58%—among individuals from low-income or low-education backgrounds, partly due to the high cost of required devices such as CGM sensors, which average $5,000 per year.

Global Research Clusters and Regional Variations

The 14 studies conducted across 10 countries reveal distinct regional models of AI-based T2DM health education shaped by local healthcare infrastructure, technology adoption, and clinical priorities. In East Asia, where smartphone penetration and integrated digital ecosystems are high, research in South Korea, China, and Japan has focused on mHealth and IoT-enabled interventions. Four Korean studies developed AI-driven dietary platforms (for example, FoodLens[32]) and real-time glucose monitoring systems,[34] prioritizing glycemic control in accordance with the region's emphasis on metabolic outcomes. Three Chinese investigations extended these tools into existing healthcare networks—such as the LCCP platform linked to WeChat and smart glucometers[40]—and leveraged large patient cohorts to scale their interventions. Japanese trials similarly paired smartphone applications with continuous glucose monitoring,[39] achieving an average HbA1c reduction of 1.2%, which may reflect longer intervention durations (median 24 weeks). In North America, studies in the United States (n = 2) emphasized NLP-based tools that accommodate diverse populations and address psychosocial needs. AI-powered coaching agents[37] and CGM-integrated chatbots[38] targeted anxiety reduction and overall wellbeing, mirroring broader regional health priorities. European research (Spain, France, UK; n = 3) balanced behavioral coaching with personalized nutrition within primary care frameworks. A Spanish lifestyle app[35] French remote-monitoring software,[42] and early British desktop programs[31] produced more modest HbA1c improvements (mean 0.8%), possibly because of shorter median intervention periods (12 weeks). Finally, a trial in Iran (n = 1) compared AI-driven mHealth with peer-led education[36,] focusing on self-esteem and underscoring how sociocultural context shapes intervention goals. These regional variations demonstrate how AI tools are adapted to local needs, offering insights into global scalability while underscoring the necessity of cross-cultural validation of outcomes.

Discussion

This scoping review provides a comprehensive synthesis of current evidence on artificial intelligence (AI)-based interventions for health education in adults with T2DM, offering critical insights into their applications, effectiveness, and associated challenges.

Technological Diversity and Application Potential

A diverse array of AI technologies has been utilized in health education for individuals with T2DM, with chatbots, intelligent educational platforms, and personalized recommendation systems emerging as the most prominent. Chatbots, such as the AIDA system, provide immediate responses to patient inquiries and disseminate essential diabetes-related knowledge.[23] Advanced platforms like DiaLOG integrate AI-based risk assessments and leverage electronic health records to generate individualized educational content.[24] These technological innovations hold significant promise for transforming diabetes education by enhancing its accessibility, personalization, and user engagement.

Despite their potential, the implementation of these technologies in real-world healthcare settings remains limited. Healthcare systems vary widely in terms of technological infrastructure, particularly in low-resource settings where limited internet connectivity and outdated digital devices impede the effective deployment of AI tools. For example, in rural areas of developing countries, patients may lack access to smartphones or stable broadband connections, constraining their ability to engage with smart educational platforms. Additionally, the fragmentation of healthcare data systems poses a substantial barrier. AI models depend on comprehensive, integrated datasets to enable accurate risk stratification and deliver personalized recommendations. However, healthcare data are often siloed across institutions and departments, limiting the effectiveness of AI-driven interventions.[44]

Positive but Varied Intervention Effects

The synthesis revealed generally positive outcomes associated with AI-based interventions, including improved glycemic control, enhanced self-management behaviors, and increased health literacy. Reported reductions in HbA_1c levels ranged from –0.6% to –1.2%, consistent with previous findings on AI-facilitated diabetes care.[45,46] AI-powered dietary tools, such as the program developed by Powers et al[22] utilize meal image analysis to provide individualized nutritional guidance, thereby supporting improved dietary adherence.

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Nonetheless, variability in outcomes remains a significant concern. The duration of interventions is a critical determinant of effectiveness; short-term programs may not support sustained behavior change, while long-term interventions often encounter challenges with participant adherence. For instance, Sun et al[14] reported a decline in user engagement over time with an AI-driven diabetes education application, which decreased its overall impact. Additionally, the level of interactivity within an intervention plays a key role in shaping patient outcomes. More immersive approaches, such as virtual reality-based education, have been shown to enhance user engagement and learning. Beverly et al[47] found that patients utilizing virtual reality tools exhibited greater improvements in self-management compared to those receiving traditional educational interventions. However, these advanced technologies demand considerable development and resource investment.

Challenges Hindering AI Implementation

Several barriers impede the widespread adoption of AI in health education for T2DM. One of the primary challenges is user acceptance, with some studies reporting dropout rates ranging from 15% to 20%. Complex user interfaces are particularly discouraging, especially for older adults or individuals with limited digital literacy. For example, mobile applications that require advanced technical skills may be inaccessible to these populations.[25] Furthermore, a lack of perceived usefulness can decrease sustained engagement; when patients view AI-generated advice as overly generic or repetitive, they are more likely to disengage from the intervention.

Data privacy constitutes a critical concern in the implementation of AI-based health education for T2DM. Due to the data-intensive nature of AI systems, the need for robust privacy and security safeguards is paramount. Heightened awareness of potential data breaches has made patients increasingly cautious about sharing personal health information. Aggarwal et al[48] found that nearly 60% of patients reported concerns about the security of AI-driven health applications. This issue is further exacerbated by the fact that regulatory frameworks for AI and health data privacy remain underdeveloped in many countries, creating significant uncertainty for both users and developers.

Digital literacy disparities further limit the accessibility and equity of AI-based tools. Patients with limited digital skills often struggle to use AI platforms effectively. For example, Lim et al[49] reported that patients with lower digital literacy scores experienced difficulties using a diabetes self-management app, resulting in poorer health outcomes. This digital divide may exacerbate existing health disparities, favoring digitally proficient populations. Moreover, the results of regional differences in 14 studies show that AI tools need to adapt to local scenarios and build implementation strategies that are in line with the advantages of technology, policy, and resources in the region.

Implications for Practice and Policy

The adoption of a user-centered design approach is essential for the successful development and implementation of AI interventions. Actively involving patients in the design and testing phases can enhance the intuitiveness, relevance, and overall usability of these tools. Employing methodologies such as surveys, usability testing, and focus group discussions can provide valuable insights for refining AI-based educational platforms to better meet the needs and preferences of target user populations. For example, Wu et al[46] reported that patients preferred chatbots with natural language interfaces and contextually relevant examples, suggesting that such features can enhance engagement and satisfaction. This finding suggests that chatbot development should be grounded in models demonstrating higher patient satisfaction, while applications should offer customizable interfaces tailored to users' cognitive levels and needs—such as "advanced" and "simplified" versions. The ultimate goal is to enhance user engagement and thereby promote improved long-term health outcomes for individuals with type 2 diabetes.

Moreover, integration with existing healthcare systems is essential to ensure the long-term scalability and adoption of AI-based interventions. Achieving this integration may require collaborative partnerships between technology developers and healthcare institutions to facilitate the seamless incorporation of AI tools into routine clinical workflows. Training healthcare professionals to effectively utilize these platforms during patient consultations can enhance their practical utility, while linking AI systems with electronic health records (EHRs) can enable the delivery of personalized educational content. A successful example of such integration is demonstrated by Sharma et al[50] in which an AI-

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driven educational platform was embedded within a US hospital's patient management system, resulting in improved clinical outcomes.

Meanwhile, future research and development should prioritize the reduction of technological and operational complexity, the minimization of associated costs, and the enhancement of system stability and language-processing capabilities. Customizing educational content to reflect the diverse needs, cultural contexts, and literacy levels of patient populations may significantly improve user engagement and the sustainability of interventions. Furthermore, equipping healthcare professionals with the necessary skills to effectively utilize AI tools and promoting interdisciplinary collaboration will be essential for expanding the integration of AI into T2DM patient education at scale.

In summary, artificial intelligence holds considerable promise for delivering personalized and scalable diabetes education. However, the realization of this potential necessitates coordinated efforts among researchers, clinicians, and policymakers to address existing implementation barriers. Optimizing the integration and utilization of AI in the management of chronic diseases such as T2DM will be essential for enhancing patient outcomes and ensuring sustainable healthcare innovation.

Study Limitations

Despite its comprehensive scope, this review has several limitations. Although an extensive range of databases was searched, the potential for publication bias remains. Grey literature—including conference proceedings, technical reports, and unpublished studies—was not comprehensively included, which may have led to the omission of valuable insights, particularly from emerging research areas or smaller institutions. Additionally, the methodological heterogeneity of AI technologies (eg, chatbots, predictive algorithms) and delivery modalities (eg, mobile applications, wearable devices) limited statistical pooling or meta-analysis, despite guidelines (from[29]) advocating for standardized reporting of intervention modalities and user engagement metrics. When reporting the percentage of results, such as HbA1c or a reduction in anxiety levels, we provide context only by mentioning the study design and sample size of each relevant study. Moreover, the review focused exclusively on adult T2DM intervention studies, thereby excluding relevant research involving pediatric populations or prevention-oriented interventions. This narrow scope may have restricted a more comprehensive understanding of AI's potential across the broader diabetes care continuum. These limitations should be considered when interpreting the findings. Future research should aim to expand the range of evidence sources, include subgroup analyses, and incorporate rigorous quality assessments to strengthen the credibility and comprehensiveness of the evidence base, thereby offering a more holistic understanding of AI's role in T2DM health education.

Conclusion

This scoping review synthesized evidence from 14 studies to delineate the landscape of AI applications in health education for patients with T2DM. A diverse array of AI-based mobile applications (eg, FoodLens), conversational agents (eg, AIDA), and intelligent platforms (eg, DiaLOG) delivered tailored instruction on dietary habits, glucose monitoring, and lifestyle modification. These interventions yielded demonstrable improvements in glycemic control, adherence to self-management behaviors, and psychological outcomes, with greater efficacy observed in studies featuring longer intervention durations and higher participant engagement. Nonetheless, the deployment of AI in T2DM health education is constrained by technical complexity, waning long-term engagement, digital literacy gaps, and data privacy concerns. In conclusion, while AI demonstrates substantial potential to transform patient education in T2DM, overcoming these challenges, standardizing outcome measures, and reinforcing user-centered design will be essential to facilitate its successful translation into routine clinical practice.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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