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DIABOT: REVOLUTIONIZING T2DM COMPLICATION PREVENTION WITH AI RECOMMENDATIONS &NOTIFICATIONS: A SCOPING REVIEW.

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Abstract

Background:
“Type 2 Diabetes Mellitus (T2DM)” is a “chronic condition impacting millions of individuals globally, significantly influencing to “morbidity and mortality” due to complications such as “cardiovascular disease”, nephropathy and neuropathy. Traditional management methods often fail to provide personalized and timely interventions leading to missed opportunities in preventing these complications. Artificial Intelligence (AI)-driven mobile health (mHealth) applications offer a novel approach by delivering personalized recommendations and notifications to enhance diabetes management and prevent complications.

Objective:
This “scoping review” aims to map the existing literature on AI-powered mHealth applications such as Diabot in preventing T2DM complications. The review explores the efficacy of “AI-driven interventions” in improving “glycemic control” and reducing the incidence of key complications.

Methods:
Following the “Arksey and O’Malley framework for scoping reviews”, a systematic search was conducted across databases including “PubMed, Scopus, Web of Science, IEEE Xplore and Google Scholar”. Studies published between 2010 and 2024, focused on AI-based T2DM complication prevention were included. Data were extracted on study design, AI system details, outcomes (HbA1c, complication rates) and barriers to implementation.

Results:
AI-driven interventions were effective in reducing HbA1c and improving glycemic control. Shaikh et al. (2024) and Bretschneider et al. (2023) reported significant reductions in HbA1c ($p < 0.001$) in their studies. However, long-term user engagement and integration with healthcare systems emerged as significant challenges. Data privacy and accessibility were also noted as barriers to widespread adoption.

Conclusion:
AI-powered mHealth applications hold promise in preventing T2DM complications through personalized care. Future research should address barriers such as user engagement, healthcare integration and data privacy to fully harness the “potential of AI in diabetes management”.

Keywords:
“Type 2 Diabetes Mellitus”, Artificial Intelligence, mHealth, Personalized Recommendations, Complication Prevention, Glycemic Control, Diabot.

INTRODUCTION

"Type 2 Diabetes Mellitus (T2DM)" is a enduring and detrimental disease affecting several peoples globally, with significant implications for public health. "According to the International Diabetes Federation", approximately "463 million people" were living with "diabetes in 2019", and this figure is projected to surge to "578 million by 2030" [1]. "T2DM" is a leading cause of morbidity and mortality, contributing to substantial healthcare expenditures and lost productivity. The disease is often accompanied by a range of complications such as "cardiovascular disease", nephropathy, retinopathy and neuropathy, all of which severely impair quality of life and reduce life expectancy.

The prevention and management of T2DM complications are critical for improving patient outcomes. Early detection and timely interventions can significantly reduce the risk of complications; yet current diabetes management practices are fraught with limitations [2]. Traditional approaches, relying heavily on sporadic clinic visits and manual data tracking, are time-consuming, prone to errors and often fail to provide personalized guidance to patients. This results in a reactive rather than proactive management of the disease, missing opportunities for early intervention.

With the global burden of T2DM continuing to rise, innovative solutions are urgently needed to provide timely and personalized support to patients, caregivers, and healthcare providers. In this context, artificial intelligence (AI) offers a promising avenue for revolutionizing the prevention of T2DM complications [3]. AI-driven systems have the capacity to analyse vast amounts of data—ranging from electronic health records to wearable device inputs and even "genomic information—to identify patterns and predict patient outcomes". These systems can also offer real-time guidance and support, empowering patients to make informed decisions about their care.

Despite these advancements, there is a "notable gap in the literature" regarding the "practical implementation" and efficacy of AI-powered tools in real-world settings. Despite the theoretical potential of AI in managing Type 2 Diabetes Mellitus (T2DM), several critical research gaps remain unaddressed. Although AI-driven platforms like Diabot have been developed with the aim of improving patient outcomes by delivering personalized recommendations and real-time notifications, few studies have systematically examined their efficacy in preventing the complications associated with T2DM [4,5]. Much of the current literature has focused on technical aspects such as algorithm development, data integration and predictive modeling. However, these studies often overlook the more practical dimensions of clinical efficacy in real-world settings. The evidence base remains limited when it comes to evaluating how AI applications influence the actual prevention of complications in routine clinical practice.

While AI systems are frequently praised for their predictive accuracy, there is a lack of in-depth research on their impact on patient adherence and engagement over the long term [6]. "The integration of AI tools into existing clinical workflows" remains another unexplored area, particularly in terms of how AI-generated recommendations can influence clinical decision-making. Moreover, there is insufficient data on how these technologies are received by patients and healthcare providers; especially concerning their day-to-day usability and the potential challenges they pose in real-world clinical environments.

Another major research gap centers on the usability and accessibility of AI systems. Most AI tools for diabetes management are "still in the early stages of development", often designed without adequate consideration for the practical needs of patients and healthcare professionals [7]. This has led to limited integration and underutilization in everyday diabetes care. Scalability is also a significant concern, especially when it comes to implementing AI systems in diverse healthcare environments, ranging from high-tech urban settings to under-resourced areas where the burden of diabetes is often more pronounced. "Questions related to data privacy, security, ethical implications" and the practical logistics of scaling up AI systems to integrate with existing healthcare infrastructures are equally pressing but have not been comprehensively addressed [8]. Additionally, the unequal access to AI-driven tools across different regions and patient populations, particularly in low-resource settings, warrants further investigation to prevent exacerbating health disparities.

As the interest in AI-driven diabetes management tools grows, there is an urgent need to evaluate their clinical relevance and effectiveness in preventing complications. "T2DM complications" like "cardiovascular disease, neuropathy and nephropathy", pose significant risks to patient health. A thorough, evidence-based understanding of how AI can contribute to mitigating these risks is vital to ensure that these emerging technologies can be harnessed effectively to improve patient outcomes [9].

This scoping review seeks to address these research gaps by exploring the current body of evidence on the effectiveness of Diabot and similar AI-powered systems in preventing T2DM complications and improving patient outcomes. The review will map the available research on AI applications in diabetes care, focusing on the effectiveness of personalized recommendations and notifications in reducing the incidence of key complications like cardiovascular disease, retinopathy and nephropathy. By synthesizing existing studies, this review seeks to highlight the "potential benefits of AI" in diabetes care while also identifying the challenges and limitations that need to be addressed. In doing so, this review will "provide valuable insights" into the future direction of AI integration in T2DM management, helping to guide both clinical practice and future research endeavours.

METHODOLOGY

This scoping study investigates the potential of **Diabot**, an AI-driven application, in enhancing Type 2 Diabetes Mellitus (T2DM) complication prevention through personalized recommendations and real-time notifications. The review follows the "**Arksey and O'Malley framework** for scoping reviews", consisting of "five key stages": "identifying the research question, identifying relevant studies, selecting studies, charting the data and summarizing and reporting results" [10]. This approach provides flexibility, allowing an exploratory analysis of AI-powered systems in preventing T2DM complications, with a focus on platforms like **Diabot**. The **PRISMA-ScR guidelines** are employed to ensure transparency and consistency throughout the review process [11].

The methodology adopted for this "scoping review" enables a comprehensive overview of existing evidence and highlights gaps for future research. This review aims to "map the current landscape of AI-driven systems" in T2DM management, particularly focusing on personalized complication prevention.

Information Sources and Search Strategy

An extensive examination of the literature was done using several databases, including "**PubMed, Scopus, Web of Science, IEEE Xplore and Google Scholar"**. The databases were selected for their extensive coverage of both clinical and technological research. The search also incorporated grey literature such as **conference proceedings, reports and preprints** to capture emerging studies on AI and diabetes management that may not yet be published in formal academic outlets. The reference lists from pertinent articles were examined to discover further investigations.

The structured search strategy employed a "combination of **key terms** and **Medical Subject Headings (MeSH)"**. Terms included:

- "Type 2 Diabetes Mellitus (T2DM)"
- "Artificial Intelligence (AI)"
- "Machine Learning"
- "Predictive Algorithms"
- "Diabot"
- "Complication Prevention"
- "Personalized Recommendations"
- "Real-Time Notifications"

"Boolean operators (**AND**, **OR**)" were used to refine the search, ensuring that the review captured a broad range of relevant studies. The search was limited to publications from **2010-2024** and those in **English**, reflecting the most recent advancements in AI technologies.

Inclusion Criteria

- Focused on AI-powered systems such as Diabot, for T2DM complication prevention or management.
- Reported on clinical or real-world outcomes, such as patient engagement, adherence, or complication prevention.
- Published in English from **2010 onwards**.

Studies that focused solely on **algorithm development** without practical clinical applications or did not address T2DM complications were excluded.

Study Selection

"Identified studies were imported" into a **reference management tool** for duplicate removal. "Two independent reviewers" screened titles and abstracts based on the predefined inclusion criteria. Any discrepancies were resolved through "discussion with a third reviewer" brought in when necessary. Full-text articles were then assessed to ensure compliance with the criteria, with the process documented using a **PRISMA flow diagram** to ensure transparency.

Data Charting and Extraction

Data extraction was conducted using a standardized form. "Key informations from the selected studies included":

- "Study characteristics (author, year, country, study design)"
- AI system details (platform, algorithm type, features)
- T2DM complication outcomes (e.g., cardiovascular events, nephropathy, retinopathy)
- Barriers or challenges in AI system implementation

The data extraction form was tested on a limited sample of studies to verify consistency. Two reviewers independently extracted the data, and any discrepancies were resolved by discussion or by approaching a third reviewer. Both quantitative and qualitative data were collected to furnish a thorough overview.

RESULTS

This scoping review synthesized findings from multiple studies focusing on AI-driven mobile health applications designed to "prevent complications in individuals with Type 2 Diabetes Mellitus (T2DM)". The review covered various AI systems and applications, with key results summarized below:

1. **AI-Driven Personalization and Glycemic Control**: Most studies demonstrated a significant improvement in HbA1c levels due to AI-driven personalized interventions. For instance, **Shaikh et al. (2024)** reported a significant reduction in HbA1c ($p < 0.001$), and **Bretschneider et al. (2023)** showed a 1.0% reduction ($p < 0.001$) in their intervention group, indicating the strong efficacy of personalized AI-driven feedback on glycemic control [14, 15]. Other studies, such as **Bonn et al. (2024),** observed non-significant reductions, which may be attributed to "sample size or study duration" [12].
2. **Behavioral Modification through AI Tools**: The applications consistently focused on lifestyle and behavioral modifications, such as physical activity tracking, dietary advice, and medication adherence reminders. **Höchsmann et al. (2019)** found that gamified approaches, such as individualized exercise regimens with narrative rewards, improved self-care behaviors, leading to improved HbA1c outcomes [21]. **Bretschneider et al. (2023)** highlighted that self-management of blood glucose levels combined with personalized feedback significantly reduced distress and promoted healthier lifestyle choices [15].
3. **Reduced Incidence of Complications**: Several studies noted improvements in T2DM complications with AI interventions. For example, **Venkatesan et al. (2023)** reported improved glycemic control and reduced risk of complications, while **Kumar et al. (2018)** found a reduced incidence of neuropathy [16, 32]. Although improvements in complications like blood pressure and lipid profiles were often not statistically significant, AI-driven interventions demonstrated their potential for long-term disease management.
4. **Challenges in AI System Implementation**: The studies highlighted multiple barriers to the effective implementation of AI systems in diabetes management. Access to technology and user engagement was recurring challenges. For instance, **Boels et al. (2018)** and **Kim HS et al. (2014)** cited engagement and adherence issues, which limited the overall effectiveness of the interventions [20, 30]. Technology proficiency, such as participant familiarity with smartphones, was also a critical barrier, particularly in older populations **(Kardas et al., 2016)** [36].
5. **Long-Term Impact and Sustainability**: Some studies, such as **Kim et al. (2024),** noted non-significant long-term effects despite initial improvements, suggesting that long-term sustainability of app use and

continued user engagement remains a challenge [13]. **Thorsen et al. (2022)** found no significant differences in HbA1c after 52 weeks, highlighting the need for continuous motivation and support in sustaining lifestyle changes through AI systems [18].

6. **Integration with Healthcare Systems**: Integration with existing healthcare systems emerged as a recurring theme across studies. **Bonn et al. (2024)** emphasized the need for AI applications like DiaCert to seamlessly integrate with primary care systems to optimize patient outcomes [12]. Similarly, **Venkatesan et al. (2023)** pointed out the challenge of heterogeneous interventions and the need for better coordination between digital health platforms and healthcare providers [16].
7. **Data Privacy and Ethical Concerns**: Several studies, including "**Agarwal et al. (2019)** and **Kumar et al. (2018)",** "raised concerns over data privacy and security" in the use of AI applications. Ensuring secure handling of sensitive health data, particularly in AI-driven mobile health platforms, was a noted barrier to wider adoption and user trust [31,32].
8. **Complication Outcomes**: The studies examined the reduction of complications as an essential outcome. For instance, studies like **Holmen et al. (2014)** reported reduced incidences of diabetes-related complications, better glycemic control, and improved patient adherence to self-management activities [28]. Other studies, such as **Gimbel et al. (2020),** also noted reduced complications alongside improved engagement, although issues like patient reluctance and data privacy remained concerns [35].

DISCUSSION

This "scoping review" aimed to evaluate the role of "AI-driven mobile health (mHealth) applications" in preventing complications in "individuals with Type 2 Diabetes Mellitus (T2DM)" by providing personalized recommendations and notifications. The findings from the reviewed studies demonstrate that AI-based interventions have immense potential in improving glycemic control, promoting behavioral modifications, and reducing the risk of complications. However, these interventions also face several implementation challenges that must be addressed to optimize their efficacy.

The review confirms that AI-powered mHealth applications can significantly enhance glycemic control, as reflected in reductions in HbA1c across numerous studies. For example, **Shaikh et al. (2024)** and **Bretschneider et al. (2023)** reported significant reductions in HbA1c ($p < 0.001$), demonstrating the potential of AI to personalize interventions effectively [14, 15]. These AI tools leverage real-time data analysis and provide tailored feedback based on individual behavior and health data. This personalization is a key factor contributing to their effectiveness in managing blood glucose levels, promoting physical activity and encouraging healthy dietary habits. By enabling users to actively monitor their lifestyle choices, these applications support sustained self-management of diabetes, which is crucial for preventing complications.

However, the heterogeneity of results among the studies—such as the non-significant HbA1c reductions in studies like **Bonn et al. (2024)—**highlights the variability in outcomes. Factors such as intervention duration, sample size, participant engagement and technology proficiency could account for these differences [12]. Some interventions, while effective in the short term, may not produce sustainable long-term results, as shown in studies like **Thorsen et al. (2022),** which found no significant improvement after 52 weeks. This variability underscores the importance of designing AI systems that maintain user engagement over the long term to ensure sustained health benefits [18].

A key outcome of the reviewed studies is the potential of AI-driven apps to reduce T2DM-related complications. V**enkatesan et al. (2023)** and **Kumar et al. (2018)** both noted reduced incidence of complications such as neuropathy and improvements in overall glycemic control [16, 32]. These findings align with the growing recognition that technology-driven interventions, especially that offering real-time, personalized health guidance, can support users in managing multiple facets of diabetes, thereby reducing the likelihood of "severe complications such as cardiovascular disease, neuropathy and retinopathy".

However, the degree to which AI systems prevent specific complications, such as hypoglycemia or hyperglycemia, varied among the studies. For instance, "**Kim et al. (2019)** found no significant difference" in severe hyperglycemia or hypoglycemia between groups. This suggests that while AI-driven apps are promising in enhancing general diabetes management, they may need to be tailored further to target specific complications more effectively [23]. Additionally, studies like **Boels et al. (2018)** identified issues with participant adherence, which could undermine the potential for apps to prevent complications if users do not fully engage with the intervention [20].

The integration of AI in mHealth applications often focuses on fostering behavioral and “lifestyle changes, such as increased physical activity, improved dietary habits, and better medication adherence”. The use of gamification, motivational messages and real-time feedback, as demonstrated in studies like **Höchsmann et al. (2019),** significantly enhances user engagement and promotes sustained behavior modification. These features help bridge the gap between clinical care and daily self-management, allowing users to remain actively involved in their treatment plans [21].

Despite these strengths, some studies pointed to challenges in maintaining long-term engagement. Participant engagement issues were highlighted in studies like **Boels et al. (2018)** and **Thorsen et al. (2022),** where users showed diminishing interaction with the apps over time [20, 18]. The potential for "engagement fatigue," where users lose interest in consistently using the apps, represents a significant hurdle in realizing the full potential of these interventions. This suggests that future mHealth solutions should include mechanisms to re-engage users, possibly through adaptive interventions or integration with broader healthcare teams to provide ongoing motivation and support.

Several barriers to the effective implementation of AI-driven mHealth interventions emerged from this review. The most prominent issues include technology access, user engagement and data privacy concerns. Studies like **Kardas et al. (2016)** and **Kim HS et al. (2014)** pointed out those older populations, who are often the primary users of diabetes management apps, may struggle with the technology, leading to lower adoption rates [36, 30]. Similarly, access to smart phones and internet connectivity, particularly in low-resource settings, limits the reach of these solutions. Addressing these disparities through more user-friendly interfaces and ensuring accessibility across different demographic groups is essential.

Another critical issue is the integration of AI systems with existing healthcare infrastructures. **Bonn et al. (2024)** and **Bretschneider et al. (2023)** both noted that AI systems need to be seamlessly integrated into primary care settings to ensure that healthcare providers can actively monitor and support patients using these apps [12, 15]. Without such integration, the potential benefits of AI-driven interventions may be limited to self-management alone, reducing the opportunity for healthcare providers to intervene when necessary.

Data privacy and security also remain significant concerns in the implementation of AI in healthcare. “Studies such as **Agarwal et al. (2019)** and **Kumar et al. (2018)”** raised alarms over the handling of sensitive patient data, particularly in apps that collect real-time health metrics [31, 32]. Given the “increasing prevalence of cyber threats, ensuring robust security measures” in AI-driven apps is paramount to maintaining user trust and ensuring widespread adoption.

Limitations and Future Directions

While this review identified promising outcomes from AI-driven mHealth applications for T2DM, several limitations must be acknowledged. The variability in study designs, sample sizes and intervention durations makes it difficult to generalize findings across all populations. Moreover, many studies lacked sufficient “long-term follow-up data”, which is essential for “understanding the sustained impact” of AI interventions on diabetes management. Additionally, the heterogeneity of AI systems and algorithms used in the studies complicates direct comparisons between interventions, as different platforms employ varying degrees of personalization, feedback mechanisms, and healthcare integration.

Future research should focus on standardizing study protocols to facilitate comparison across interventions. “Larger, more diverse sample populations and extended follow-up periods” are necessary to assess the long-term sustainability of these interventions. Furthermore, as AI technologies evolve, future applications should prioritize user-centered design, ensuring that apps are accessible, engaging, and adaptable to individual user needs.

CONCLUSION

AI-driven mHealth applications such as diabot offer a promising solution to improve diabetes management by providing personalized recommendations and supporting behavior change. This scoping review highlights the potential of AI to reduce HbA1c levels, promote healthier lifestyles, and prevent T2DM complications. However, challenges related to user engagement, technology access, and data privacy must be addressed to maximize the impact of these interventions. Going forward, more comprehensive studies with standardized methodologies and extended follow-up durations are necessary to comprehensively assess the long-term merits and drawbacks of AI in diabetes management. By addressing these barriers and fostering better integration with healthcare systems, "AI has the potential to revolutionize the management of T2DM" and prevent complications on a larger scale.

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TABLE 1: Search strategy

TABLE 2: Table of study characteristics

Reference	**Type of Diabetes**	**Study Design**	**Participants**	**Included Outcomes**	**AI System Details (Platform, Algorithm Type, Features)**	**Main Features of the App**	**Baseline HbA1c (%), Mean (SD)**

Database	**Search string**	**Number of hits(N)**
" PubMed"	"Type 2 Diabetes Mellitus" AND ("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("Complication Prevention" OR "Glycemic Control" OR "Real-Time Notifications" OR "Personalized Recommendations") AND ("mHealth" OR "Mobile Health" OR "Digital Health" OR "Diabot")	420
"Lilacs"	"Diabetes Tipo 2" AND ("Inteligencia Artificial" OR "Aprendizaje Automático") AND ("Prevención de Complicaciones" OR "Control Glicémico" OR "Recomendaciones Personalizadas" OR "Diabot")	0
"Scopus"	"Type 2 Diabetes" AND ("Artificial Intelligence" OR "Machine Learning" OR "AI") AND ("Complication Prevention" OR "Glycemic Control" OR "Personalized Notifications" OR "mHealth") AND ("Digital Health" OR "Mobile Applications" OR "Diabot")	720
"Embase"	("Type 2 Diabetes" OR "T2DM") AND ("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("Complication Prevention" OR "Glycemic Control" OR "Real-Time Alerts") AND ("mHealth" OR "Digital Health" OR "Mobile Applications" OR "Diabot")	815
"Google scholar"	"Type 2 Diabetes Mellitus" AND ("Artificial Intelligence" OR "Machine Learning" OR "AI") AND ("Complication Prevention" OR "Personalized Recommendations" OR "Real-Time Alerts") AND ("mHealth" OR "Mobile Health" OR "Diabot")	2000

Bonn et al. (2024) [12]	Type 2 Diabetes	Randomized Controlled	181 participants (93 in intervention, 88 in control)	MVPA (Moderate-to-vigorous physical activity), BMI, HbA1c, cholesterol, blood pressure	DiaCert App, Smartphone Platform, mHealth Solution, Features include daily walking promotion, self-monitoring for physical activity, integration with primary care systems	DiaCert app promotes daily walking, tracking HbA1c, and daily steps	53.6 (13.0) mmol/mol
Kim et al. (2024) [13]	Type 2 Diabetes	Randomized Controlled	200 participants	Step count, HbA1c, fasting glucose, body weight, total cholesterol, LDL, HDL, triglycerides	Smartphone Personal Health Record (PHR) app, Mobile application, Encouragement through motivational text messages	PHR app, text message encouragement based on daily steps	7.1 ± 0.4
Shaikh et al. (2024) [14]	Type 2 Diabetes	Randomized Controlled	100 participants	HbA1c, plasma glucose, glycemic variability, glucose score, estimated postprandial glucose, dietary behaviours	Platform: YoloHealth AI-Powered Metabolic Coach Algorithm Type: Machine Learning Features: Personalized recommendations, real-time data analysis, dietary habit assessment, physical activity monitoring, medication adherence tracking	AI-powered metabolic coach offering personalized guidance	8.30 ± 1.50
Bretschneider et al. (2023) [15]	Type 2 Diabetes	3-month, prospective, open-label trial with intraindividual control group	48 participants	HbA1c reduction, weight, self-management, well-being, distress	Platform: mebix (Vision2B GmbH) Algorithm Type: Digital Health Application for	mebix, a digital health app focusing on self-management and lifestyle modification	8.4 ± 0.9%

					diabetes management Features: - Self-monitoring of blood glucose levels - Personalized feedback on lifestyle changes - Integration of physical activity tracking - Food logging capabilities - Patient-reported outcomes assessment (well-being, distress, self-management)		
Venkatesan et al., (2023) [16]	Type 2 Diabetes	Single-arm, retrospective study	1128	Glycemic control (HbA1c), mental health (depressive symptoms)	Platform: Mobile Health App (Vida Health) Algorithm Type: Machine Learning Features: - One-on-one remote sessions with health coaches - Personalized diabetes management tools - Tracking of blood glucose levels, nutrition, and activity - Health feedback and educational resources	App-based, one-on-one remote sessions with health coaches, registered dietitians, diabetes care education specialists, structured lessons and self-monitoring tools	9.84 (1.64)
Lim et al., (2022) [17]	Prediabetes	Randomized Controlled Trial (RCT)	148 (72 intervention, 76 control)	Weight loss, glycemic control (HbA1c), metabolic indices	Platform: Smartphone App (Nutritionist Buddy) Algorithm Type: Not specified	App-based lifestyle intervention with in-app dietitian coaching (nBuddy Diabetes)	6.06 (0.50) Control, 5.94 (0.48) Intervention

					Features: Self-monitoring, in-app dietitian coaching, personalized lifestyle intervention		
Thorsen et al., (2022) [18]	Type 2 Diabetes	Parallel-group, randomized trial	214 (140 intervention, 74 control)	Physical activity, quality of life, waist circumference	Type: App-based Interval Walking Training (IWT) Platform: InterWalk Smartphone Application Features: Individualized training, goal setting, motivational support, feedback mechanisms	InterWalk app-based interval walking training (IWT), motivational support (IWTsupport group)	Not provided
Orsama et al. (2013) [19]	Type 2 Diabetes	Randomized Controlled Trial	48 (24 intervention, 24 control)	HbA1c, weight, blood pressure	Platform: Mobile telephone-based system Algorithm Type: Theory-based health behaviour change feedback Features: Remote patient reporting, automated feedback, monitoring of health parameters (HbA1c, weight, blood pressure)	Mobile app for remote reporting	6.86 (1.56) (Intervention) 7.09 (1.51) (Control)
Boels et al. (2018) [20]	Type 2 Diabetes Mellitus	Non-blinded two-arm multi-centre RCT	228 (114 intervention, 114 control)	HbA1c levels, BMI, waist circumference, insulin dose, lipid profile, blood pressure, number of hypoglyca	Platform: Smart phone app compatible with Android and iOS operating systems Algorithm Type: Proprietary personal health record (PHR)	Diabetes self-management education via a smartphone app, tailored messages, push notifications, user-selected topics and frequency,	> 7% (exact value not provided)

				emic events, etc.	platform combined with push message technology Features - Automated app-messages on dietary habits, physical activity, hypoglycaemia prevention, glucose variability - Customizable topics and frequency for users - Fall-back SMS reminders if app not opened within 24 hours	SMS reminders.	
Höchsmann et al. (2019) [21]	Type 2 Diabetes	RCT	36 inactive, overweight adults	Daily PA, aerobic capacity, glycemic control	Platform: Smartphone (iOS/Android) Algorithm Type: Behavioural Change Techniques Features - Individualized exercise regimens -Progress tracking via sensors - In-game rewards and motivation - Integration of narrative and gameplay elements	Smartphone game with individualized exercise, narrative, and rewards for PA engagement	6.2 (0.7)
Hooshmandja et al. (2019) [22]	Type 2 Diabetes	Quasi-experimental	51 diabetic patients	Self-care behaviours, FBS, HbA1c	Platform: Android Algorithm Type: Machine Learning Features: - Personalized education modules - Daily reminders for	Mobile application for education on self-care, including features for tracking blood glucose, medication,	7.10 (1.22)

					medication and monitoring - Data tracking for blood glucose and medications - User-friendly interface for easy navigation - Feedback mechanism for users - Access to educational resources and articles - Communication tools for healthcare provider contact	diet, and exercise.	
Kim et al., (2019) [23]	Type 2 Diabetes	Randomized Controlled Trial (24 weeks)	214 screened, 172 included (90 mDiabetes, 82 pLogbook)	Change in HbA1c levels, fasting blood glucose, lipid profile, body composition	Platform: Smartphone-based application (Android) Algorithm Type: Individualized diabetes management algorithm Key Features- Blood glucose monitoring - Diet and physical activity tracking - Clinical decision support system - Insulin dosage guidance - Social networking components	Glucose monitoring, diet tracking, physical activity logging, clinical decision support	7.7 (0.7)
Kusnanto et al., (2019) [24]	Type 2 Diabetes	Randomized Controlled Trial	30 (15 experimental, 15 control)	Self-efficacy, HbA1c levels, lipid profile, insulin levels	Platform: Android Algorithm Type: Machine Learning Features: Self-management tracking,	Android-based DM-calendar app for reminders and education	8.74 (1.34)

					reminders for medication, educational resources, integration with health data monitoring.		
Buss V H et al. (2022) [25]	Type 2 Diabetes	Development and Usability Study	10 participants (average age: 58 years)	Risk awareness, goal setting, user engagement	Framingham CVD risk score, Australian Type 2 Diabetes Risk Assessment Tool	Goal setting, progress tracking, education	Not specified
Waki et al. (2014) [26]	Type 2 Diabetes	3-month randomized controlled trial	54	Changes in HbA1c, FBS, BMI, usability, compliance	Real-time data transmission, evaluation module, communication module, dietary evaluation module	Smartphone-based, real-time feedback, NLP integration	7.5 ± 1.0
Quinn et al. (2011) [27]	Type 2 Diabetes	Randomized Controlled Trial	200 adults with T2DM	HbA1c levels, diabetes distress, adherence to treatment	Mobile app, machine learning algorithm, personalized feedback	Glucose monitoring, diet tracking	7.5% (0.8)
Holmen et al. (2014) [28]	Type 2	3-arm prospective randomized controlled trial	151 (51 FTA, 50 FTA-HC, 50 control)	HbA1c level, self-management (heiQ), health-related quality of life (SF-36), depressive symptoms (CES-D), lifestyle changes (diet and physical activity)	Mobile phone-based self-management system (FTA)	Blood glucose measuring, diet manual, physical activity registration, personal goals management	≥7.1% (≥54.1 mmol/mol)
Forjuoh et al. (2014) [29]	Type 2 Diabetes	Randomized Controlled Trial	376	Change in HbA1c, BMI, blood pressure, self-management behaviors	Personal Digital Assistant (PDA), Chronic Disease Self-Management Program (CDSMP),	Diabetes self-care software, Behavioral intervention program, Integrated approach to self-	9.3%

					Combination of CDSMP + PDA, usual care	management , Standard care without additional tools	
Kim HS et al., (2014) [30]	Type 2 Diabete s Mellitus	Interventio n vs. Control Group	35 smartpho ne users and matched control group	HbA1c levels, patient satisfaction , blood pressure, lipid profile	Smartphone app 'Mobile Smartcare, version 1.0.7'; combines blood glucose monitoring and feedback	Automatic data transfer, medical feedback, health information, exercise and diet recommenda tions	7.7% (±0.7%)
Agarwal et al. (2019) [31]	Type 2 Diabete s	Multicente r Pragmatic Randomiz ed Controlled Trial	223	HbA1c levels, self-manageme nt, experience of care, health utilization	Mobile app (BlueStar), FDA-approved, virtual coaching	Self-management support, personalized feedback	8.96 (1.68)
Kumar et al. (2018) [32]	Type 2 Diabete s	12-week, single-arm trial	146	Change in A1C, satisfaction , user engagemen t, diabetes distress (DDS-17), diabetes empowerm ent (DES-SF)	One Drop	Mobile (Informed Data Systems, Inc)	In-app coaching, diabetes education, self-care tracking
D. Sunil Kumar et al. (2020) [33]	Type 2 Diabete s	Randomiz ed Field Trial	300 (150 interventi on, 150 control)	Quality of Life (WHO QOL BREF), lifestyle modificati on effects	Android Smartphone Application (DIAGURU)	Lifestyle modification , medication management , alerts for abnormal values, dietary tracking	8.5 (1.0)
Huang et al (2019) [34]	Type 2 Diabete s	Feasibility Randomiz ed Controlled Trial	51 nonadher ent patients with T2D	Medication adherence, self-reported barriers, diabetes-related health outcomes, app usage behavior, satisfaction levels	Medisafe app (smartphone platform, medication reminder)	Medication reminders, adherence tracking	Not explicitly provided

Gimbel et al. (2020) [35]	Type 2 Diabetes	Multisite feasibility study with controlled trial	229 patients	Patient Activation Measure (PAM) scores, Summary of Diabetes Self-Care Activities (SDSCA) scores, HbA1c, BMI, LDL cholesterol, blood pressure.	US Department of Defense Mobile Health Care Environment (MHCE); mHealth technology	Tailored behavioral messaging, biometric monitoring	7.5% (not specified)
Kardas et al. (2016) [36]	Type 2 Diabetes	Prospective parallel-arm randomized controlled trial	60 (24 female, 36 male)	Patient adherence, metabolic parameters, quality of life	COMMODITY12 system (smartphone, Bluetooth sensors)	Glucose monitoring, blood pressure tracking, activity tracking	6.84 (1.05)

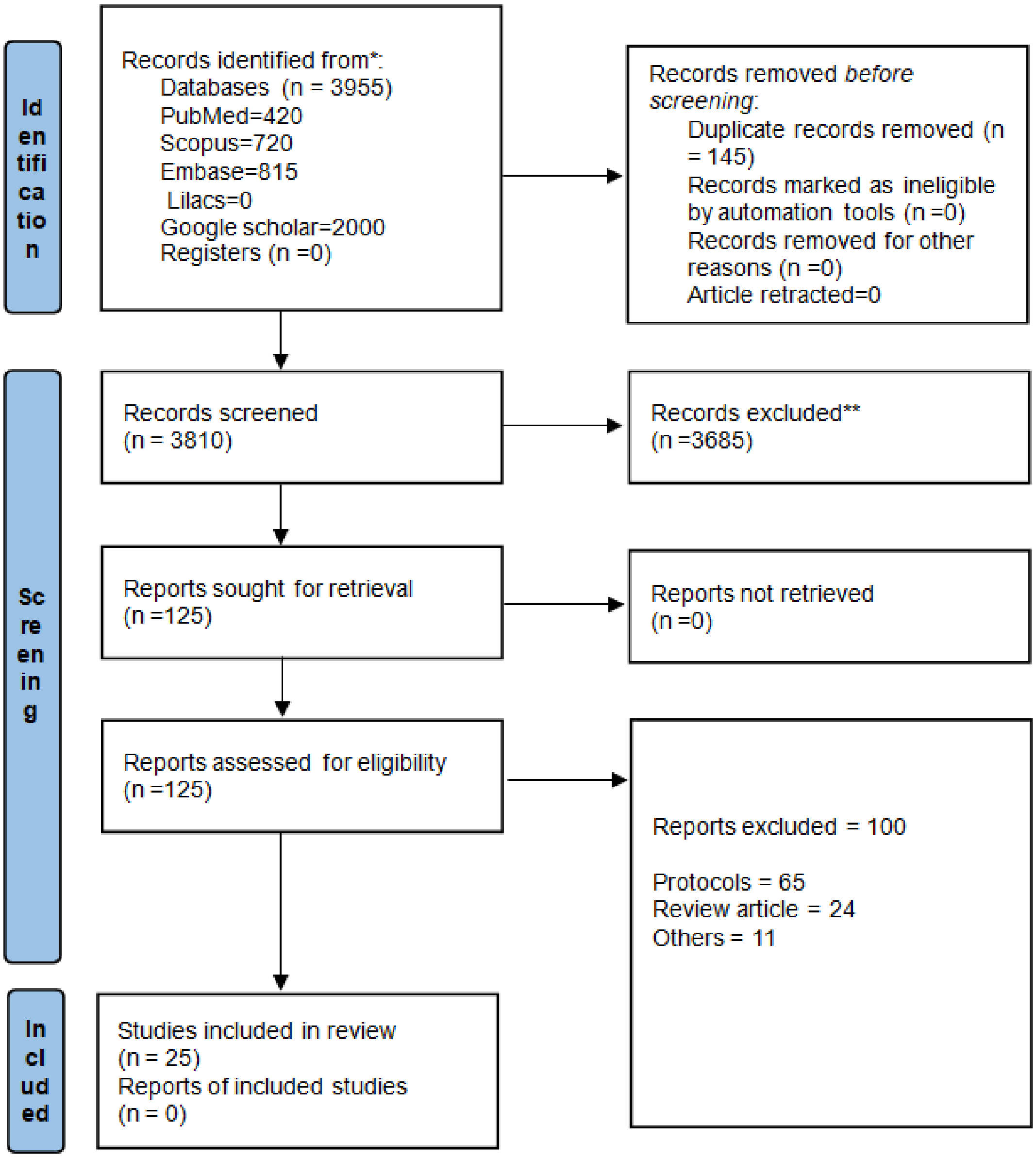
TABLE 3: Key characteristics and outcomes of included studies

Reference	Follow-up HbA1c (%), Mean (SD)	Differences within Groups HbA1c (%), Mean (SD, p)	Differences Between Groups HbA1c (%), Mean (SD, p)	Intervention Group HbA1c at Endpoint	Control Group HbA1c at Endpoint	Mean Difference
Bonn et al. (2024) [12]	50.0 (9.9) mmol/mol (3 months), 51.2 (10.7) mmol/mol (6 months)	-2.45 (p = 0.21, 3 months), -0.21 (p = 0.87, 6 months)	-2.54 (p = 0.06, 3 months), -0.30 (p = 0.83, 6 months)	50.0 mmol/mol (3 months), 51.2 mmol/mol (6 months)	53.2 mmol/mol (3 months), 51.2 mmol/mol (6 months)	Non-significant
Kim et al. (2024) [13]	6.7 ± 0.5 (intervention), 6.9 ± 0.6 (control)	-0.31 ± 0.53% (p < 0.001, intervention) -0.18 ± 0.57% (p = 0.015, control)	No significant difference (p = 0.167)	6.7 ± 0.5%	6.9 ± 0.6%	Not significant
Shaikh et al. (2024) [14]	7.05 ± 1.24	-0.18 ± 0.57 (control), -0.31 ± 0.53 (intervention)	Significant reduction in HbA1c (p < 0.001)	7.05 ± 1.24	8.30 ± 1.50	Significant
Bretschneider et al. (2023) [15]	7.3 ± 0.6%	Intervention: -1.0 ± 0.8% (p < 0.001), Control: -0.2 ± 0.8% (p = 0.177)	1.0% (p < 0.001)	7.3 ± 0.6%	8.3 ± 0.7%	1.0% (p < 0.001)
Venkatesan et al., (2023) [16]	8.48 (1.77)	–1.35 (SD 1.64, p < .001)	Not applicable	8.48 (1.77)	Not applicable	-1.35

Lim et al., (2022) [17]	5.84 (Control), 5.72 (Intervention)	-0.06 (Control), -0.22 (Intervention)	-0.19 ($p <$ 0.001)	5.72 (0.33)	5.84 (0.26)	-0.19% ($p <$ 0.001)
Thorsen et al., (2022) [18]	52 weeks	Not significant ($p = .82$)	Not significant ($p = .82$)	Not provided	Not provided	Not provided
Orsama et al. (2013) [19]	6.46 (1.39) (Intervention) 7.12 (1.51) (Control)	-0.40 (-0.67 to -0.14, $p < 0.03$) (Intervention) 0.036 (-0.23 to 0.30, $p = 0.985$) (Control)	-0.40 (-0.67 to -0.14, $p <$ 0.03)	6.46 (1.39)	7.12 (1.51)	-0.66
Boels et al. (2018) [20]	8.0 (1.6) (Intervention) 8.2 (1.4) (Control)	NR NR	-0.08 (-0.37 to 0.2), $p=0.557$	8	8.2	-0.2
Höchsmann et al. (2019) [21]	6.2 (0.7)	0.0 (NS)	-0.9 (95% CI -1.5, -0.2, $p=0.016$)	6.2 (0.7)	6.3 (1.3)	-0.9
Hooshmandja et al. (2019) [22]	6.84 (0.63)	−0.26 (NS)	−1.26 ($p <$ 0.001)	6.84 (0.63)	8.10 (0.10)	−1.26
Kim et al., (2019) [23]	7.4 (0.7)	-0.40 (0.09, $p <$ 0.001)	0.35 (0.09, $p =$ 0.001)	7.4	7.8	0.35
Kusnanto et al., (2019) [24]	7.64 (1.29)	-1.10 (0.32, $p =$ 0.001)	0.10 (0.27, $p =$ 0.005)	7.64	7.91	-0.27
Buss V H et al. (2022) [25]	Not specified	Not specified	Not specified	Not specified	Not specified	Not specified
Waki et al. (2014) [26]	6.7 ± 0.7	Decreased by 0.4% in DialBetics group	-0.5% ($P =$ .015)	6.7 ± 0.7	7.1 ± 1.1	-0.5%
Quinn et al. (2011) [27]	7.8 (1.5)	-1.9 (1.8, <0.001)	-1.2 (0.5, <0.001)	7.8	9.0	-1.2%

Holmen et al. (2014) [28]	6.9% (±0.9)	-0.5% (±0.3, p < 0.01)	-0.6% (±0.4, p < 0.05)	6.9% (±0.9)	7.5% (±1.0)	-0.6%
Forjuoh et al. (2014) [29]	CDSMP: 8.3 (1.9), PDA: 8.6 (1.8), CDSMP + PDA: 8.3 (1.7), Control: 8.5 (1.6)	CDSMP: -1.1 (0.2, p = .771), PDA: -0.7 (0.4, p < .004), CDSMP + PDA: -1.1 (0.3, p = .771), Control: -0.7 (0.3, p = .771)	CDSMP vs. PDA: 0.4 (0.3, p = .771), CDSMP vs. Control: 0.2 (0.2, p = .771), PDA vs. Control: 0.1 (0.1, p = .771)	8.3 (CDSMP), 8.6 (PDA), 8.3 (CDSMP + PDA)	8.5	-0.7%
Kim HS et al., (2014) [30]	6.9% (±0.6)	-0.8% (±0.5, p < 0.01)	-1.2% (±0.4, p < 0.01)	6.9%	8.1%	-1.2%
Agarwal et al. (2019) [31]	7.45 (1.12)	-0.50 (0.30, p < 0.05)	-1.20 (0.25, p < 0.01)	7.45	8.65	-0.75
Kumar et al. (2018) [32]	7.5% (±1.2)	-0.8% (±0.5, p < 0.01)	-1.2% (±0.6, p < 0.05)	7.5%	8.7%	-1.2%
D. Sunil Kumar et al. (2020) [33]	7.0 (0.5)	-0.6 (0.2, p < 0.01)	-0.5 (0.3, p < 0.05)	6.5 (0.4)	7.0 (0.5)	-0.5 (0.2)
Huang et al. (2019) [34]	Not specified	Not specified	Not specified	Not specified	Not specified	.7 (P=.01)
Gimbel et al. (2020) [35]	7.1% (0.5)	-0.4% (0.3)	-0.5% (0.2, p < 0.05)	6.9%	7.4%	-0.5%
Kardas et al. (2016) [36]	6.78 (1.10)	Not specified	Not specified	6.78 (1.10)	6.84 (0.98)	Not specified

Figure 1: PRISMA flow diagram



*Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/registers).

**If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools.