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Original Article

A systematic literature review for understanding the effectiveness of advanced techniques in diabetes self-care management

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ABSTRACT

This article includes a systematic review that identifies and summarizes the many behavioral change techniques (BCTs), behavioral health theories, and advanced techniques based on artificial intelligence (AI) currently used to manage diabetes. The review focuses on assessing the efficacy of diabetes self-care applications that leverage these cutting-edge techniques in their development and use. The study provides the latest comprehensive review and the findings of the report through the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 reporting guidelines. After carefully reviewing and choosing pertinent studies from well-known bibliographic databases, the review finds that self-care treatments favor behavior change, blood glucose reduction, healthier habits, and substantial weight loss. According to the results, investigations that use these methodologies and ideas and AI-based ones are more likely to succeed. The evaluation ends by highlighting its shortcomings and outlining potential future research and application design areas. It also highlights the possibility of incorporating BCT methodologies, theories, and AI-based techniques in creating self-management interventions. The knowledge gained from this systematic review can help application developers create frameworks for effective diabetes self-care interventions based on the identified cutting-edge techniques.

1. Introduction

Diabetes is a severe disorder that comes from high blood sugar levels. It is a lifelong disease that can lead to high blood pressure, kidney disease, and heart failure [1-4]. There are two categories of diabetes, such as Type 1 diabetes (T1D) and Type 2 diabetes (T2D). T1D diabetes, which cannot be prevented, is characterized by insufficient insulin in children, while Type 2 diabetes, which comprises about 90 % of all cases, is the most popular type of diabetes. The increasing number of people with diabetes has become a worldwide crisis, which puts a huge problem on the health system. For instance, the National Diabetes Statistics Report showed that about 13 % of the US population are diabetics [1]. According to global estimates [6], about 9 % of the world population is diabetic, which is expected to rise to over 12 % by 2030 [2]. The growing number [3] of diabetics is believed to be associated with aging, obesity, and the nutritional lifestyle of people [3]. Healthcare providers can use the data collected from advanced self-care management systems to develop individualized care plans tailored to each patient's unique needs. By incorporating patients' behavioral patterns and progress data into care plans, healthcare providers can set realistic goals that align with patients' preferences and capabilities. This individualized approach enhances patient engagement and optimizes the effectiveness of self-care interventions.

These trends have become alarming, which begs the need for scientists and technologists to devise effective solutions for diabetes management. With the prevalence of diabetes cases across the globe, numerous applications have been designed for diabetes self-care management. It has been indicated that diabetes self-care applications are among the most commonly downloaded applications on the google play store [4]. Different research works have shown that diabetes self-care applications can significantly improve various clinical outcomes associated with diabetics [5-7]. Earlier research examined the effectiveness

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of self-care applications for diabetes qualitatively [8,9]. Moreover, various meta-analyses [10-12] have been conducted that investigated the effectiveness of self-care applications for diabetes management based on quantitative evidence. However, most existing studies should have explored the influence of BCTs on self-care management [12,13]. Mainly the existing mHealth apps utilize a restricted use of BCTs and insufficient features, except self-monitoring [14,15]. Moreover, diabetic patients believe that e-self-management health apps should be engaging and involve many features (functions) encompassing a wide range of content, including emotional and psychological assistance [16]. Since diabetes management is directly associated with behavior that needs proper adjustment [17-20], the influence of individual BCTs on diabetes management cannot be ignored. Thus, there appears to be a great deal of uncertainty about whether these mobile and internet health apps improve health outcomes and whether these mHealth apps are a cost-effective approach for delivering Diabetes Self-Management Education and Support (DSME) in the real world [17,18,21].

Essentially BCTs are observable aspects that can lead to effective behavior regulation [10,22]. Furthermore, there are several claims that theoretical consideration can result in a better design of interventions [23-27]. However, little is known of the individual techniques that impact health behavior change in diabetics leading to the improvement of technical outcomes [28]. While previous studies quantitatively examined the influence of BCTs in Dietary-based interventions [29], Internet-based interventions [30], and activity-based interventions [31], there is a need for investigating the diabetes self-management applications that emphasize the role of BCTs. In recent years, AI and ML technologies are quickly developing that utilize the capabilities of mHealth and overcome the limitations of the current solutions. In recent years, AI-based technologies have considered behavioral perspectives to create a conversational, interactive experience for a diabetic patient to provide a personalized and standardized intervention that addresses a wide range of patient need and expectation at a larger scale [32].

Past reviews on self-care applications have investigated the relationship between the effectiveness of the application and its features in diabetes management. Applications with significant effectiveness used passive and interactive features, while applications without significant effects are likely to have utilized only passive features [33]. In passive features, the participant's interaction is unnecessary, while in interactive features, the participant responds to content in real time. Another study [34] explored different features in self-care applications. It showed that interactive features were more efficient than passive features at better medication adherence in patients having type 2 diabetes. However, the study only emphasized the management of type two diabetes, and it is not yet clear which application features are most efficient. In examining the effectiveness of advanced techniques in diabetes self-care management, it is crucial to differentiate between pediatric and adult populations. The review aims to compare and contrast the outcomes and effectiveness of these techniques within each population, taking into account specific factors such as developmental stage, cognitive abilities, psychosocial factors, and individualized care needs.

Therefore, the main goal of the review paper is to examine the efficiency of the current diabetes self-care applications that incorporate these advanced methods such as BCTs, Health Behavioral Theories, and AI-based advanced methods in their design and implementation and suggest future lines of research and development. Moreover, to our knowledge, this is the only review in the existing literature focusing on studies that involve BCTs, Health Behavioral Theories, and AI-based advanced methods to develop diabetes self-care management systems.

Therefore, principally, the main contributions of the paper are as follows:

- To investigate the effectiveness of health BCTs and theory-based interventions for diabetes self-management.
- To identify the BCTs commonly integrated into self-care management interventions.
- To investigate the common features used in diabetes self-care management interventions.
- To investigate the effectiveness of the AI-based applications that involve BCTs and theory-based interventions for diabetes self-management.
- To identify the challenges and future direction for the technology enabled-diabetes self-care systems.
- To propose a more effective Machine Learning and Artificial Intelligence solution that integrates behavior changes and the individualized care of traditional Diabetes Self-Management Education and Support (DSME) programs and takes advantage of the scalability of Internet-based and mobile health (mHealth).

2. Materials and methods

An SLR method was conducted, which adopts the PRISMA approach for presenting the SLR [35,36]. PRISMA offers a consistent and replicable method to identify literature. It also provides a guide for selecting, recognizing, and assessing the research articles [37]. The PRISMA process utilized for the current SLR is illustrated in Fig. 1. The detail of the SLR process is presented in the following subsections:

2.1. Data sources and search strategy

Nine online digital libraries were used to conduct the search procedure to collect relevant papers. The searched online databases in this study include Google Scholar, Scopus, Web of Science, ScienceDirect, Embase, EBSCOhost, SAGE, PubMed, and Taylor & Francis Online. To obtain the latest and comprehensive review, 2010 to 2022 was considered the period for the SLR. The search terms were divided into two parts such as (1) Relevant materials related to diabetes, mHealth applications (internet and Mobile based applications), BCTs, and behavior change theories, (2) Relevant materials related to diabetes, mHealth Applications, Artificial intelligence, Machine Learning, BCTs, behavioral changes.

Keywords for Part 1:

"(diabetes)" AND "(mHealth)" OR "(Mobile App)" AND "(diabetes)" OR "(Internet based Application)" AND "(diabetes)" OR "(((diabetes)" AND "(mHealth)" AND (behavior change techniques))" OR "(behavioral change)" OR "behavior modification)" OR "(((diabetes)" AND "(Internet based application)" AND (behavior change techniques))" OR "(behavioral change)" OR "behavior modification)" OR "(((diabetes)" AND "(Mobile Apps)" AND (behavior change techniques)" OR "(behavioral change)" OR "behavior modification))".

Keywords. for Part 2:

"((Diabetes) AND (Artificial Intelligence) AND (Internet-based application))" OR "(behavior modification") OR "behavior change techniques" OR "(behavioral change))." OR "((Diabetes) AND (Artificial Intelligence) AND (mHealth))" OR "(behavior modification") OR "(behavior change techniques)" OR "(behavioral change))."

Following similar studies reported in [10-12,38,39], citations of previous literature were examined to obtain more relevant articles for the review.

2.2. Study inclusion and exclusion criteria

To comprehensively identify the relevant studies, a manual search was also considered in addition to the search terms used in the automatic search (as described in section A). In the identification stage, using keywords for part 1, 3961 studies were obtained, including 3893 records from automatic searching (through digital databases) and 68 articles from manual searching from citations. In the screening stage, 2761 published articles were selected after removing duplicates, unsuitable, and irrelevant publications. The remaining documents were further screened based on titles and abstracts, and eventually, 2375 articles were removed. The full-text assessment was then applied to 386

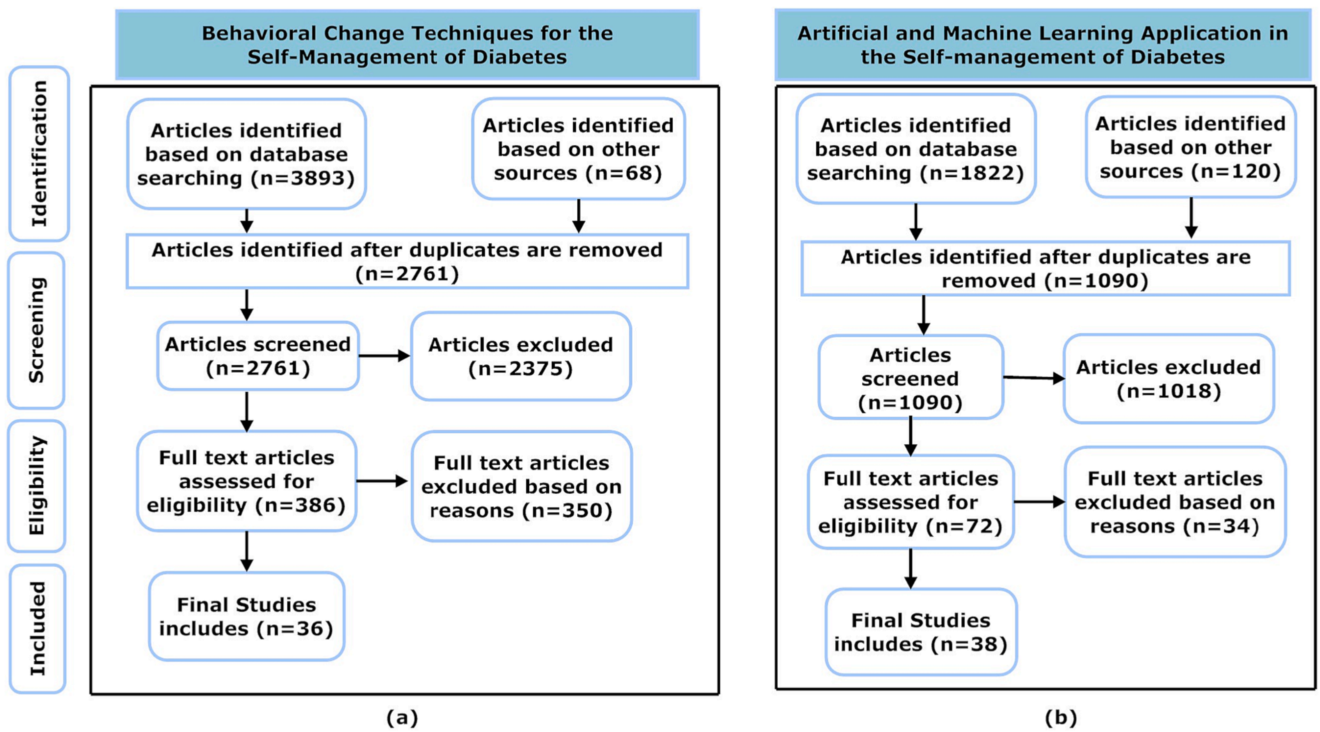

Fig. 1. (a) Illustrates the selection process of literature to review the BCTs for the self-management of diabetes, and (b) demonstrates the selection process of literature to review artificial and machine applications in the self-management of diabetes.

remaining records. Finally, 36 articles were obtained after removing 350 articles based on the inclusion and exclusion criteria and the quality evaluation criteria. Additionally, using keywords for part 2, a total of 1942 studies were obtained, involving 1822 records from automatic searching (through digital databases) and 120 articles through manual searching from citations. In the next screening stage, 1090 published articles were chosen after removing duplicates, irrelevant, and unsuitable publications. The remaining documents were further screened based on titles and abstracts, and eventually, 1018 articles were deleted. The full-text assessment was then employed on 72 remaining records. Finally, 36 articles were obtained after removing 36 articles based on the inclusion and exclusion criteria and the quality evaluation criteria.

Specifically, experimental and quasi-studies were considered for the current SLR, which examined the efficacy of self-care applications for people 18 years and above at risk of becoming diabetics. Selected studies were those published in English and peer-reviewed in either conference proceedings or journals. Excluded studies include the following: (1) unpublished articles, (2) books, letters, thesis, and reviews, (3) gestational, secondary diabetes, or pre-diabetes, (4) Studies on mixed populations of adults and children; and (5) Applications for insulin pumps only.

Inclusion Criteria:

- Study Type: Experimental and quasi-experimental studies that evaluate the efficacy of self-care applications for individuals aged 18 years and above at risk of developing diabetes.
- Publication Language: Studies published in the English language.
- Publication Type: Studies published in peer-reviewed journals or conference proceedings.
- Relevance to Self-Care Applications: Studies focusing on self-care applications that aim to promote diabetes self-management, including behavioral change techniques, behavioral health theories, and AI-based advanced techniques.

Exclusion Criteria:

- Unpublished Articles: Studies that are not published in peer-reviewed journals or conference proceedings.
- Books, Letters, Thesis, and Reviews: Non-primary research articles such as books, letters, theses, and review papers.
- Gestational, Secondary Diabetes, or Pre-diabetes: Studies specifically focusing on gestational diabetes, secondary diabetes, or pre-diabetes conditions.
- Mixed Populations of Adults and Children: Studies that include mixed populations of both adults and children, where it is difficult to distinguish the impact of self-care interventions specifically on the adult population.
- Applications for Insulin Pumps Only: Studies that solely focus on self-care applications designed for insulin pump management rather than broader diabetes self-management.

2.3. Data extraction

The 36 articles obtained from keyword part 1 were then taken to the bibliographic software (Mendeley) for synthesis. The extracted data included characteristics of studies and interventions, including the countries where the study was conducted, platforms used for the interventions, percentage of baseline weight loss, and glycemic status. When the mean weight loss percentage was not stated, this was manually determined based on the mean baseline weights and the mean weights at postintervention follow-ups. As detailed information from authors can be difficult in most cases, it should be noted that only the freely available materials (such as the main text, development procedures, supplementary materials, etc.) are considered for the data extraction, application features identification, and BCTs coding process. The methods used to collect data in the included studies were examined to assess the reliability and validity of the findings. These methods may include surveys, interviews, clinical measurements, or technological data collection tools. Details on the data collection methods have been provided to give readers insights into the rigor of the data collection process.

2.4. Coding of behavior change techniques

The list of BCTs taxonomy reported in reference [22] was particularly considered to code the absence or presence of each technique from the reviewed articles. The coding process was conducted separately and independently based on the primary papers, protocols, and related studies to assess the selected studies better. The BCT training materials and the original study procedures reported in reference [22] were used to obtain a proper and appropriate coding process for the BCT's taxonomy application. Based on previous studies [40,41], it was observed that similar research works could have explained the same standardized interventions. However, it was also observed that the interventions might be explained differently in the literature of each study where, for instance, some BCTs present in a particular study would be unavailable in another study and vice versa. Therefore, an imputation technique is applied in this study to address these issues to obtain the missing BCTs.

2.5. Application feature identification

A thematic analysis [42] was conducted based on three stages of all intervention information to identify features. To this end, the descriptions and coding of each application component and its platform are first described. In a situation where several studies assessed the same standardized intervention, the imputation procedure was also conducted. Second, features were categorized based on the level of interactivity between the application and user, as either two-way interaction (interactive) or one-way interaction (passive). We completed these first two stages on a random sample of all application descriptions to check for reliability. Third, all interactive and passive features were collectively pooled, analyzed, and discussed. Based on this analysis, common themes among the interactive and passive features were obtained accordingly. The themes or clusters were later categorized as interactive or passive features and labeled according to each theme.

2.6. Quality assessment

Analyzing the SLR data and evaluating its quality is equally significant to mitigate the issue of bias in extrapolating a study. Essentially, a significant bias from the research method could significantly affect the results of a poorly conducted study and thus require cautious interpretation. Therefore, such studies must be excluded or at least be identified as such to provide an unbiased conclusion in the SLR. It is also essential to use the proper criteria to assess the quality of evidence and any inherent bias in each study. Thus, to ensure the quality of the selected studies, we used the National Institute of Health and Care Excellence (NICE) quality assessment checklist for the quantitative intervention analysis [43,44]. The NICE checklist involves twenty-seven item criteria that enable appraisal of external and internal validity where each criterion was attained, with "++" showing the lowest risk of bias or highest quality. The appropriateness of the data analysis techniques employed in the studies was evaluated. The use of appropriate statistical tests and rigorous data analysis methods contributes to the reliability and robustness of the findings.

2.7. Data synthesis

As noted earlier, one of the contributions of this study is to summarize and investigate the efficacy of self-care applications for diabetes management and the impacts of the BCTs and application features. Thus, a narrative synthesis strategy was employed to present and organize the information extracted from the reviewed articles, with descriptive analysis and statistical information summarized in tables. However, as most of the reviewed papers presented in the main effectiveness analysis of the interventions did not present the weight loss percentage and other important parameters, the available data needed to be more sufficient for conducting a proper *meta*-analysis. The data analysis techniques employed in the studies were evaluated to determine the rigor of the data analysis process. These techniques may include descriptive statistics, inferential statistics, thematic analysis, or content analysis. Information on the data analysis techniques used in each study has been included to help evaluate the trustworthiness of the findings.

2.8. Outcomes assessment

Glycemic status (Fasting glucose or A1c) and body weight were considered the primary outcomes of interest. Body weight was considered the primary definition of effectiveness because of its direct link with diabetes conditions; it is also reported more often in diabetes self-care studies than in other fields [11,40,45]. Intervention efficacy was defined concerning average weight reduction of $\geq$ 5 % of baseline weight because this value is considered clinically substantial [46] and mainly corresponds to common benchmarks of weight reduction for twelve-month diabetes self-care interventions [45,47]. Essentially, interventions of less than six-month were considered adequate if an average of more than 3 % weight was lost in less than six-month period while interventions of more than twelve-month duration were considered adequate if an average of more than or equal to 5 % weight reduction was attained in at least twelve months follow up. Considering the above conditions, the application in the reviewed studies was categorized as short-term effective, short-term ineffective; long-term effective; and long-term ineffective. More specifically, interventions of more than twelve months were categorized as short-term (ST) and long-term (LT) follow-ups. Relations were examined between the types of BCTs, and features of the intervention recognized in the long-term against short-term interventions. Like relevant studies in reference [46], features and BCTs were deemed effective at each respective time (ST or LT) if discovered in at least 55 % of effective interventions. To enhance the presentation of the most relevant and impactful findings, we have focused on highlighting the key findings that have significant implications for advancing diabetes self-care management. These findings include the effectiveness of advanced techniques in changing behaviors, promoting healthier lifestyle habits, reducing blood glucose levels, and achieving significant weight reduction. Additionally, the commonly used behavior change techniques, behavioral health theories, and AI-based advanced methods were identified and analyzed.

2.9. Research questions

Formulating research questions (RQs) is essential in defining a study's overall purpose and expected outcomes. The main RQs in this SLR are as follows:

- RQ1: How effective are self-care management applications/ interventions based on integrating behavioral techniques in diabetes management?
- RQ2: What BCTs are commonly integrated into self-care management applications?
- RQ3: What common features are used in diabetes self-care management applications?
- RQ4: How to utilize AI and ML techniques to change and sustain patient behaviors with the individualized care of conventional DSME programs while taking full benefit of mHealth to a large scale?
- RQ5: What are the challenges and future direction of the diabetes self-care application?

3. Results

3.1. Publication type and distribution

The years of the publication of the articles considered for the SLR varied between 2010 and 2022. Fig. 2 presents the distribution of the selected papers considered for the SLR based on the year of publication.

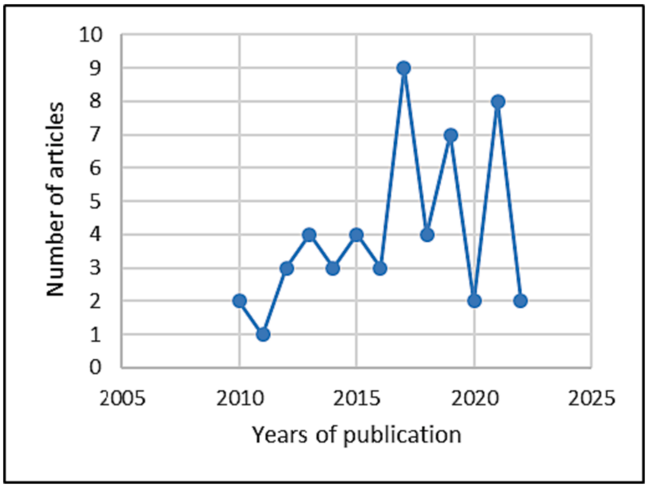

Fig. 2. Number of papers published based on the year of publication.

It shows that a significant number of publications on self-care applications for diabetes patients were conducted between 2010 and 2022, with a fluctuating trend across the period. Fig. 2 shows that the number of publications started to rise from 2011 (in which one paper was published) to 2013 (in which four papers were published). It also shows that the highest number of papers published was nine and eight in 2017 and 2021, respectively, while the lowest was in 2011 (only one paper was published). Fig. 3 illustrates the distribution of the publication type considered in this SLR. Only journal articles and conference proceedings were considered for the review. Therefore, many publications were journal articles with fewer conference papers.

3.2. Study characteristics

Table 1 summarizes the characteristics of all 36 studies obtained from the Part 1 keywords. As illustrated in Fig. 4, the review provides a summary of the participant characteristics such as age range and BMI, further details on the demographics, including gender distribution, ethnicity, socioeconomic status, and any specific population subgroups targeted, were not explicitly discussed. Future research should consider providing more comprehensive information on participant demographics to better understand the representativeness and generalizability of the findings to different populations. Moreover, the studies were conducted in different countries, which include Australia [48-50], USA[51-62], Germany [63], India [64,65], Hong Kong [66], Netherland [67,68], Taiwan [69], China [66,69,70], Saudi Arabia[71,72], Iran [73], Malaysia [74], Norway [75-77], Indonesia [2], Switzerland 74 [68], and Denmark [78]. Table 1 and Fig. 4 show that most of the selected articles that met our criteria are from the US, with 12 articles at 33 %, followed by Australia and China at 8 % each, India, Netherlands, Malaysia, and Saudi Arabia at 6 % each, while Taiwan, Indonesia, Switzerland, Denmark, Germany, and Hongkong with 3 % paper each. Table 1 also shows that both randomized controlled trials, non-randomized control trials, and observational and single-arm studies were adopted as the study design. Intervention duration in the reviewed articles ranged between 3 months to 24 months. The selected studies used an average of 55 participants with a mean age range of 18 to 70. The participants' mean Mass Body Index (MBI) ranged from 25 to 35 Kg/m2. As illustrated in Fig. 5, different platforms used for the interventions included mobile phones [49,50,56,58,60,63,65-68,70-72,74,77-80], websites [40,48,51,81] DVD [59,61] and hybrids of mobile applications [52,55,62,69,73-75], and electronic mails [64] shows that 56 % of the interventions used Mobile phones, 13 % used the web, 22 % used a combination of both mobile and phone. In comparison, 6 % and 3 % were based on the DVD and Email platforms, respectively, as shown in Fig. 5.

3.3. Research question results

RQ1: What is the effectiveness of diabetes self-care management applications?

Table 2 summarizes the weight lost at each follow-up for different interventions in the reviewed studies. Table 2 shows that the weight reduction across the studies ranged from 0.73 % to 8.0 % and from 0.93 % to 7.5 % in the short-term and long-term interventions, respectively. It is worth noting that the respondents used interventions for 7.8 months, losing about 3.6 kg on average. Based on the primary effectiveness criteria of this SLR (as discussed in the previous section 2.8), most of the interventions were effective in the short-term [48,50-52,54,58-62,69,71,74,75,77,80,81,84]. These include those utilized mobile phones, websites, and both mobile phones and websites. More specifically, twelve interventions were short-term ineffective [2,51,54-56,64,65,67,72,74,79,85]. Six interventions were long-term effective

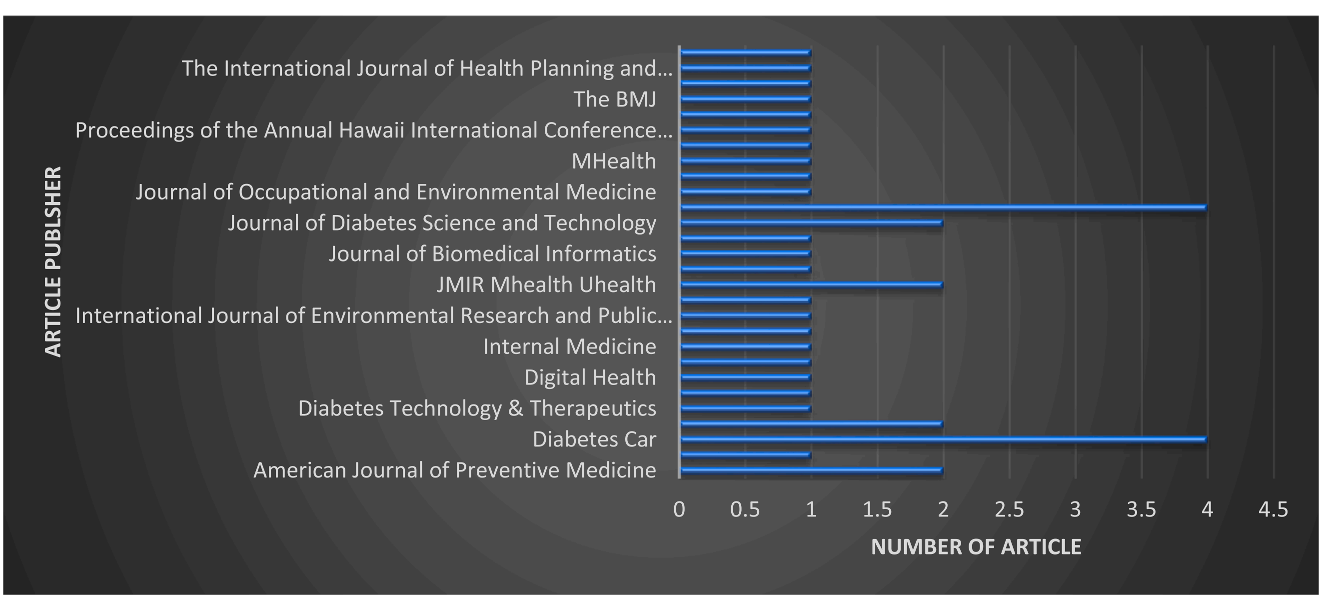

Fig. 3. Names of the publishers and the number of published articles.

Table 1
Summary of the characteristics of all 36 studies.

Reference	Source of Publication	Country	Intervention	Platform	Theoretical Basis	Study Design	Study Duration	Participants; Gender; Mean age; BMI,	Limitations
[48]	Journal	Australia	PULSE	Website	Social Cognitive Theory	Randomized Controlled Trial	6 months	n = 53; Mean age: 52 years; Male:100 %; Mean MBI: 32 kg/m2;	RCTs may have limited external validity due to strict inclusion and exclusion criteria, which can result in a sample that does not fully represent the diverse population with diabetes.
[63]	Journal	Germany	mHealth	Mobile App	NR	Observational study	12 months	n = 109; Mean Age: 49.6 years; Female: 60.6 %; Mean MBI: 32.2 kg/m2	Lack of randomization and control over the intervention assignment. This lack of control makes it difficult to isolate the effects of the interventions from other factors that may be influencing the outcomes.
[51]	Journal	USA	Alive-PD	Website	Learning Theory; Theory of Planned Behavior; Social Cognitive Theory;	Randomized Controlled Trial	6 months	n = 163; Mean Age: 55.8 years; Male: 68.1 %; Mean BMI: 31.1 kg/m2	Participant blinding may not always be feasible in behavioral interventions, potentially introducing bias.
[52]	Journal	USA	Omada Program	Website and Mobile App	Social Cognitive Theory. Transtheoretical model	Single arm Prospective study	12 months	n = 501; Mean Age: 68.8 years; Female: 64 %; Mean BMI: 33.6 kg/m^2	Social Cognitive Theory and Transtheoretical Model lack standardized definitions and measurement tools. This defining and measuring key constructs may introduce variability and hinder the comparison and synthesis of findings across studies.
[55]	Journal	USA	mHealth	Website and Mobile App.	Social Cognitive Theory; Self-Care Behaviors Framework	A single-arm prospective pilot study	12 weeks	n = 13; Mean age: 24.4 years; Female: 76.9 % Mean BMI: 35.6 kg/m^2	Inaccurate reporting of self-care behaviors or outcomes can introduce bias and affect the validity of the findings. The use of different measurement methods or tools can make it challenging to compare and combine results.
[56]	Journal	USA	Sweetch Mobile	Mobile App.	Just-in-time Adaptive intervention design.	Observational study	3 months	n = 38; Mean age: 57.2 years; Female: 63 %. Mean BMI: not reported	Factors such as perceived intrusiveness, burden of data collection, or intervention fatigue may affect participant engagement and adherence.
[57]	Journal	USA	mHealth	Mobile App.	Social Cognitive Theory; Transtheoretical model	Randomized Controlled Trial	12 months	n = 78; Mean age: 47.7; Female: 70.5 %. Mean BMI: not reported	Limited predictive power in explaining specific behavior change outcomes or identifying the most effective intervention strategies.
[58]	Journal	USA	mDPP	Mobile App.	Social Cognitive Theory; Transtheoretical model	Randomized Controlled Trial	5 months	n = 3; Mean age: 57.1 years; Female: 76.7 %. Mean BMI: 32.2 kg/m2	These theories may not fully capture the unique needs and challenges faced by individuals, limiting their applicability to diverse populations.
[59]	Journal	USA	GLB-DVD	DVD	Social Cognitive Theory ; Transtheoretical model	Non-randomized Controlled Trial	3 months	n = 22; Mean age: 57.3 years; Male: 40 %. Mean BMI: 32.9 6.1 kg/m2	Theories may not fully account for the individual variability in response to interventions and behavior change

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Table 1 (*continued*)

Reference	Source of Publication	Country	Intervention	Platform	Theoretical Basis	Study Design	Study Duration	Participants; Gender; Mean age; BMI,	Limitations
[64]	Journal	India	Lifestyle modification in	Short Message Service (SMS) and Email	NR	Randomized Controlled Trial	12 months	n = 133; Mean age: 36.8 years; Male: 74.4 %. Mean BMI: 27 kg/m2	SMS and email communication raise privacy and security concerns, particularly when exchanging personal health information or sensitive data.
[54]	Journal	USA	E-LITE	Websites	Social Cognitive Theory. Transtheoretical model	Randomized Controlled Trial	15 months	n = 81; Mean age: 51.8 years; Male: 54.3 %. Mean BMI: 31.7 kg/m2	Social Cognitive Theory and the Transtheoretical Model often emphasize static constructs and fail to capture the dynamic nature of behavior change processes.
[60]	Journal	USA	Noom Coach	Mobile App.	Social Cognitive Theory. Transtheoretical model	Single-arm prospective study	24 weeks	*n* = 43; Mean Age: 52.15 years; Female:86%; Mean BMI: 35.50 kg/m2	They may not fully capture the complexity of behavior change processes over time.
[61]	Journal	USA	GLB-DVD	DVD	Social Cognitive Theory; Transtheoretical model	Prospective quasi-experimental study	6 months	n = 113; Mean age: 52.4 years; Female: 85 %. Mean BMI: 36.2 kg/ms2	These theories may not fully capture the complex interplay between individual, social, and environmental factors, limiting their ability to explain the multifaceted nature of behavior change in real-world contexts.
[40]	Journal		GLB-Internet	Website	Social Cognitive Theory. Transtheoretical model	Prospective quasi-experimental study	3 months	n = 50; Mean age: 51 years; Male: 55 %. Mean BMI: 30.7 kg/m2;	Both Social Cognitive Theory and the Transtheoretical Model focus on individual-level factors and may overlook the broader social, cultural, and environmental influences on behavior change.
[65]	Journal	India	mHealth	Mobile App	Transtheoretical Model	Randomized Controlled Trial	24 months	n = 271; Mean age: 54.1 years; Male: 100 %. Mean BMI: 25.8 kg/m2;	RCTs often require significant resources, time, and logistical support. It can be challenging to conduct large-scale RCTs due to budgetary constraints, limited availability of research personnel, and other practical limitations.
[62]	Journal	USA	USA Omada	Web and Mobile App	Social Cognitive Theory. Transtheoretical model	Quasi-experimental Single-arm	12 months	n = 187; Mean age: 43.9 years; Female: 85 %. Mean BMI: 36.7 kg/m2	People differ in their motivations, cognitive abilities, cultural backgrounds, and personal circumstances, which can influence their engagement in behavior change and the effectiveness of interventions.
[53]	Journal	USA	Omada	Web and Mobile App	Social Cognitive Theory; Transtheoretical model	Observational study	24 months	n = 634; Mean age: 46 years; Female: 58.4 %. Mean BMI: 34.5 kg/m2	The model's applicability and effectiveness may vary depending on the specific behavior and population under study
[66]	Journal	Hong Kong	Mobile Diabetes App	Mobile App	Social Cognitive Theory; Transtheoretical model	Randomized Controlled Trial	24 months	n = 54; Mean age: 54.1 years; Male: 90.7 %. Mean BMI: 25.6 kg/m2	Recruitment and retention of participants in RCTs can be challenging. Low participation rates or high dropout rates may

(continued on next page)

Table 1 (*continued*)

Reference	Source of Publication	Country	Intervention	Platform	Theoretical Basis	Study Design	Study Duration	Participants; Gender; Mean age; BMI,	Limitations
									introduce selection bias and affect the representativeness of the study sample.
[67]	Journal	Netherland	TRIGGER	Mobile App	Health Belief Model; Transtheoretical Model of Behavior Change; Self-Regulation Theory; Fogg Behavior Model	Randomized controlled trial	6 months	n = 48; Mean age 58.6; Female 41.7 %. Mean BMI: 24.5 kg/m2	RCTs are often conducted under controlled settings with specific inclusion and exclusion criteria, which may limit the generalizability of the findings to broader populations or real-world contexts.
[69]	Journal	Taiwan and China	Health4Life	Mobile and Web	Theory of Planned Behavior; Transtheoretical Model of Behavior change	Randomized Controlled Trial	18 months	N = 81; Mean Age: 63:71; Female: 39 %. Mean BMI: 30 kg/m2	Ethically inappropriate or impractical to assign participants to a control group if there is an existing standard of care or a known effective intervention
[72]	Journal	Saudi	Social mobile diabetes management system	Mobile App	Cognitive behavioral therapy	Non-randomized controlled Observational study	6 months	n = 54; Mean age: 54.1 years; Male: 90.7 %. Mean BMI: 25.6 kg/m2	While CBT can be effective in the short term, maintaining treatment gains over the long term and preventing relapse may require additional strategies and ongoing support.
[68]	Journal	Switzerland	Planner	Mobile App	COM-B model; behavior change techniques; behavior. change theory; human-centered design	Non-randomized controlled observational study	24 months	n = 54; Mean age: 54.1 years; Male: 90.7 %. Mean BMI: 25.6 kg/m2	(BCTs) can vary across different taxonomies or frameworks. There is no universally agreed-upon set of BCTs, and different models may include different techniques or categorize them differently.
[2]	Journal	Indonesia	DM-calendar app	Mobile App	Self-Efficacy	Randomized controlled trial	3 months	N = 8; Mean Age:29.5 Female: 53.3 %. Mean BMI: 40.6 kg/m2	Low participation rates or high dropout rates may introduce selection bias and affect the representativeness of the study sample.
[70]	Journal	China	mHealth management application	Mobile App	Cognitive behavioral therapy	Randomized controlled trial	6 months	N = 27; Mean Age: 57; Female: 48.33 % BMI: not reported	The applicability and effectiveness of CBT may vary across different cultural groups or individuals with diverse backgrounds.
[51]	Journal	Australia	Mobile usability	Mobile App	Comb	Observational study	12 months	n = 815; Mean age = 13.89; Male: 34 % BMI:25.6 kg/ m2	Mobile apps involve the collection and storage of personal health information, raising concerns about data privacy and security.
[73]	Journal	IRAN	Mobile self-care	Mobile App and Web	Transtheoretical Model of Behavior Change, Theory of Planned Behavior.	Mixed Method Design	4 months	n = 32 Mean Age:45 Female: 43.4 % Mean MBI: 46.6 kg/ m2	Mobile apps often focus on short-term behavior change and may not adequately address the challenges of long-term maintenance
[82]	Conference	Malaysia	i-Prevent Diabetes	Mobile App and Website	NR	Quantitative and qualitative methods	6 months	n = 50 Mean Age: 60 Male: 55 %, Mean BMI: 42.4 Kg/ m2	Absence of human interaction may limit the social support component of behavior change and the ability to address complex emotional or psychosocial factors
[75]	Journal	Norway	Diabetes care for young	MOBILE and Web	NR	Mixed Method Design	3 months	n = 12, Mean Age: 20, Female: 39 %, Mean BMI: 23.3	Mobile apps may need to incorporate strategies for sustained engagement, follow-up, and tracking

(continued on next page)

Table 1 (*continued*)

Reference	Source of Publication	Country	Intervention	Platform	Theoretical Basis	Study Design	Study Duration	Participants; Gender; Mean age; BMI,	Limitations
									to promote long-term behavior change
[78]	Journal	Denmark	socio-material diabetes app	Mobile	socio-material	Non-randomized controlled observational study	1 month	n = 25, Mean Age: 36, Male: 41 %, Mean BMI	Ensuring robust data protection measures, obtaining informed consent, and complying with relevant privacy regulations are essential to maintain user trust and safeguard sensitive information
[50]	Journal	Australia	My Care Hub Mobile type 1&2	Mobile	Information-Motivation-Behavioral Skills Model; social cognitive theory -	Mixed Method Design	7 days	N = 12; Mean Age:43; Male:38 %; Mean BMI: 40.6 kg/m2	The generalizability of the model to other health behaviors or diverse populations is not well-established.
[71]	Journal	Saudi	Diabetes management Type 2	Mobile	NR	Randomized controlled trial	6 months	n = 20; Mean Age:48; Female:55 %; Mean BMI: Not reported	RCTs often require significant resources, time, and logistical support.
[83]	Journal	Sweden	Web-based support system Type 2	Website	NR	Mixed Method Design	3 months	N = 13; Mean Age: 67; Mean BMI: 29.05 kg/m2	Recruitment and retention of participants in RCTs can be challenging.
[81]	Journal	Italy	MyT1DHero Type 1	Mobile App	social cognitive theory (SCT) and self-determination theory (SDT)	Mixed Method Design	1 month	N = 20; Mean Age:55; Female: 40 %; Mean BMI:	Mobile apps may need to incorporate strategies for sustained engagement, follow-up, and tracking to promote long-term behavior change
[74]	Journal	Malaysia	Behavioral framework	Mobile App	Transtheoretical Model of Behavior Change, , Health Belief Model, Self-Determination; Theory of Planned Behavior Theory, Self-Regulation Theory	Mixed Method Design	6 weeks	N = 40; Mean Age: 32 years; Male:37.9 %; Average BMI: Not reported	Low participation rates or high dropout rates may introduce selection bias and affect the representativeness of the study sample.
[77]	Journal	Norway	FTA App	Mobile App	TTM for health counseling) Theory	Randomized control trial	12 weeks	N = 17; Mean Age = 58.6 years; Male: 55; Mean BMI: Not reported	It can be challenging to conduct large-scale RCTs due to budget

[52,54,70,72,81,84]. Finally, ten interventions were long-term ineffective [53,62-66,74,75,78,79].

RQ2: What is the effectiveness of advanced techniques, including behavioral change techniques, behavioral health theories, and AI-based methods, in managing diabetes self-care?

Table 3 shows a summary of the BCTs used in the reviewed studies. It shows that 30 different BCTs were coded for all the interventions included in the reviewed articles, with an average of 11.6 BCTs per intervention (ranging from 2 to 8). Ten behavior change techniques were recognized in at least 55 % of long- and short-term interventions. More specifically, goal setting (behavior) was identified in 58.33 % of the total interventions and recognized in 75 % of both short-term and long-term, respectively. Problem-solving and goal setting (outcome) were identified in 61.11 % of all interventions and recognized in 75 %, 85 %, and 100 %, 68.75 % of the Short Term and Long Term. Feedback on behaviors and self-monitoring on behavior were identified in 61.11 % and 80.56 % of the total intervention and recognized in 85 %, 100 %, and 68.75, 81.25 % of short-term and long-term, respectively. At the same time, self-monitoring of outcomes of behavior and social support (unspecified) were identified in 77.7 % and 61.11, while in the short-term and long-term, 100 %, 95 %, and 75 %, 62 % were identified, respectively. Finally, information about health consequences, credible sources, and adding objects to the environment was identified in 50 %, 55.56 %, and 58.33 % of the total intervention, respectively, and 65 %, 80 %, 90 %, and 68.75, 43.75, 56.25 were identified in the short and long term, respectively. Short-term interventions applied an average of 19 BCTs per intervention (ranging from 0 to 20), compared to 7.8 (ranging from 1 to 16) among the long-term interventions. Two behavior change techniques were recognized at a noticeably higher frequency in short-term interventions, which include self-monitoring of behaviors and self-monitoring of the outcome of behaviors (recognized in 100 % of the short-term interventions). Meanwhile, three BCTs with high frequencies in long-term interventions include problem-solving, action planning, and information about antecedents, with 100 %, 93.75 %, and 87.5 %, respectively.

RQ3: What are the common features used in diabetes self-care management applications?

Table 4 summarizes the features used in the interventions of the reviewed studies. Ten application features related to passive and interactive features were recognized through the thematic analysis of

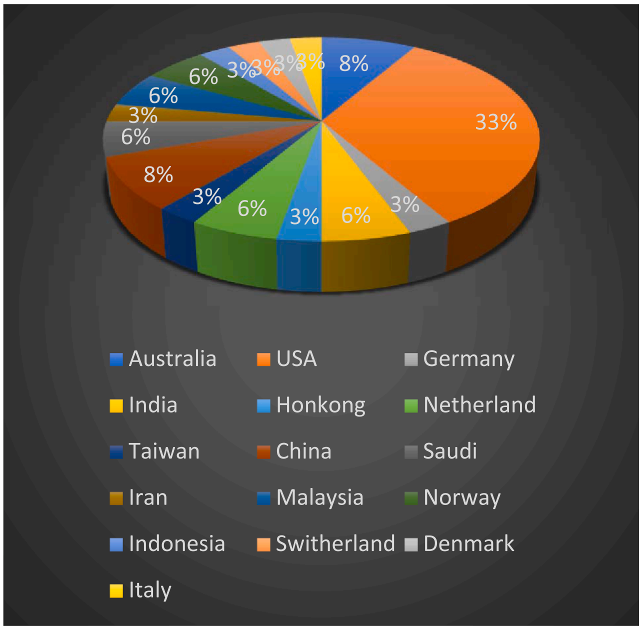

Fig. 4. Countries and the percentage of papers published.

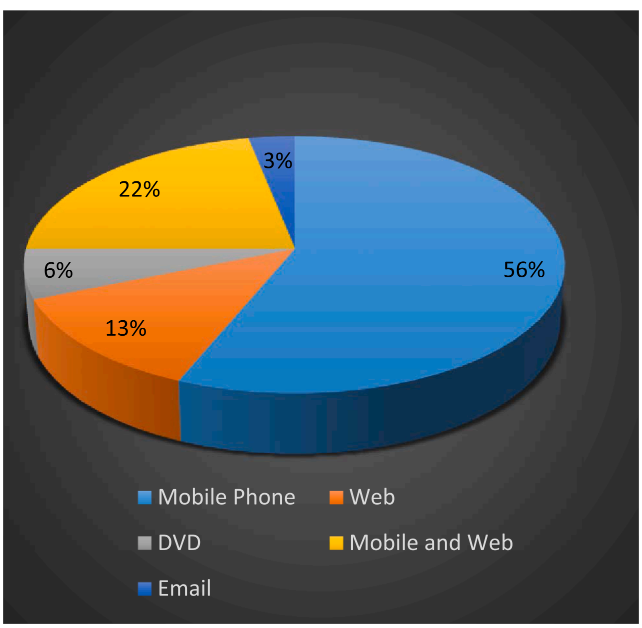

Fig. 5. Different platforms used for the interventions included mobile phones.

intervention detail. The passive features include health and lifestyle information; activity tracking; weight and bio-measure tracking; diet tracking, and reminders and prompts. The interactive features include interactive health and online health coaching; lifestyle lessons; gamification; social media and support, and automated feedback. Interventions utilized an average of 4.27 features (ranging from 2 to 21), which include 2.44 passive features (ranging from 16 to 21) and 1.8 interactive features (ranging from 2 to 19). Two application features (passive) were recognized in at least 50 % of the interventions: activity tracking and health and lifestyle information identified in 100 %, 65.0 %, and 43.75 %, 81.25 % of short-term and long-term, respectively. On the other hand, three interactive features, which include interactive health and lifestyle lessons, online health coaching, and social media and support, were identified in at least 55 %. From Table 4, the most frequently used passive and interactive features in the reviewed literature are health and lifestyle information and interactive health and lifestyle, which were recognized in 21 % and 20 %, respectively.

RQ4: How to utilize AI and ML techniques to change and sustain patient behaviors with the individualized care of conventional DSME programs while taking full benefit of mHealth to a large scale?

Most existing apps concentrate on only a few requirements of a diabetic patient (e.g., glucose monitoring or nutrition guidance), and few findings, as evident from Table 3, concentrate on the psychological or behavioral barriers to effective diabetes self-management. The developments in artificial intelligence (AI) and specifically in Natural Language Processing (NLP) and ML have created apps to computerize tasks involving intelligent behavior, learning from prior interaction with the patients, and possible behavior adaptation, thereby delivering real-time answers to real-life problems, namely self-management of diabetes [18,21,32,86,87]. AI-based technologies, namely physical activity monitoring and tracking, meal recommendation systems, notification systems for taking drugs, and interactive evidence-based chatbots for answering personalized questions that they may have about their condition, thereby addressing the diabetic patient's need at a larger scale. Researchers have recently emphasized that a balanced diet is pivotal in a successful diabetes self-management program [National Diabetes Services Diabetes-Related Complication. [(accessed on 18 December 2022)]. Available online: https://www.ndss.com.au/]. Therefore, it is important to have a robust recommendation system for an improved self-management of diabetes. A survey by authors in [88], which studied the nutrition recommendation systems particularly and utilized the PRISMA outline, identified 25 articles that apply several varieties of NR techniques. The survey found that knowledge-based and hybrid are the most popular recommendation systems. In contrast, the collaborative recommendation system was among the least popular nutrition recommendation systems. Further, the study showed that the rule- or ontology-based algorithms-based recommendation system is more widely used for developing a nutrition recommender system than deep learning or K-Means clustering algorithm. Additionally, the study found that mobile app-based nutrition recommendation systems are most popular at 28 % compared to web-based applications, with a percentage of 20 %. While many stand-alone food recommendation systems currently promote a healthy lifestyle, these techniques still need to include BCTs in the diabetes self-management regime of diabetic patients [89,90]. The mHealth diabetes intervention techniques that employ BCTs can reduce the number of clinician visits and improve long-term medication adherence [91]. Table 5 summarizes the AI and ML-based techniques utilized to monitor change and sustain patient behaviors with the individualized care of conventional DSME programs while taking advantage of the mHealth app to a greater extent.

In [92], the authors implemented a nudge-inspired AI-driven health platform for the self-management of diabetic patients. The app developed was based on the 4-cycle design science research methodology (A4C-DSRM) and was co-designed in collaboration with the patients and clinicians. The cross-platform mobile app involves (a) developing and implementing a micronutrient detection algorithm (MDA) that utilizes AI-driven image analytics for nutrition management and behavior intervention techniques by implementing nudge theory that enables the patients to undergo a sustained behavior change in diabetic patients. Further, a web-based application was built for the doctors to allow an enhanced patient-doctor communication pipeline for an improved self-management regime of diabetic patients. In [76], the authors describe the design and implementation of an app to enhance the self-management of diabetes by patients using an ML approach and demonstrate and evaluate the effectiveness of the proposed ML system in managing blood sugar in diabetic patients. The exclusive attainments of the developed ML-based mobile apps were (1) designing and developing an ML algorithm (K-Nearest Neighbor Algorithm (KNN)) based food recommendation system for self-diabetic management, (2) scheduling and prompting diabetic patients via the proposed mobile app to take their blood glucose readings and prescribed medicines for doctor's

Table 2
The Percentage of Weight Lost at Each Follow-Up for Interventions Included in the Basic Effectiveness Analysis.

Study/Intervention	Short Term				Long Term			
	3 *months*	4 *months*	5 *months*	6 *months*	12 *months*	15 *months*	18 *months*	24 *months*
[48]	−3.74 %	–	–	−4.85 %	–	–	–	–
[83]	−5.3 %	–	−4.5 %					
[51]	–	–	–	−3.60 %	–	–	–	–
[50]	−5.2 %	–	–	−4.7 %	–			
[52]	–	−6.5 %	–	−8.0 %	−7.5 %	–		–
[71]	−3.85 %	–	−4.3 %					
[55]	−2.50 %	–	–	–	–	–	–	–
[72]		–	−2.37 %			5.02 %		
[56]	−1.9 %	–	–	–	–	–	–	–
[57]		–	–	−1.93 %	−1.35 %	–	−6.7 %	–
[58]	−5.8 %	–	−6.8 %	–	–	–	–	–
[59]	−5.6 %	–	–	–	–	–	–	–
[51]			−3.91 %	−2.38 %				
[64]	−0.73 %	–	–	−1.48 %	−2.35 %	–	–	–
[54]	−4.9 %	–	–	−4.7 %	–	−5.0 %	–	–
[60]	–	−5.65 %	–	−6.58 %	–	–	–	–
[2]	−2.63 %				5.2 %			
[61]	−5.67 %		–	−3.49 %	–	–	−4.6 %	–
[84]	−6.26 %		–	−3.11 %	–	–	−5.25 %	–
[77]	−4.96 %	–	–	−3.7 %	–			
[62]	–	−5.0 %	–	–	−4.7 %	–	–	−4.2 %
[67]	−2.02 %	–	–	−2.80 %	−2.24 %	–	–	–
[69]		−5.2 %			−45.9 %			
[75]	−4.76 %	–	–	−6.03 %	−4.8 %	–	–	–
[70]						−5.3 %		
[53]	–	−4.6 %	–	–	−0.93 %	–	–	–
[73]	−4.81 %	–	–	−6.23 %	–			
[66]	–	–	–	−0.69 %	−1.57 %	–	–	−1.47 %
[68]		–	–	−2.85 %	−3.25 %			
[63]		−4.2 %			−2.9 %			
[40]	−5.71 %	–	–	−4.03 %	–	–	–	–
[78]						−4.0 %		
[74]	−2.8 %	–	−6.8 %	–	–	–	–	–
[81]	−6.67 %	–	–	–	–	–	−6.4	–
[74]			−2.95 %	−3.37 %				
[65]	–	–	–	−0.54 %	−1.82 %	–	–	−2.34 %

intervention for diabetes management, (3) encouraging and tracking activities of users for facilitating real-time monitoring and thereby providing personalized interventions to self-diabetes care, and (4) providing an interactive visual interface to provide help to understand the meaning of their readings in a clinical perspective and creating a good link between the diabetic patient and clinician using cognitive science-based chatbots and e-mail. In [93], the authors proposed a voice-based AI-powered virtual personal assistant to assist Native American diabetic patients in understanding food and nutrition-related information and handling their everyday diet. Furthermore, the communication and recommendation offered by the voice-based assistant were customized for each user's cultural, social, and physical profile. The suggested virtual voice assistance was implemented on the Amazon Alexa platform. Unsupervised learning using Natural Language Processing and Automatic Speech Recognition was used for text and voice management. The Knowledge database management of the voice-based AI-powered virtual personal assistance tool was executed using semantic reasoning. Therefore, it would be easy to be accepted by the target audience. The experimental evaluation of the proposed voice-based personal assistant tool obtained an accuracy of recommendation of 100 %, and the conversation success rate varied from 76 % to 87 %. In [94], focus on a non-invasive type-I diabetes diagnosis method for children based upon the evaluation of physical activity. The main predictors for diabetes monitoring were weekly minutes of brisk activity and weekly step counts. The association of the weekly steps number and the incidence of type-I diabetes was implemented based on a comprehensive review of the data employing clustering and classification algorithms. The authors indicate that type-I diabetes can be identified by assessing the patient's physical movement. Therefore, the application provides a non-invasive and versatile detection process that can be tested anywhere. The AI-based system can be implemented on a mobile device. The Random Forest algorithm-based approach provided the most acceptable findings and achieved the highest accuracy in detecting type-1 diabetes using physical movement. In [95], the authors proposed an autonomous device named the Intelligent Diabetes Assistant (IDA) that diagnoses and prioritizes care of diabetic patients based on the results noticed on the system. The IDA involves knowledge-based applications to assess the level of seriousness of a patient, aid in making medical decisions, and provide a near real-time diagnosis and monitoring of foot ulcers. The system's usefulness in learning, efficiency, and satisfaction was estimated using System Usability Scale (SUS). In [96], the authors proposed a customized food recommendation system (Ramus) to recommend food and nutrition for patients with diabetes. The electronic medical report and stored patient's taste preferences were used to train and develop Ramus. In [97], the authors proposed a PAL to provide day-to-day supervision procedures for diabetic children aged 7 to 14. The PAL provided care for the three basic needs of the Self-Determination Theory: competence, relatedness, and autonomy. In [98], the authors developed a robot assistant to perform duties such as diet Monitoring and management of users with diabetes based on the Internet of Things. In [99], the authors proposed a personal robot and app named Charlie for children with diabetes, providing social, cognitive, and affective assistance for the self-management of diabetes. In [100], the authors proposed a robot named Robin to assist with seeming emotional comfort, self-effectiveness, and insulin management, in children aged between 7 and 12 years suffering from Type 1 diabetes. In [101,102], the authors presented a novel eHealth structure that includes humanoid robots to encourage a developing multidimensional process

Table 3
A summary of the BCTs used in the reviewed studies.

CLUSTER	BCT	All STUDIES		SHORT TERM		LONG TERM	
		N = 36	%	N = 20	%	N-16	%
1. Goals and planning							
1.1	Goal setting (behavior)	21	58.33	15	75.00	12	75.00
1.2	Problem-solving	22	61.11	15	75.00	16	100.00
1.3	Goal setting (outcome)	22	61.11	17	85.00	11	68.75
1.4	Action planning	17	47.22	14	70.00	15	93.75
1.5	Review behavior goals	16	44.44	13	65.00	10	62.50
1.7	Review outcome goals	3	8.33	12	60.00	0	0.00
2. Feedback and monitoring							
2.2	Feedback on behavior	22	61.11	17	85.00	11	68.75
2.3	Self-monitoring of behavior	29	80.56	20	100.00	13	81.25
2.4	Self-monitoring of outcome(s) of behavior	28	77.78	20	100.00	12	75.00
2.7	Feedback on the outcome(s) of behavior	14	38.89	11	55.00	0	0.00
3. Social support							
3.1	Social support (unspecified)	22	61.11	19	95.00	10	62.50
3.2	Social support (practical)	2	5.56	11	55.00	9	56.25
3.3	Social support (emotional)	5	13.89	0	0.00	8	50.00
4. Shaping knowledge							
4.1	Instruction on how to perform the behavior	17	47.22	12	60.00	10	62.50
4.2	Information about antecedents	6	16.67	12	60.00	14	87.50
5. Natural consequences							
5.1	Information about health consequences	18	50.00	13	65.00	11	68.75
6. Comparison of behavior							
6.1	Demonstration of the behavior	7	19.44	12	60.00	10	62.50
6.2	Social comparison	9	25.00	14	70.00	9	56.25
7. Associations							
7.1	Prompts/cues	6	16.67	12	60.00	10	62.50
8. Repetition and substitution							
8.2	Behavior substitution	11	30.56	12	60.00	10	62.50
8.3	Habit formation	15	41.67	13	65.00	0	0.00
8.4	Habit reversal	14	38.89	12	60.00	9	56.25
8.7	Graded tasks	5	13.89	12	60.00	1	6.25
9. Comparison of outcomes							
9.1	Credible source	20	55.56	16	80.00	7	43.75
10. Reward and threat							
10.1	Material incentive (behavior)	3	8.33	12	60.00	3	18.75
10.2	Material reward (behavior)	2	5.56	12	60.00	9	56.25
11. Regulation							
11.2	Reduce negative emotions	14	38.89	12	60.00	10	62.50
11.3	Avoidance/reducing exposure to cues for the behavior	14	38.89	2	10.00	10	62.50
11.4	Adding objects to the environment	21	58.33	18	90.00	9	56.25
14. Scheduled consequences							
14.4	Reward approximation	14	38.89	0	0.00	9	56.25
The Average number of BCTs per intervention		11.6		19.0		16.8	

for the self-management of diabetes patients. The network layout utilizes the Inter of Things to a cloud-centric frame by controlling existing domain procedures to connect and handle physical layer entities. The AI-based framework includes capillary networks, comprising a medical sensor series linked to a humanoid robot via the Internet to a web-based diabetes management center. A usable prototype of the humanoid robotic system was built. The end-to-end design and suitability were validated in a clinical pilot assessment showing encouraging results depicting that patients and care providers are receptive to the novel prototype. The results showed that the Application of robots as a device to help diabetes self-management in children was well received by users, with an overall patient acceptability of 86.7 %. In [103], the authors present a method that integrates ML algorithms and symbolic reasoning to identify high-level lifestyle behaviors using sensor data taken mainly from the diabetic patient's smartphone. The authors compared five machine-learning methods on supervised and unsupervised data to study the trade-off between recognition and labeling effort accuracy. In an evaluation of real-life test data, the highest accuracy of 83.4 % and an F-score of 0.82 was attained by the Multi-Classifier Adaptive Training (MCAT) technique, capable of progressively adapting to every single customer. In [104], the authors employed a game-theoretic method to customize the food preferences of diabetic users. The AI-based food recommendation system provides various sets of choices as input. The virtual counselor prompts about the mistakes in the food habits of the diabetic users and recommends them the food items the user should have to self-management diabetes. The AI-based system even suggests various exercises the user should perform during the year. In [105], the authors describe "snap-n-eat," a mobile (android) and desktop-based food recognition system. The snap-n-eat system can identify food items and automatically assess the nutrition and calorific content without user involvement. Hierarchical segmentation is a deep learning technique to fragment a food item's image into regions. The features from different regions were extracted and scaled using a linear support vector machine classifier. These regions were classified into different foods with an accuracy of 85 %. Further, the system estimates the portion size to assess the nutrition and calorific content of the food items present on the plate. However, the system was not designed and tested exclusively for diabetes patients. Yet the proposed system is generally appropriate for individuals' in-tent to obtain information related to their regular diet.

RQ5: What are the challenges and future directions of the diabetes Self-Care Application?

The present section summarizes the gaps detected in current diabetic self-management apps and future directions to bridge the gaps identified. We reviewed major leading IOS and Android diabetes self-management platforms using keywords, namely diabetes and self-management, screened based on their total download count and ratings as tabulated in Supplementary Table S1. A total of eleven

Table 4
A summary of applications' features.

FEATURES	ALL INTERVENTIONS		SHORT TERM		LONG TERM	
	N = 36	%	N = 20	%	N = 16	%
Passivefeatures						
Health and lifestyle information	21	58.33	13	65.0	13	81.25
Activity tracking	19	52.78	20	100.0	7	43.75
Reminders and prompts	17	47.22	14	70.0	9	56.25
Diet tracking	15	41.67	16	80.0	2	12.50
Weight and measure tracking	16	44.44	15	75.0	1	6.25
Average passive features per intervention	2.444	6.790	3.810	10.833	2	5.56
InteractiveFeatures						
Interactive health and lifestyle lessons	20	55.56	12	60.0	6	37.50
Social media and support	19	52.78	14	70.0	9	56.25
Online health coaching	18	50.00	16.	80.0	1	6.25
Automated feedback	13	36.11	8	40.0	0	0.00
Gamification	2	5.56	3	15.0	3	18.75
Average interactive features per intervention	1.8	5.09	2.52	12.6	1	3.30
Average total features per intervention	4.278	11.883	3.694	18.194	3	8.85

applications were identified and screened to list the behavior feature set provided and find out if the application uses any ML and AI-based features for the self-management of diabetes.

While type II diabetes is associated with nutrition mismanagement and a sedentary lifestyle, most diabetes self-management applications offer features for the abovementioned areas. Nevertheless, there are obvious gaps in features such as ML or AI-based nutrition recommender and planner, clinical support, fitness logger, BP visualizer, calories burned estimator, and behavioral intervention (BI) techniques. Furthermore, most apps lack research background and theories, such as the nudge theory, to support their credibility. Thus, many such diabetes self-management applications might not fit the intended purpose of diabetic patients to self-manage their diabetic condition. None of the applications have an ML or AI-based food tracker, personalized nutrition recommender system, and AI-driven image analytics-based meal logging (micronutrient detection) platform for diabetes self-management. An improved nutrition management system allows enhanced glycemic control for patients, thereby ensuring diabetic patients avoid a hypo or hyperglycemic state. Theory and ML or AI-based Behavioral Intervention features were poorly defined and covered by these applications. Because many studies have advocated the benefits of incorporating behavioral interventions as a part of the mHealth application for diabetes self-management, yet most of the applications available in the app store [8] fail to implement BCTs originating from tried-and-proven methods, namely nudge theory [38]. Lack of comprehensive Feedback engine features such as promoting formalized behavioral contracting, promoting regular self-monitoring by monitoring frequency of use, and promoting goal setting. The feedback is provided to patients based on the knowledge the system learns from present data and the guidelines programmed. Moreover, most apps do not provide AI-based systems targeted to support patients in making appropriate decisions by delivering advice concerning exercise, meals, or medication, such as an insulin bolus calculator.

In the future, we can propose an all-inclusive diabetes self-management application that will contain fundamental and advanced features such as nutrition, blood glucose levels, clinical services, physical activity, medication, and personalized features (e.g., insulin bolus calculator, fitness recommendation, calories burned predictor, nutrition recommendation). In addition, the proposed diabetes self-management application will employ a comprehensive feedback approach that ensures communication with stakeholders. It will also implement theories and AI-based behavioral intervention features to ensure the patients bond to their self-management schemes for a long time. A complete flow diagram of the proposed all-inclusive AI and BCTs feature-based diabetes self-management application is illustrated in Fig. 6.

The system architecture for the diabetes self-management system shown above in Fig. 6 is the theoretical model that states the framework, behavioral interactions, and multiple module views that emphasize the proposed system's design and architecture. The presented architecture graphically provides a formal illustration of the processes within the diabetes self-management platform and the dataflows between the system components. The proposed diabetes self-management system architecture depicts the following components (1) Diabetes patient fitness manager, (2) Diabetic patients medication management, (3) Diabetic patient's nutrition management, (4) Patient's clinical data management, (5) Diabetic patient's behavior intervention recommender, (6) Feedback modules for patients and doctors via a personalized Intelligence system (PIS), (7) Diabetes detection module based on user information, fitness, and clinical information's, and (8) data validator module operated by the doctor to validate the user nutrition, medication, and blood glucose information's as well as feedback generated by the PIS. Fig. 7 shows the corresponding activity flow diagram for the diabetes pre-diction module. The diabetes detection module predicts the diabetic status of the user. The diabetes detection system uses the knowledge-based approach, where the machine learning algorithm predicts diabetes in an end user using the user's profile and a knowledge base that involves fitness and clinical information. The steps followed for the diabetes prediction system are defined in the flowchart provided below in Fig. 7.

4. Discussion

In this SLR, several studies comprised 36 reviewed and assessed interventions. The SLR aims to summarize and analyze the existing works on diabetes self-care applications and examine the efficacy of the interventions in diabetes management. The SLR also attempts to identify the most effective BCTs, and application features commonly applied in the existing studies. Based on the selected studies, this research discovered that in the short term, most diabetes self-care technologies successfully attained significant weight loss, as observed by a mean weight reduction of at least 3 % of baseline weight. However, most interventions cannot achieve a 5 % loss of weight benchmark for clinical significance in the long term. Comparable results on the effectiveness of diabetes self-care applications and inter-study heterogeneousness were presented in past studies [10-12,38,39].

Generally, applications which utilized a higher number of BCTs were more efficient. This corroborates the previous studies [106-108]. Seven BCTs were commonly identified in the interventions. These include goal setting (outcome), goal setting (behavior), self-monitoring, feedback on behavior, self-monitoring of the outcome of behavior, problem-solving, and social support (unspecified). These BCTs match the suggested behavior change components defined in the IMAGE toolkit for diabetes prevention [109].

Problem-solving is the most effective behavior change technique in encouraging participants to generate potential strategies for health behavior change and then select and apply the most proper strategy. Generally, evidence suggests that the applications comprising many BCTs were more likely to be more effective. Furthermore, some unique sets of BCTs were commonly identified in long-term and short-term interventions. Like BCTs, interventions that applied more features were more efficient. Similar results were reported in [22] and [27]. They showed that self-care applications were more efficient in diabetes management when interactive features were used. Three features (including diet tracking, health and lifestyle information and advice,

Table 5
Ummary of the review of the ai and ml-based intelligent diabetes assistant implemented in recent years.

Reference	country	Intelligent assistant	Technique used	Target Users	Format	Performance of the AI models	Limits of the AI model
[92]		Nudge-Inspired AI-Driven Health Platform	Macronutrient Detection Algorithm (MDA) and MobileNet v1 as the backbone CNN	Adults with diabetes.	Mobile and Web Application	Food_v1 attained a 70 % accuracy for European food items and only 45 % accuracy for Indian food items.	No pilot study using patients; It is not a generic model as the classification accuracy for European meals is satisfactory but very bad for Indian meals.
[76]		Diabetes Intelligent Meal Recommender Module. The Educational Module with Food Recognition Capabilities. The Activity and Reminder Module	KNN Tensor Flow Model Cordova Plugin	Adults with diabetes.	Mobile and Web Application	Food recognition and classification model accuracy achieved over 95 %	No hardware modules for insulin pumps and control.Other machine learning algorithms, namely Random Forests, Support Vector Machines, Fuzzy C-Means, and K-Means were not explored.No hardware module can ascertain the number of calories burned after each activity.
[93]		A Personalized Virtual NutriAmazon's intelligent assistant Alexa.	Unsupervised learning utilizing Natural Language Understanding and Automatic Speech Recognition was employed for text and voice treatments. Knowledge database management was performed using semantic reasoning.	Diabetic adults of Native American ethnicity	Amazon's intelligent assistant Alexa.	The Intelligent system obtained the highest accuracy of 100 %, and the conversation success rate ranged from 76 % to 87 %.	The training data comprises only 150 conversations. Therefore, the system was not evaluated in real-life conditions. Furthermore, Alexa failed in several real-life settings as Alexa could not understand the user's intent or match up with the natural language phrases with intent. Therefore, the efficacy of Alexa on diabetes self-management was not assessed.
[94]		Accelerometers: Perceive the spurt in body movement. Pedometer: Documents the step numbers. ActiGraph: Keeps all physical activity forms, such as pushing or climbing.	Decision Tree Forest	Diabetic children's	Mobile Device	The decision Tree Forest model achieved the highest prediction accuracy of 86.09 %, precision of 84.87 %, and specificity of 84.35 %).	The training data is small as the study comprised 115 healthy children and 215 children with type 1 diabetes.
[95]		Intelligent Diabetes Assistant: Automated diagnosis and prediction of severity of foot ulcers and Diabetic Retinopathy.	CNN	Adults	Mobile device	This classification module achieves the highest accuracy at 98 %	Small Training and testing image data
[96]		Ramus System for Food and nutrition recommendation system	Unsupervised learning utilizing the NN technique on EHR data.	Adults	App	Not revealed	No information on data set size. The model is purely theoretical.
[97]		PAL	A hybrid AI approach: Symbolic reasoning approaches combined with ML methods. Children's knowledge level was tracked using a combination of Gaussian processing, collaborative filtering, and covariance matrices. Feature extraction for tracking a child's emotional state using a Gated Recurrent Unit model, Adaptive belief, goal, and emotion-based clarifications is managed using a Cognitive Agent Architecture Framework. Finally, a human-agent discussion was performed by implementing a dialogue-managing framework.	Help with the daily diabetes care of children ages 7 to 14.	PAL	The PAL proved to support the three basic needs of the Self-Determination Theory: autonomy, relatedness, and competence.	Lack of improved personalized predictions on the patient's health condition (such as hypo or hyperglycemic). Need further technical enhancement, such as integrating children's diabetic measurement and administration devices in the PAL system.
Mall et al., 2017–2018 [98]		Robot assistant: Diet Monitoring and Management of Diabetic Patients.	Blood pressure examination, medical sensors for examining blood glucose levels. Pulse rate checking, weight estimation. Network sensors such as Bluetooth and Wi-Fi modules. Dietary sensors such as EMG Sensors. HTTP/HPPTS procedures support the security section.	Adult with diabetes	Robot	Not revealed	No information on data set size. The model is purely theoretical.

(continued on next page)

Table 5 (*continued*)

Reference	country	Intelligent assistant	Technique used	Target Users	Format	Performance of the AI models	Limits of the AI model
[99]		Charlie: A robot friend for children with diabetes providing social, cognitive, and affective assistance for self-management of diabetes.	Unsupervised learning using Natural Language Understanding and Automatic Speech Recognition was employed for text and voice processing.	Children aged 7–14 with type 1 diabetes.	Personal Robot and Apps	Nondisclosed.	Lack of information about the AI models and the dataset used to train the AI models.
[100]		Robin: a cognitively and motivationally independent affective robot toddler with "robot diabetes" to assist with seeming emotional comfort, self-effectiveness, and insulin management, in children with Type 1 diabetes.	Sensors: (1) sonars attached to the robot's chest to prevent crashing with things, and to sense hugs from users, (2) Head touch sensor to sense strikes, (4) Gyroscopes: to detect the robot has fallen, (3) Foot bumpers: to detect accidents, (5) Simulated sensors to sense the homeostatically-controlled vital internal attribute levels. Actuators: (1) to offer its internal state report (2) running actions related to behaviors and needs. Four types of Action selection: (1) Socialize: Search for the person to hug, (2) Hunger: Seek meals, (3) Play: Explore/ dance, and (4) Fatigue: Take up a seat and relax/communicate exhaustion.	Children aged 7–12 with type 1 diabetes.	Personal robot.	Nondisclosed.	No information was revealed regarding the AI models and the dataset used to train the AI models.
[101,102]		Robot assistant	Natural Language Understanding and Automatic Speech Recognition were utilized for text and voice treatments. Capillary network.	Management of Type-1 in children.	Robots	Not revealed.	No information was revealed regarding the AI models and the data to train the model. Therefore, the efficacy of the AI models on diabetes self-management was not assessed.
[103]		Activity Recognition	Multi-Classifier Adaptive Training (MCAT) technique for activity recognition. Symbolic reasoning is employed for data quality refinement.	Adults with diabetes.	Mobile App	The highest accuracy was 83.4 %, and an f-score of 0.82 for the MCAT model.	The MCAT technique performance for recognizing "eating" activity, with an F-score of 0.68, is unsatisfactory. The efficacy of diabetes self-management was not assessed.
[104]		Games and personalization of the remedial education	Game	Older people and children with type-2 diabetes.	Non-disclosed.	Not revealed.	No information was revealed regarding the AI models and the data to train the model. Therefore, the efficacy of the AI models on diabetes self-management was not assessed.
[44]		Food recognition and nutrition estimation system "Snap-n-eat."	Support vector machine model for the food classification.	Adults who need information about their diet in general.	Desktop and Mobile (Android) apps.	accuracy 85 %	No more than 15 predefined types of meal items were employed. Only 2000 images (100–400 for each food category) were used as the training data set. The efficacy of the tool for diabetic patients was not assessed—a limited number of scales were used for the evaluation of the app.

and activity tracking) were frequently identified as effective interventions – suggesting that these features may constitute a practical core set that future applications should integrate as a base standard. Self-care applications have been introduced to address the accessibility barriers of face-to-face interventions. As the findings generally suggest, interventions that apply more BCTs and features are more efficient; smartphones and websites may be the most suitable platforms due to their increasingly high functionality and implementation rates. Health behavioral theories are vital to promoting behavioral changes in physical activity and a healthy diet. These are equivalent to evidence-based intervention, which largely depends on how these theories are used in the intervention design [10,11,38]. Even though technology could have a positive influence on the self-care of diseases, such as diabetes, technology itself is not sufficient unless the information is tailored appropriately and the patients themselves are fully motivated [12]. It has been shown in similar studies that the efficacy of mobile and web-based interventions is linked with extensive usage of the BCTs, features, and theories [10,11].

Self-care intervention development is a novel technique. It is an important emerging direction in information science as more research must be done in this field. However, existing research confirmed that applications designed based on the BCTs and behavioral change theories provide better clinical outcomes [10,11]. Therefore, it can be argued that an ideal self-management intervention should incorporate BCTs and behavioral health theories in the design process to achieve sustainable performances that can help users meet their clinical goals. Mobile apps and wearable devices equipped with sensors can facilitate real-time monitoring of blood glucose levels, physical activity, medication adherence, and provide personalized feedback and reminders to support self-care behaviors. Advanced methods may also include decision support systems that utilize individual patient data, clinical guidelines, and predictive analytics to provide tailored recommendations for treatment plans, medication adjustments, and lifestyle modifications.

The present systematic review has also presented an understanding of the application of ML and AI technologies in diabetes self-management and behavioral changes, along with a discussion of the current challenges [18,86] and perspective for future studies. In the earlier section, several AI-based approaches available in the literature for diabetes tracking and monitoring were analyzed. One of the current review's objectives was to know the intent, performance, and limitations of the AI concept applied to these apps. In addition, we found a series of studies to evaluate the latest efforts of AI-enabled solutions for diabetes management.

Fourteen AI and ML-based eHealth systems were identified, varying from robots and digital therapeutics to virtual assistants and apps. Therefore, apart from screens and visual electronic mediums for diabetes self-management, amazon Alexa and digital assistant tools provide voice-based assistance to diabetic patients. The fourteen AI-based application provides distinct functions for diabetes self-management. Six AI-based applications and robot assistants were developed to assist diabetic patients in managing their nutrition. [76,92,93,96,98,105]. Out of these five AI-based systems, specific applications offer personal recommendations depending on lifestyle, individual taste, and genetic features. However, few of them provide automatic meal calorific and nutritive data, and few other AI-based tools teach diabetic users of proper dietary behaviors or habits through discussion and coaching. Three AI-based applications aid diabetic users in managing their physical and daily activity [76,94,98]. One application assists in the diagnosis and thereby concentrates on diabetic patients based on the results obtained using the IDA system [95]. In comparison, applications were developed for managing diabetes in children ages 7 to 14 [97,99-102,104] Thus, with their diverse medium and system architecture, these AI systems focus on individual patient groups, categorized based on patient age, ethnicity, type of diabetes, and living environment. Implementing such varied AI-based applications seems the choice of the day as type-1 and type-2 diabetes are two different disorders that impact a wide range of individuals from varied socio-economic backgrounds and occur at very different stages of human life.

These AI systems employ different ML algorithms for classification. For example, Joachim et al., 2022 [92], utilized a micronutrient detection algorithm (MDA) that used AI-driven image analytics for nutrition management and behavior intervention techniques by implementing nudge theory to enable users to undergo a sustained behavior change during their course of diabetes self-management. Sowah et al., 2020 [76], built a Tensor flow neural network model to classify food, employing the KNN algorithm for meal recommendation and using cognitive sciences to create a chatbot for enabling patients to interact with the system for appropriate diabetes self-management. Maharjan et al., 2019 [93], proposed a voice-based Artificial Intelligence-powered virtual assistant to help Native American diabetic patients accomplish their everyday diet and understand food and nutrition-related information. Czmil et al., in 2019 [94], proposed a non-invasive type-1 diabetes detection system for children and adolescents between the ages of six and 18 years, achieving the highest accuracy of 86.09 % and specificity of 84.35 % using the decision tree forests algorithm. Wijesinghe et al., 2019 [95] proposed the IDA that comprised of knowledge-based modules for classifying the severity level of diabetic retinopathy (DR) and foot ulcers (DFU), a clinical decision support system for a real-time foot ulcer recognition and foot boundary assessment. Vaskovsky and Chvanova, in 2019 [96], designed a neural network for personalizing food items for individuals with a genetic precedence for diabetes. Neerincx et al. 2019 [97] in their paper presented a Socio-cognitive engineering (SCE) method to guide the current research and development for extended robot-human interaction and prolonged blended care of children with diabetes. The study represents a novel human-agent/robot system with a progressing collective intelligence. The current research and development methodology and the human-robot partnership framework can be employed as the basis for the advanced development of extended human-robot partnerships "in real life environment." Mall et al., in 2017 [98], developed a Robot Assistant to enhance the eHealth care platform connected via IoT for providing individualized diet monitoring and multi-care management of diabetic patients. The simplified architecture of the software application built using the multi-layer approach based on the principle of object virtualization and automatic service delivery enables an individual with a minimum knowledge of the platform to develop various applications from it. Blanson Henkemans et al., in 2017 [99], developed a robot system for providing social, cognitive, and affective emotional support for the self-management of Children with type 1 diabetes mellitus (T1DM) in a pleasant and safe environment. The project aimed to assist children, their parents, and healthcare professionals cooperatively in managing children with Type-1 diabetes. The video 'Learning with Charlie' demonstrates the effective interaction of diabetic children and robot buddies in a camp setting who are trained in T1DM by robots via diabetes self-management educative activities. Cañamero and Lewis in 2016 [100] demonstrated the ability of Robin, a "New AI," to develop a friendly friend that meets the affective and therapeutic requirements of the end users (diabetic children) better than other methods normally employed in child–robot interaction and assistive robotics. Al-Taee et al., 2016a, Al-Taee et al., 2016b [101,102] employed robots as a novel method to help manage Type-1 diabetes in children, which diabetic children positively endorsed. Cvetković et al., in 2016 [103] compared five ML-based methods using supervised and unsupervised sensor data obtained primarily from the patient's smartphone to identify high-level daily life events. MCAT, a semi-supervised learning method capable of real-time learning using mainly unsupervised data, obtained the highest accuracy of 83.4 %. Demongeot et al., in 2015 [104], employed AI-based food and exercise recommendation systems for the self-management of diabetes. Zhang et al., in 2015 [105] developed the Snap-n-Eat app using hierarchical segmentation to fragment an image of food into different regions and later employ feature selection algorithms to select important features from these regions and, based on the

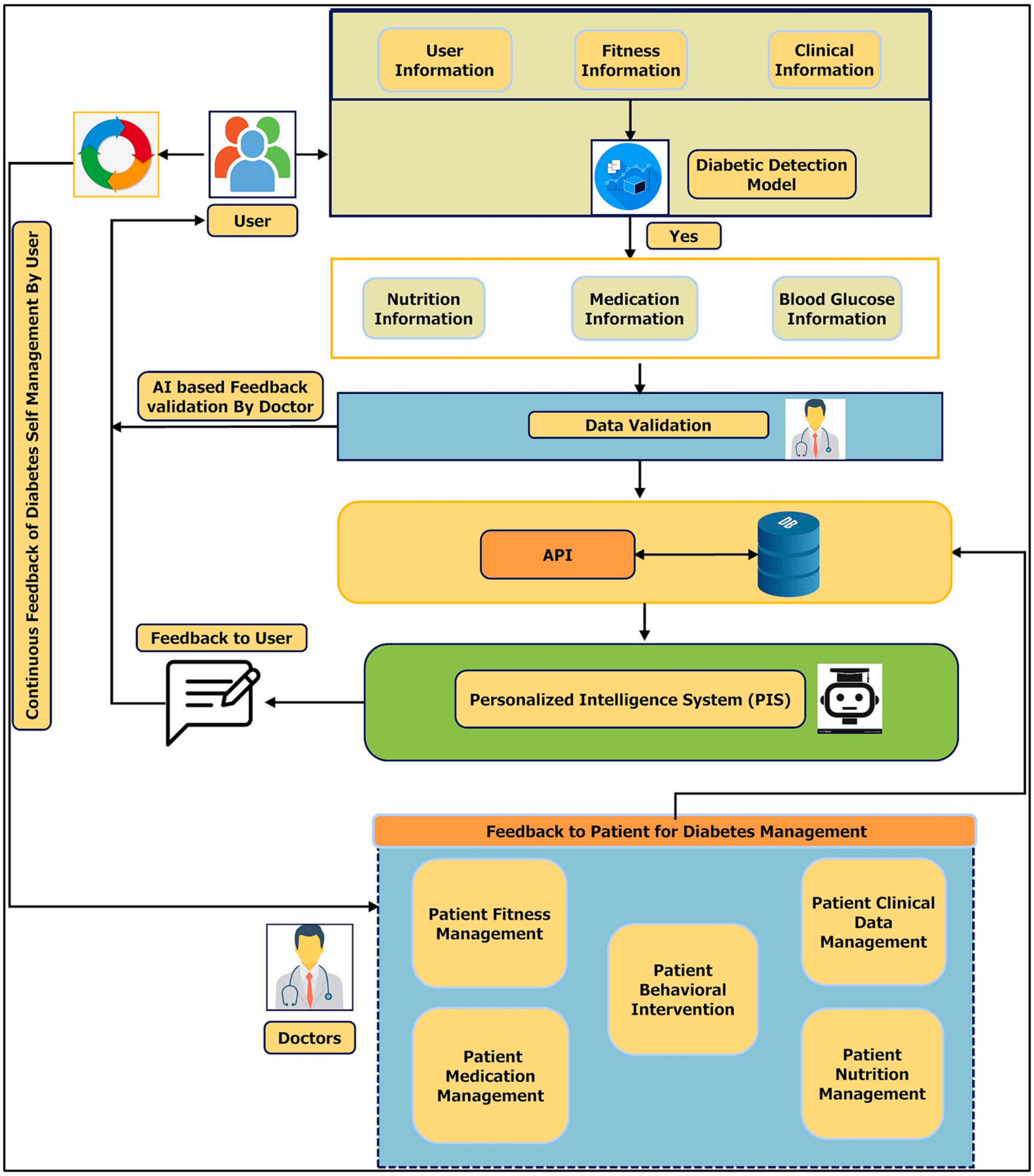

Fig. 6. Illustrates the system architecture of the proposed framework for an all-inclusive AI and BCTs feature-based diabetes self-management application.

extracted features using Linear Support Vector Machine (LbSVM) classifier, classify food into a category with an accuracy of 85 %. The AI-based application we reviewed shows the growing significance of AI-based methods for diabetes self-management. We believe these AI-based techniques will promote more research into implementing AI-based techniques to build applications based on the extracted knowledge from patient data.

In our review of the available diabetes self-management applications, we observed that most of the applications focus on managing the nutrition and the poor lifestyle of patients with diabetes. Nevertheless, we can observe gaps in the sections such as personalized nutrition recommender, fitness logger, and clinical feedback. Improved nutrition management and fitness logger modules allow for improved glycemic control, which is crucial for effective diabetes self-management. Additionally, most, if not all, identified diabetes self-management applications poorly cover theory or AI-based behavioral interventions that could fail to offer patients with better diabetes self-management strategies in the long run. Despite evidence from previous studies regarding the benefits of incorporating theory and AI-based BITs based protocol as a part of diabetes mHealth solutions, the mainstream applications developed and offered in the different app stores [8] hardly implement BITs that are based on standard theories such as nudge theory or AI-based BI methods [110,111]. Policymakers play a crucial role in supporting the implementation and scalability of advanced self-care management systems. In the discussion section, we address the policy implications of the findings, such as the need for regulatory frameworks that ensure patient data privacy and security, reimbursement policies to incentivize healthcare providers, and standards for interoperability and data sharing.

Therefore, we would recommend that the researchers develop diabetes self-management applications that contain features that involve both basic and advanced features such as nutrition recommendation,

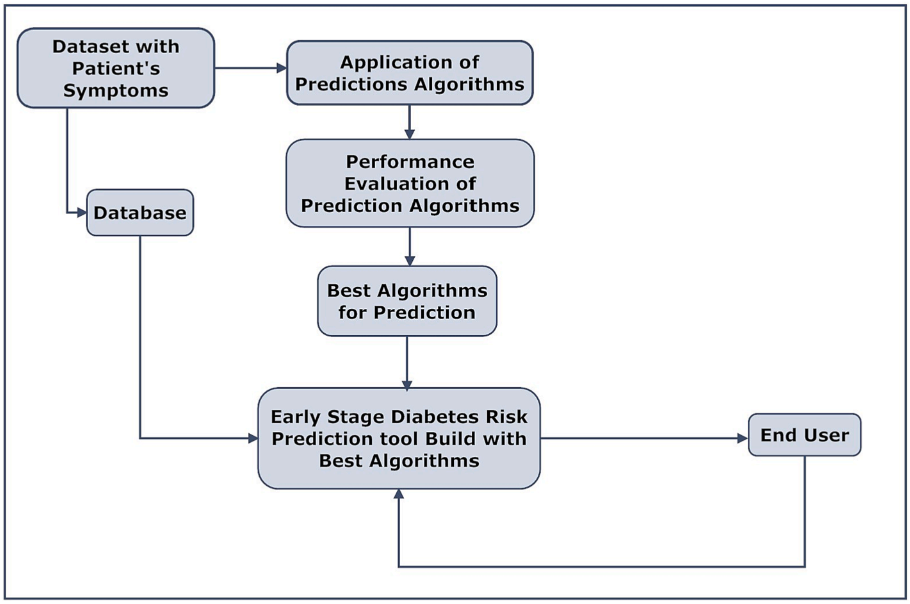

Fig. 7. Illustrates the flow chart for the diabetes prediction module in the proposed diabetes self-management application.

fitness recommendation, calories burned predictor, and insulin bolus calculator. Additionally, the application should involve communication between the stakeholders, implement theory and AI-based BI that enhances the efficacy of the application in managing diabetes, and enable diabetic patients to attach to their self-management plans for the long term. The adoption of advanced self-care management systems may face technological barriers, such as limited access to reliable internet connectivity, lack of familiarity with digital technologies among healthcare professionals, or technological infrastructure limitations in certain clinical settings. Overcoming these barriers requires investment in appropriate technology infrastructure, training, and ongoing technical support. Therefore, the effectiveness and utility of advanced self-care management systems for diabetes, it is important to acknowledge that the effectiveness and usability of these systems may vary across different patient populations. Factors such as age, cultural background, socioeconomic status, health literacy, and technological familiarity can influence the adoption and outcomes of self-care interventions. Future research should consider the specific needs, preferences, and characteristics of diverse patient populations when designing and implementing advanced self-care management systems.

5. Conclusion

This study presented a review to investigate the influence of the self-care application for diabetes management compared to standard care for achieving glycemic control, emphasizing the impact of BCTs and theories. Corroborated by past reviews, this research discovered evidence in reviewed studies that the use of self-care applications could achieve improvement in weight loss and A1c levels of the person with diabetes as compared to traditional care. Essentially, it is discovered that using BCTs is linked with A1c reduction. In addition, the SLR provided numerous theoretical and practical implications. Most notably, despite the importance of integrating BCTs and behavior theories in intervention design and given that the application of the theories could have been clearer in how it impacts application features, this study identified the importance of integrating BCTs and theories to intervention components for better performance.

One of the findings of this review showed that existing studies that applied BCTs and behavioral health theories in the development of interventions for diabetes self-management appeared to be more effective. The present SLR can help application developers design efficient self-care applications for diabetics. Having identified the potential of integrating BCT techniques and theories into developing self-management interventions, formulating a framework to design effective self-care interventions based on specific BCT and theories should be urgently addressed. There is also a need for an explicit elaboration on how BCTs and theory are applied as a basis for future application development.

Moreover, our SLR also identified the usefulness of AI for diabetes management. The article reviewed represents various forms of AI-based eHealth applications being developed to assist diabetic patients in implementing proper dietary and physical activity behaviors in the self-management of diabetes. Various AL or ML methods and symbolic and semantic reasoning were employed in the systems identified in the present SLR. These systems had different use cases and formats and were aimed at several diabetic groups. The AI-based robots offered a knowledge level enhancement of diabetes in type-1 diabetic children following their interaction with the robot assistant and PAL. The AI-driven eHealth applications support the self-management of diabetes in diabetic patients by offering automatic activity and food detection, customized activity and meal item recommendations established on the internal and external attributes of a user, educative simulation activities, and feedback on the behavior of diabetic patients. The additional benefits of an AI-based system are the computerization of tasks, namely activity monitoring, calorific content, and nutritive food calculations. AI also provides an opportunity to form novel mediums to connect with certain user groups, namely ethnic minorities or obese persons, older people, and children. Ultimately, customization of eHealth apps for individual users for the highest adoption and efficacy.

Even though this study provides valuable information that can help both researchers and designers of diabetes management applications, there are drawbacks to be considered when extrapolating and interpreting the findings of this SLR. One of the main challenges of this study is related to the fact that the results primarily rely on the terms used in the search strategy and the effectiveness of the search engines. An effort to overcome this drawback was made by using a combination of terms usually used in the literature review on self-care applications for diabetes management. This paper considered only studies published in purely English language with strict exclusion/inclusion criteria, so the number of studies that satisfy the eligibility criteria was not enough, limiting the ability to generalize the study's findings. Additionally, the data extraction method presented some uncertainty and error because some studies were implicit about their design considerations. As a result, some design descriptions that are either directly reported or referenced can easily be missing from the paper. However, an independent verification and assessment were conducted to mitigate this issue, and all the drawbacks that might affect the findings were addressed. The value of *meta*-analyses demonstrates pooling data from multiple studies to generate more precise estimates of treatment effects. Future research endeavors could consider conducting a *meta*-analysis if there is a sufficient number of studies with comparable methodologies and outcome measures. This would allow for a quantitative synthesis of the data and provide more robust conclusions regarding the effectiveness of advanced self-care management systems for diabetes.

Another limitation concerns identifying BCTs and application features, which depend on the intervention's description. This is a common limitation of many existing studies [10-12,38,39]. Although the imputation method addressed this to some extent, imputation was only applied to generalize BCTs from other articles with similar interventions. Furthermore, BCTs were only considered present if their availability was clearly described in detail in all independent interventions. Furthermore, as a *meta*-analysis was not possible (nor an aim of this review), overall intervention effectiveness was not provided. As there was wide heterogeneity in sample size between studies, an intervention's efficiency may have been influenced by the statistical impact of each study. However, to provide the effectiveness of each intervention, certification criteria and international benchmarks are used in assessing an intervention where only the primary outcomes are used. Moreover, studies with varying designs, such as quasi-observational, random, and non-random trial studies, were reviewed, which may have resulted in many biases. However, self-care applications are developed for real-world applications, and random trial situations are not likely to be compared with those in which the interventions are routinely completed. Finally, the present review on the AI-powered systems is not a comprehensive SLR, and it can be possible that other forms of AI-based systems exist and thus were not included in the SLR. Largely the currently available diabetes self-care systems do not include AI or lack research publications related to the development and efficacy of the AI-based modules present in most self-care systems for diabetes users. Therefore, it caused trouble in finding relevant research material during the review process. Most systems at a pilot research stage were recognized, and these systems have not, for the most part, shown their efficacy on diabetes patients. Despite these limitations, this study provides significant research potential to future developers and researchers of mobile applications for diabetes self-care management on the necessary factors to consider during application design. A critical evaluation of the quality and reliability of the included studies is crucial for ensuring the credibility and validity of the conclusions drawn in this review. While the review provided an overview of the findings from the included studies, it is important to acknowledge the limitations and potential biases that may affect the robustness of the evidence. Factors such as study design, sample size, data collection methods, and data analysis techniques can influence the internal validity and generalizability of the findings. However, a comprehensive quality assessment of the included studies was not explicitly conducted, which may limit the ability to fully ascertain the reliability of the evidence. Future research should consider incorporating a more rigorous quality assessment process, utilizing appropriate tools and criteria to evaluate the methodological rigor, risk of bias, and overall quality of the included studies. Recommendations and practical implications for healthcare providers and individuals managing diabetes in the context of advanced self-care management systems includes. Healthcare providers should stay informed about the latest advancements in self-care management systems, including technologies, behavioral change techniques, and AI-based interventions. Regularly updating their knowledge will enable them to provide evidence-based recommendations and guidance to patients. Collaboration with technology experts, including developers, designers, and researchers, can help healthcare providers understand the capabilities and limitations of advanced self-care management systems. This collaboration can also facilitate the identification of appropriate tools and interventions that align with patients' needs and preferences.

However, this study examines the links between individual BCTs, application features, and their efficacy, but the causal pathway was not determined. Therefore, future research must identify the most effective application features for other population instances, such as gender, geographic location, and ethnicity. As specific applications have basic requirements, preventing the post hoc testing of specific features [10,39], future interventions could consider specific features during the design stage. However, this procedure is subject to time commitments and many resources, and a measure is required to ensure that the process helps assess real-world efficiency. More studies are also required to identify the sustainability costs and implementation for the features by mode of delivery to enhance cost-effectiveness. Future studies should focus on evaluating the long-term efficacy of advanced self-care management systems. Assessing the sustainability of interventions and their impact on long-term glycemic control, lifestyle behaviors, and overall well-being is crucial for understanding the lasting benefits of these interventions. Research should explore the effectiveness of personalized and tailored approaches within advanced self-care management systems. Investigating how individual characteristics, such as health status, preferences, and social determinants, influence the optimal design and delivery of self-care interventions can enhance patient engagement and outcomes. Comparative effectiveness research can help identify the most effective advanced self-care management systems by comparing different interventions, technologies, and delivery modes. Comparative studies can guide healthcare providers and policymakers in making informed decisions about the implementation and allocation of resources.

While the number of AI-based research projects has risen in the last two decades, a small amount of research has been performed to integrate AI into diabetes self-management applications. And as we know, diabetes management needs a profound change in the lifestyle of diabetic patients and a determined mind to conquer essential barriers to bring about transformation in diabetic patients. The shortage of appropriate education and knowledge about diabetes and the challenge of defying old unhealthy behaviors to build healthier ones are among the top barriers to transforming the lifestyle of diabetes patients [112]. Therefore, in future research and SLR, the implementation and investigation of the efficacy of AI-based modules in the eHealth systems for diabetes self-management will have to be evaluated, whether these AI-based systems indeed can assist diabetic patients overwhelm the barriers as mentioned earlier and transform the lifestyle of diabetic individuals. This review highlights the potential of self-care applications and the importance of integrating BCTs and theories in intervention design. It also emphasizes the value of AI in supporting diabetes self-management. Future research should address the challenges related to implementation in real-world clinical settings, further explore the effectiveness of interventions, consider diverse populations, and examine long-term sustainability and cost-effectiveness.

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CRediT authorship contribution statement

Alhuseen Omar Alsayed: Conceptualization, Methodology, Software, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing. **Nor Azman Ismail:** Conceptualization, Validation, Resources, Writing – review & editing, Supervision. **Layla Hasan:** Validation, Investigation, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Asif Hassan Syed:** Methodology, Software, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Farhat Embarak:** Methodology. **Aminu Da'u:** Methodology, Software, Formal analysis, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aej.2023.08.026.

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