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REVIEW ARTICLE

Smartphone Applications to Prevent Type 2 Diabetes: A Systematic Review and Meta-Analysis

Esrat Jahan, MPH,[1,2] Rawan Almansour, MSc,[3] Kiran Ijaz, PhD,[4] Shaira Baptista, PhD,[5] Leticia Bezerra Giordan, MD,[6] Rimante Ronto, PhD,[1] Sarah Zaman, PhD,[7,8] Edel O'Hagan, PhD,[7,*] Liliana Laranjo, PhD[7,*]

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Introduction: Evidence supporting the use of apps for lifestyle behavior change and diabetes prevention in people at high risk of diabetes is lacking. The aim of this systematic review was to determine the acceptability and effectiveness of smartphone applications (apps) for the prevention of type 2 diabetes.

Methods: PubMed, Embase, CINAHL and PsychInfo were searched from 2008 to 2023. Included studies involved adults at high risk of developing diabetes evaluating an app intervention with the aim of preventing type 2 diabetes. Random-effects meta-analyses were conducted for weight loss, body mass index (BMI), glycated hemoglobin, and waist circumference. Narrative synthesis was conducted for all studies, including qualitative studies exploring user perspectives.

Results: Twenty-four studies (n=2,378) were included in this systematic review, including 9 randomized controlled trials (RCTs) with an average duration of 6 months, 10 quasi-experimental and 7 qualitative studies. Socially disadvantaged groups were poorly represented. Six RCTs were combined in meta-analyses. Apps were effective at promoting weight loss [mean difference (MD) −1.85; 95% CI −2.90 to −0.80] and decreasing BMI [MD −0.90, 95% CI −1.53 to −0.27], with no effect on glycated hemoglobin and waist circumference. No studies reported on diabetes incidence. Qualitative studies highlighted the need for app personalization.

Discussion: Smartphone apps have a promising effect on preventing type 2 diabetes by supporting weight loss. Future robust trials should include diverse populations in co-design and evaluation of apps and explore the role of artificial intelligence in further personalizing interventions for higher engagement and effectiveness.

INTRODUCTION

Type 2 diabetes is a common and costly, chronic, metabolic condition characterized by elevated blood glucose levels.[1] As of 2021, 529 million people worldwide were diagnosed with diabetes,[2] and 95% of all cases corresponded to type 2 diabetes.[3] The World Health Organization's most recent report attributed almost 1.55 million deaths to diabetes, making it the 9th leading cause of death globally.[4,5] The economic

From the [1]Department of Health Systems and Population, Macquarie University, Sydney, NSW, Australia; [2]Maternal and Child Health Division, International Centre for Diarrhoeal Disease Research, Dhaka, Bangladesh; [3]College of Applied Medical Sciences, King Faisal University, Al Ahsa, Saudi Arabia; [4]Affective Interactions lab, School of Architecture, Design and Planning, University of Sydney, Sydney, NSW, Australia; [5]The Australian Centre for Behavioural Research in Diabetes, Deakin University and the University of Melbourne, Melbourne, Victoria, Australia; [6]Northern Beaches Hospital, 105 French's Forest Rd W, French's Forest, Sydney, NSW, Australia; [7]Westmead Applied Research Centre, Faculty of Medicine and Health, University of Sydney, Sydney, NSW, Australia; and [8]Department of Cardiology, Westmead Hospital, Sydney, NSW, Australia

Address correspondence to: Liliana Laranjo PhD, Westmead Applied Research Centre, Westmead Hospital, Level 5, Block K, Entrance 10, Hawkesbury Road, Westmead, NSW 2145, Australia E-mail: liliana.laranjo@sydney.edu.au.

*Co-senior authors.

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burden of diabetes is also substantial, with a total global expenditure of 966 billion USD in 2019, projected to reach 1054 billion USD in 2045.[6] Preventing the continued escalation of type 2 diabetes is an urgent priority on a global scale.

Modifiable lifestyle factors such as unhealthy eating habits, sedentary lifestyles and being overweight or obese are linked to a higher risk of developing type 2 diabetes.[7] Consequently, lifestyle-based interventions that encourage healthy food choices and being more physically active are encouraged to promote weight loss and reduce the risk of developing type 2 diabetes.[8-10] Smartphone applications (apps) have emerged as effective tools to promote lifestyle changes and support health behavior modifications in both healthy individuals and clinical populations.[11-15] In healthy adults, interventions delivered via apps lead to weight reductions of 1.04 kgs,[12] and significant increases in physical activity[13] when compared with usual care. Similarly, apps have supported people with diabetes making lifestyle changes that led to improvements in glycated hemoglobin (HbA1c; blood marker of metabolic control).[14,15] However, evidence supporting the use of apps for lifestyle behavior change and diabetes prevention in pre-diabetes populations is lacking.

Existing systematic reviews that have included people with pre-diabetes have largely focused on a mix of various digital health technologies, mostly text messaging and web-based platforms, and with heavy reliance on low-quality evidence from single-arm or pre-post studies.[16-18] To date, no systematic review and meta-analysis assessed the effectiveness of smartphone apps for diabetes prevention in individuals at high risk of developing type 2 diabetes.

This systematic review and meta-analysis aimed to analyze and assess in people at high risk of type 2 diabetes:

1) The effectiveness of smartphone apps for diabetes prevention and impact on outcomes related to diabetes (e.g., HbA1c, waist/hip circumference, weight, BMI), or lifestyle behaviors (e.g., eating habits, level of physical activity).

2) Users' perspectives, needs and preferences for specific intervention features, engagement with smartphone apps, and acceptability of the interventions.

METHODS

This systematic review is reported based on The Preferred Reporting Items for Systematic Reviews and Meta-Analyses reporting (PRISMA) statement, available in Appendix 1 (available online).[19] The review was prospectively registered on PROSPERO (CRD42020180349) and MedRxiv (https://doi.org/10.1101/2020.05.18.20106211).

Studies were included if they were experimental (randomized controlled trials or quasi-experimental), mixed methods or qualitative and met the following criteria: 1) recruited adults (between 18 and 65 years) at high risk of developing type 2 diabetes, as defined by the authors of the studies; 2) evaluated a smartphone app designed for people at a high risk of developing diabetes (as defined by the authors of the study) to prevent type 2 diabetes; 3) had any comparison in experimental studies (e.g. control group, single group pre-post) or no comparison in the case of quasi-experimental and qualitative studies; 4) had outcomes related to diabetes [e.g. glycated hemoglobin (HbA1c), waist/hip circumference, weight, BMI, or changes in lifestyle behaviors (e.g. eating habits, level of physical activity)], or user perspectives regarding the use of the intervention. No restrictions were applied on language, sample size, follow-up duration, setting or comparator.

Studies were excluded if they: 1) focused on elderly people (mean age of the sample higher than 65 years; given the different needs of this subgroup in terms of diet, physical activity and technology, leading to heterogeneous app interventions)[20]; 2) if they recruited both people at high risk and diagnosed with type 2 diabetes mellitus, and did not show the results separately for each group; 3) were published before 2008; and 4) were conference abstracts.

Two investigators (EJ and LL) developed the search strategy and searched PubMed, Embase, CINAHL and PsychInfo from January 2008 to April 2020, and updated the search in July 2023. The search was limited to studies published after 2008 after the first smartphone application stores were launched. Keywords such as "prediabetes" and "mobile phone" were used for the search (the complete search strategy is provided in Appendix 2, available online). The reference lists of retrieved full texts and grey literature such as dissertations, theses, and conference proceedings were also screened to ensure all eligible studies were included.

Two investigators (EJ and RA) piloted the screening process. Duplicates were identified and removed in Endnote and Rayyan[21] was used for screening. Titles and abstracts were independently screened by 2 investigators (EJ and RA). Full text of studies deemed eligible for inclusion were retrieved. Any disagreements were discussed between investigators and further clarification was provided by a third reviewer (LL) until a consensus was reached. Cohen's kappa statistic was used to measure inter-coder agreement at both steps of the screening process.

The data extraction template was devised through discussion with team members (EJ, RA, and LL). Data extraction was performed independently (EJ and RA). The following information was abstracted from the eligible studies: author, year of publication, country, study design, sample size, mean age of population, duration of follow-up, intervention characteristics, comparison and outcomes. The data extraction form was then cross checked between the 2 reviewers (EJ, RA) and any discrepancies were solved through mutual discussion and with the help of a third investigator (LL). Behavior-change techniques (BCTs) present in each intervention were coded by 2 investigators (EJ and LB) according to the BCT taxonomy.[22]

The included randomized controlled trials were reviewed by investigators (EJ, LL, and KI) to appraise their quality using the Cochrane Collaboration's risk of bias tool.[23]

A narrative synthesis was conducted for all included studies based on published guidance[24] by developing a preliminary synthesis of findings and exploring relationships in the data to identify patterns across studies. Meta-analyses were conducted for direct comparisons when there were 4 or more randomized controlled trials reporting on an outcome of interest (weight loss, HbA1c, BMI and waist circumference). Effect sizes were computed as differences in means or standardized mean difference and classified as negative when in favor of the intervention and positive when in favor of the control. Random effects models were used for all analyses; the between-studies variance (T^2) was estimated using the method of moments. I^2 was used to describe the proportion of the variance in observed effects that is due to variance in true effects.[25] The presence of publication bias was evaluated by the use of a funnel plot and Duval and Tweedie's trim and fill method.[26] The significance level for all statistical tests was set at $P<.05$, 2-tailed; 95% CI were calculated where applicable. RevMan 5 was used for conducting meta-analysis.

RESULTS

In total, 1,138 articles were retrieved of which 897 were excluded after abstract screening (Figure 1 and Appendix 3, available online). Full-text screening was conducted for the remaining 39 articles and 26 articles were excluded. Eleven additional papers from database search updates met the eligibility criteria and were also included, bringing the total number of included studies to 24 for final analysis. The Cohen's kappa statistic for title and abstract screening was 0.46 (moderate agreement) and 0.72 (substantial agreement) for full text screening before final agreement was reached.[27]

Twenty-four studies (n=2,378) were included in this systematic review: 9 randomized controlled trials (RCTs),[28-36] 10 quasi-experimental studies,[37-46] and 7 qualitative studies[47-51] of which 2 were part of mixed-methods studies (RCT, quasi-experimental and qualitative component)[36,46](Table 1; Appendix 4, available online). Four studies evaluated the same 2 interventions.[37,44,50,51]

Of the 24 eligible studies, most were conducted in the U.S. [12 studies, n=1,736]; 3 studies were conducted in

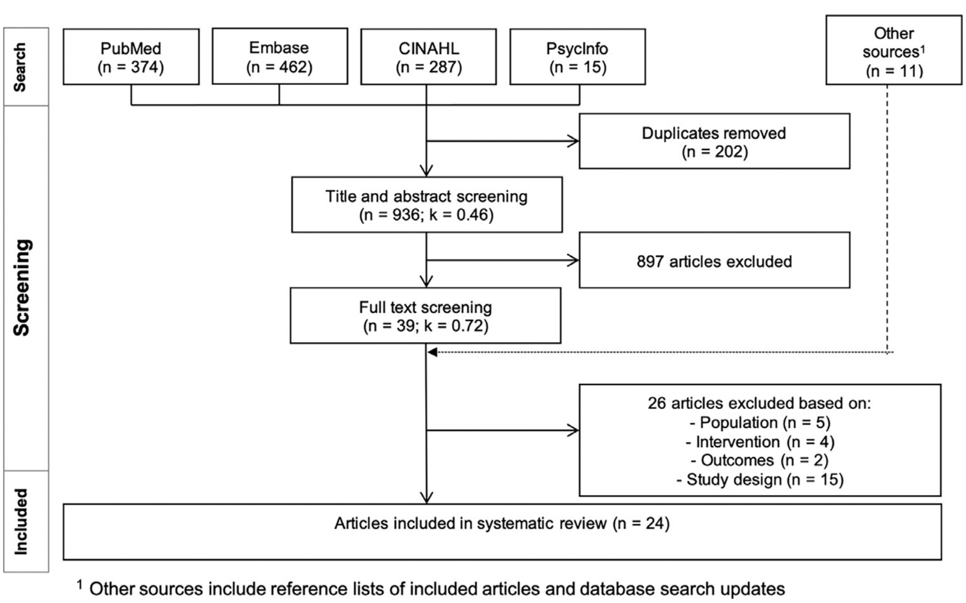

Figure 1. PRISMA flowchart of included studies.

developing countries.[28,30,32] The follow-up duration across all studies ranged from 2 to 12 months, with an average duration of 6 months in RCTs (Table 1). Sixteen studies included participants with prediabetes[28,30−40,42,43,48,50] and the remaining included other populations described by the authors as being at high risk for type 2 diabetes (e.g., previous gestational diabetes, metabolic syndrome, high BMI); 4 studies specifically included people of Latino, Filipino-American, Hispanic and Somali ethnicity.[34,38,39,46] The mean age of the participants was 51 years. Six[28,30-32,41,45] out of 19 experimental and mixed-methods studies did not report the ethnicity of participants and of the 13 studies reporting ethnicity, 6 had a majority of White participants[29,35,36,40,42,43] (Appendix 5, available online). Education level was reported in 10 studies,[28,32−34,36-39,43,44] with most participants having college or university education.

The 9 RCTs (including one RCT in a mixed methods study) had moderate to low risk of bias (Appendix 6, available online). The most common reasons for being at high risk were “blinding of participants and personnel” (n=9) and “incomplete outcome data” (n=2). There was also an unclear risk of bias in 4 separate RCTs in the domains of allocation concealment, blinding of outcome assessment, incomplete data and selective reporting. The most common comparators used in RCTs were printed education materials.[29−31,36] (Table 1).

The most common app features were physical activity and dietary intake monitoring followed by weight tracking and educational support (Appendix 7, available online). Fourteen interventions had automated real-time monitoring of physical activity (via a fitness tracker or smartphone sensors)[29,32−37,39,41,44,47,48,50,51] and 5 interventions tracked weight using a wireless scale.[36,39,43,50,51] In thirteen studies the intervention involved a human component, either in the form of messages,[28,31,39−41] phone calls, [32,50,51] or in-person sessions.[34,35,38,42,44] Two studies mentioned the use of artificial intelligence (AI) in the intervention, one to personalize content (based on context and user behavior)[43] and another study in the form of conversational AI.[45] The most common BCTs were self-monitoring of behavior which was present in 14 interventions,[28,30−35,37,38,40,41,43−45] followed by self-monitoring of outcome(s) of behavior,[29,31,32,34,35,40,41,43,45,46] and feedback on behavior and on the outcome(s) of behavior[28,30−32,37,38,40,43,45] (Appendix 8, available online). Eight apps sent reminders to the participants to track behaviors[32,35,36,38,40,45,47,49] and 7 provided participants with an option to set goals.[28,29,31,32,45,47,49] Five[29,38,39,43,46] out of 19 experimental and mixed-methods studies reported involving consumers in the co-design of the intervention (Appendix 8, available online). Health literacy considerations (e.g., readability level, voice-over of content) were mentioned in 2 studies.[39,46]

The most commonly reported outcomes were weight loss and BMI. No studies reported on new diagnoses of type 2 diabetes. Six RCTs with 1,239 participants were included in a meta-analysis that investigated the effect of a smartphone app intervention on weight loss.[29,31−35] Participants randomized to the smartphone app were more likely to lose weight in comparison with a control (mean difference (MD) −1.85, 95% CI −2.90 to −0.80; p-value=0.0005; I^2= 84%; T^2=1.26) (Figure 2). Asymmetry in the funnel plot suggested the presence of publication bias, with smaller studies reporting higher weight loss (Appendix 9, available online). Eight quasi-experimental studies found statistically significant weight reduction.[37,39−45]

Six RCTs with 673 participants reported data for the effect of a smartphone app intervention on BMI.[28−31,34,35] There was a significant difference in BMI (MD −0.90, 95% CI −1.53 to −0.27; p-value=0.005; I^2=84%; T^2=0.48) between participants randomized to a smartphone app in comparison with control (Appendix 9, available online). Four quasi-experimental studies found a significant reduction in BMI.[37,39,43,44]

Four RCTs with 534 participants reported data for the effect on waist circumference.[29,30,33,34] There was a non-significant decrease in waist circumference (MD −1.58, 95% CI −3.98 to 0.83; p-value=0.20; I^2=66%; T^2=3.95)

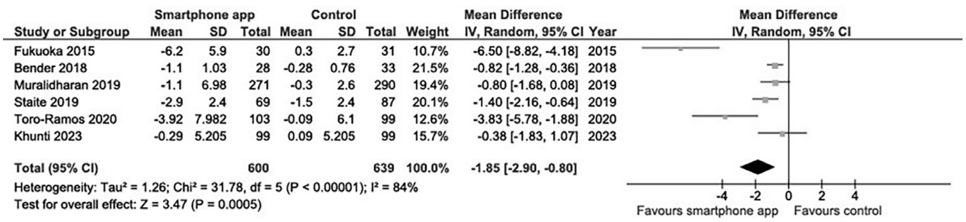

Figure 2. Forest plot of effect sizes and 95% CI representing the effect of smartphone apps on weight loss.

Table 1. Characteristics of Included RCTs

1st author, year, country	Study design	Follow-up in months	Sample size (I; C); mean age (years); % women	Population	Intervention	Comparison	Main results
Chung, 2023, Taiwan[28]	RCT (3 arms)	3	121 (79:42); 58.1; 52.9	Aged 20+ years diagnosed with prediabetes (HbA1c of 5.7%–6.4% or an FPG level of 100–125 mg/dL)	Smartphone app: self-monitoring, education, social networking, gamification, messages	Standard care (in-person education)	Between groups: ↓ HbA1c; ↓BMI; NS: PA
Khunti, 2023, UK[29]	RCT (2 arms)	12	293 (143:150); 35.1; 100	Women aged 18+ years with previously diagnosed GDM in last 5 years	Smartphone app: self-monitoring, education; activity tracker; social networking, gamification; 2 group sessions	Printed educational material	NS: weight, BMI, BP, HbA1c, lipid profile, PA
Xu, 2020, China[30]	RCT (2 arms)	6	76 (36:40); 47.7; 44	Aged 18+ years at high risk for diabetes, as measured by the American Diabetes Association screening tool (score ≥5)	Smartphone app: self-monitoring, education, social networking, automated personalized advice	Printed educational material	NS: BMI, waist circumference
Toro-Ramos, 2020, USA[31]	RCT (2 arms)	12	202 (101; 99); 56.61; 71	Aged 18+ years old and had an HbA1c level of 5.7% to 6.4% within 3 months before study enrolment	Smartphone app: self-monitoring, social networking, gamification, education; coach messages	Printed educational material	Between groups: ↓ weight; ↓BMI; NS: HbA1c
Muralidharan, 2019, India[32]	RCT (2 arms)	3	561 (271; 290); 37.8; 43	Prediabetes and/or obesity	Smartphone app: self-monitoring, videos, education; coach phone calls	Standard care	Between groups: ↓ weight; NS: 5% weight loss
Staite, 2020, UK[33]	RCT (2 arms)	12	156 (69; 87); 52.8; 69	Aged 18 to 65 years with pre-diabetes (American Diabetes Association criteria) BMI≥25 kg/m^2; (≥23 kg/m^2; if Asian)	Smartphone web app: education; activity tracker: self-monitoring; SMS: motivational messages	Smartphone app+ wearable device	NS: weight, PA, HbA1c, waist circumference, waist: hip ratio, lipid levels, BP.
Bender, 2018, USA[34]	RCT (2 arms; 2 phases)	6	61(28; 33); 41.7; 57	Aged 18+ years; self-identified as Filipino and BMI>23 kg/m2; Diabetes Risk score ≥ 5 points, fasting plasma glucose test=100–125 mg/dL, A1c> 5.6%, or OGTT)= 140–200 mg/dL	Smartphone app: self-monitoring, education; activity tracker; social networking; in-person weight checks and personal coaching	Phase 1: only tracker. Phase 2: complete intervention.	Between groups (Phase 1): ↓ weight; ↓ BMI; ↓ waist circumference; NS: Fasting blood glucose, HbA1c.
Fukuoka, 2015, USA[35]	RCT (2 arms)	5	61 (30; 31); 55.2; 77	Aged 35+ years; BMI ≥25 (≥23 for Asian-Pacific Islanders); diabetes risk score ≥5 points, FPG 100–125 mg/dL, A1c 5.7%–7.0%, or OGTT 140–200 mg/dL; physically inactive.	Smartphone app: self-monitoring (weight, PA, diet), education, videos and quizzes; pedometer; in-person coach sessions	Pedometer	Between groups: ↓weight, ↓BMI; ↓hip circumference; ↓ BP; ↑daily steps (p=0.02); NS: lipids, FPG, HbA1c
Griauzde, 2019, USA[36]	Mixed methods (feasibility RCT: 3 arms, interviews)	3	RCT (55; 16; 17; 22)	Prediabetes based on American Diabetes Association criteria of a HbA1c level 5.7%–6.4%	Smartphone app: self-monitoring and tailored feedback messages, reminders; activity tracker; wireless weight scale	Printed educational material	Retention ↑ among app plus (p = 0.004). NS: adherence rates.

AI, artificial intelligence; BMI, body mass index; BP, blood pressure; C, control; FPG, fasting plasma glucose; GDM, Gestational diabetes mellitus; HbA1c, glycated hemoglobin; HDL, high-density lipoprotein; I, intervention; IVR, interactive voice response; LDL, low-density lipoprotein; NR, not reported; NS, non-statistically significant; OGTT, oral glucose tolerance test; PA, physical activity; QE, quasi-experimental; RCT, randomized trial control; SD, standard deviation; SEM, standard error of the mean; SMS, short message service; TG, triglyceride; ↑, increase; ↓, decrease.

in participants randomized to a smartphone app in comparison with control (Appendix 9, available online). Two quasi-experimental studies reported a significant decrease in waist and hip circumference and waist to hip ratio post-intervention.[43,44]

Six RCTs with 776 participants reported data for the effect on HbA1c levels.[28,29,31,33−35] There was a non-significant difference on HbA1c levels (standardized mean difference (SMD) −0.02, 95% CI −0.64 to 0.60; p-value=0.95; I^2=94%; T^2=0.55) between participants randomized to a smartphone app in comparison with control (Appendix 8, available online). The funnel plot depicting standard error distribution demonstrated an asymmetric pattern. Asymmetry in the funnel plot suggested the presence of publication bias, with smaller studies reporting higher HbA1c reduction (Appendix 9, available online).

Two RCTs reported non-significant changes in fasting blood glucose levels and lipid profile which included triglycerides, high-density lipoprotein, low-density lipoprotein, and triglyceride to total cholesterol ratio.[33,35] Two RCTs and two quasi-experimental studies[33,35,43,44] reported on participants' blood pressure where one RCT and one quasi-experimental showed a reduction in both systolic/diastolic blood pressure in those randomized to smartphone app compared to control[35] and pre-post intervention.[44]

Health-related behaviors such as physical activity and diet were assessed in 5 quasi-experimental studies[37,38,42,43,46] and 2 RCTs.[33,35] Physical activity was measured in the form of daily steps, total number of exercise minutes and as metabolic equivalent of task (MET) hours. Two RCTs reported a significant increase in physical activity in those randomized to the smartphone app compared to control and one quasi-experimental study reported a significant increase in vegetable intake in the participants in the intervention group.[35,38,43]

Seven studies reported on qualitative data.[36,46−51] A theme that was common across studies was personalization being key to engagement.[36,46,47,49−51] Participants in these studies reported feeling unmotivated to use the app regularly when it delivered similar messages and prompts regardless of changes in their personal or social situation, indicating the need for app functions to be customizable in order to drive engagement and behavior change.[36,47,49,51] Personalized behavior change support and coaching were particularly well-received in 2 studies involving regular phone calls from health coaches,[50,51] and mentioned as desired features in 2 other studies (e.g., guidance for realistic goal-setting and ability to ask questions to an expert when needed).[46,49] Automated and real-time self-monitoring and feedback, such as with the help of activity trackers and wireless scales, were commonly mentioned as important for engagement,[36,47−51] as they were seen as a seamless way of increasing users' awareness and motivation for behavior change. Participants in several studies also indicated enjoying the social interaction and peer support provided by social networking features.[36,47,49,51]

The association between engagement with the app and weight loss was evaluated in 2 RCTs[31,32] and 4 quasi-experimental studies[39,40,44,45] (Appendix 10, available online). Engagement was measured by the number of times the participants used the app to respond to notifications,[40] logged in health-related data[31,44] or viewed the educational information provided in the app.[31,32] Five of the studies showed that participants were more likely to reduce their weight if they used the features of the app more often (at least twice weekly).[31,32,39,40,44,45] One quasi-experimental study reported that participants who responded more to prompts from the app to track their diet, physical activity and weight also had the highest percent of weight loss.[40]

DISCUSSION

This systematic review and meta-analysis exploring smartphone application interventions aimed at preventing diabetes in individuals at risk of developing type 2 diabetes found moderate quality evidence of effectiveness in achieving weight loss (1.85 Kg) and reducing BMI, but no evidence of changes in HbA1c levels or waist circumference. The average duration of RCTs was 6 months, with none reporting on the incidence of type 2 diabetes. Exploratory evaluation indicated that higher app engagement was associated with greater effectiveness in achieving weight loss. Qualitative data revealed that key factors influencing engagement and user preferences were the level of personalization, the ability to easily track progress and the inclusion of social features.

This is the first systematic review and meta-analysis to assess the impact of smartphone apps on mitigating risk factors for type 2 diabetes in at-risk individuals. Other systematic reviews have shown the effectiveness of smartphone apps in supporting weight loss, but none have focused on people at risk of type 2 diabetes.[52−56] Two meta-analyses[16,17] that did include a similar population to this study have also shown evidence of significant weight loss but did not focus on smartphone apps, including a broad mix of digital health interventions (e.g., telehealth, text-messaging), with only one included RCT evaluating a smartphone app.[35] Another systematic review (25 studies, n=8,184) investigated various mobile health interventions (e.g. text-messaging, web apps, smartphone apps) for preventing diabetes in middle aged and older people but did not conduct a meta-analysis.[18] In the present review, a reduction in glycated hemoglobin levels was not found, contrary to previous meta-analyses of apps in people with diabetes,[15,57] which is likely explained by the different target audiences of the apps and respective self-care recommendations (e.g., supporting diabetes medication adherence, lifestyle behavior change).

Sociodemographic characteristics of participants in included studies were poorly reported, with poor representation of socially disadvantaged groups. This lack of diversity has been highlighted in another meta-analysis which assessed the impact of multiple digital health technologies providing a diabetes prevention program, where the majority of participants in included studies were White and college-educated.[16] Yet, the prevalence of prediabetes seems to be higher in socially-disadvantaged groups,[58,59] raising concerns about digital health interventions not focusing on the populations who need these interventions the most and worsening health inequities.[60] Co-design with target populations following health literacy guidelines[61] is key to ensure their needs and preferences are met,[62−64] but a minority of included studies reported involving patients in the co-design process and only 2 mentioned health literacy considerations (e.g., readability of content). In addition, despite growing access to smartphones and apps,[65] there is evidence that not everyone is comfortable using mobile health technology, which perpetuates inequalities in technology access, known as the digital divide.[66−68] Future studies could consider leveraging new developments in conversational AI[69−71] to design digital health interventions that are able to "chat" with patients (e.g., via automated phone calls[72] or texting), without requiring high levels of digital or health literacy.

In line with other systematic reviews,[13,73−75] personalization was found to be a way to promote engagement and effectiveness, with 6 out of 7 included qualitative studies reporting the importance of feature customization and personalized behavior change support. Human advice and support via messages, phone calls, or in-person sessions was common in included studies but is more resource-intensive and poses problems for wide-scale implementation and dissemination, with meta-analyses failing to show higher effectiveness when humans are involved.[13,56,76] AI is becoming a feasible alternative for personalization of interventions and interactive support.[77] However, only two studies in this review included an AI component, highlighting an evidence gap and need for further robust trials in this area, with some already under way (e.g., ClinicalTrials.gov ID NCT05056376).

Automated self-monitoring and feedback on physical activity was a common feature of included interventions via the use of activity trackers and smartphone sensors and a preferred feature in qualitative analyses, as well as social networking. Apps and trackers have been shown in meta-analyses to significantly increase physical activity and reduce body weight and BMI in similar populations.[13,55,78] A systematic review assessing self-monitoring via digital health in weight loss interventions found higher engagement than with manual forms of self-monitoring (e.g., paper-based),[79] which could potentially lead to greater weight loss, as shown in the present study. Another systematic review assessing apps to manage cardiovascular risk factors found higher engagement was associated with effectiveness.[80] The addition of social networking features may also increase intervention effectiveness[81] but evidence suggests there is more variation in user preferences and engagement with social networking.[82,83]

Limitations

This systematic review had several strengths. First, the review followed a pre-registered protocol and followed the PRISMA guidelines for the reporting of a systematic review.[19] Second, an extensive search of the literature was conducted in 4 databases. Third, the language of the articles was not restricted to English to ensure all relevant articles were included. Fourth, pilot screening was conducted by the reviewers before screening for reliable results. Fifth, the agreement between independent reviewers was substantial during full-text screening.

There were a few limitations in this study which need to be acknowledged. The search strategy was not peer-reviewed, data extraction and BCT coding were not conducted independently, and inter-coder agreement could not be measured. Another limitation is that the criterion for including people at high risk of developing type 2 diabetes was based on the definitions provided by the authors of the studies. As a result, included participants varied in their characteristics (e.g., prediabetes, past gestational diabetes, metabolic syndrome). The variability in risk across the eligible participants may have contributed to the heterogeneity in meta-analyses results. This could mean that while smartphone apps were effective at promoting weight loss in the broad population of "patients at high risk of diabetes," there could be specific subgroups within that population for which these interventions don't work as well. Additional RCTs are needed to confirm these results. A third limitation is that the meta-analysis included a range of comparators (e.g., printed education materials, in person education, physical activity tracker). It is unclear whether smartphone apps are as effective as the 12-month lifestyle change program modelled in the Diabetes Prevention Program.

Findings from this systematic review suggest that smartphone apps have a small effect on weight loss and BMI in people at high risk of developing type 2 diabetes. Studies with a longer follow-up are needed to provide comprehensive insights into the sustained impact of these interventions on the incidence of type 2 diabetes. Future research should also include diverse populations such as different age groups, ethnicities and socio-economic backgrounds to assess whether these findings apply to broader populations.

Personalization of app features should be included to improve motivation and engagement with the app among the users. Clinicians could consider recommending apps that allow users to customize their experiences to improve engagement and ultimately health outcomes. Future trials should evaluate the impact of AI-driven personalization on engagement and effectiveness. Additionally, conducting further qualitative research would enhance understanding of the desired app features that can effectively increase user engagement.

CONCLUSIONS

This review suggests the value of smartphone apps in modifying risk factors for type 2 diabetes in high-risk populations, but impact on incidence of type 2 diabetes and reduction in HbA1C was not seen and requires further study, with longer duration follow-up and higher diversity in included participants. Features such as personalization, automated tracking and social networking were highly valued by participants. Future robust trials should explore the role of AI in further personalizing interventions for higher engagement and effectiveness.

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CREDIT AUTHOR STATEMENT

Esrat Jahan: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing — original draft, Writing — review & editing. Rawan Almansour: Formal analysis, Investigation, Writing — review & editing. Kiran Ijaz: Methodology, Formal analysis, Investigation, Supervision, Writing — review & editing. Shaira Baptista: Formal analysis, Investigation, Writing — review & editing. Leticia Bezerra Giordan: Formal analysis, Investigation, Writing — review & editing. Rimante Ronto: Methodology, Formal analysis, Investigation, Supervision, Writing — review & editing. Sarah Zaman: Formal analysis, Investigation, Writing — review & editing. Edel O'Hagan: Formal analysis, Investigation, Supervision, Writing — review & editing. Liliana Laranjo: Conceptualization, Methodology, Formal analysis, Investigation, Supervision, Writing — review & editing.

SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2024.01.008.

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