

REVIEW

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Effectiveness and safety of AI-driven closed-loop systems in diabetes management: a systematic review and meta-analysis

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Abstract

Background Diabetes is a metabolic disease that can lead to severe cardiovascular diseases and neuropathy. The associated medical costs and complications make timely and effective management particularly important. Traditional diagnostic and management methods, like frequent glucose sampling and insulin injections, impose physical injuries on subjects. The development of artificial intelligence (AI) has opened new opportunities for diabetes management.

Methods We conducted a meta-analysis integrating existing research, identifying a total of 1156 subjects to assess the effectiveness and safety of AI-based wearable devices, specifically closed-loop insulin delivery systems, in diabetes treatment.

Results Compared to standard controls, AI-based closed-loop systems can analyze glucose data in real-time and automatically adjust insulin delivery, resulting in reduced time outside target glucose ranges (SMD = 0.90, 95% CI = 0.69 to 1.10, $I^2 = 58\%$, $P < 0.001$).

Conclusion AI-based closed-loop systems enhance the precision and convenience of diabetes treatment. This meta-analysis providing essential references for clinical treatment and policymaking in diabetes care.

Keywords Diabetes, AI, Wearable devices, Closed-loop systems, Insulin delivery

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Introduction

Diabetes has emerged as a significant public health issue worldwide. Currently, the number of adults with diabetes globally exceeds 800 million, with the prevalence among adults rising from 7 to 14%. Notably, nearly 450 million adults aged 30 and older (approximately 59% of all adults with diabetes) have not yet received treatment [1]. Diabetes not only results in substantial medical costs [2, 3] (at least 966 billion dollars) but also increases the risk of serious complications such as diabetic retinopathy, stroke, cardiovascular disease, diabetic nephropathy, peripheral vascular disease, diabetic neuropathy [4, 5] (Fig. 1). Therefore, timely and effective diabetes management is crucial for improving quality of life of people with diabetes and alleviating the societal healthcare burden [6, 7]. However, managing diabetes is a daily challenge, and people with diabetes need to remain highly vigilant and actively engage in self-care [8, 9], includes closely monitoring glucose levels and administering insulin injections when necessary [10]. Traditional diagnostic methods often involve frequent fingerstick glucose tests,

and insulin therapy remains a cornerstone of management for many individuals [11, 12]. While these methods are clinically effective, ongoing research continues to explore ways to optimize their implementation and reduce subject burden [13, 14].

In the current context, the application of artificial intelligence (AI) in the medical field is advancing at an astonishing pace, particularly in disease management and treatment decision support [15]. AI technologies, such as machine learning (ML) and deep learning (DL), are capable of analyzing and processing vast amounts of data, revealing potential patterns and trends [16, 17]. Recent studies have demonstrated AI's capability to predict both immunological progression in type 1 diabetes using continuous glucose monitoring (CGM) and genetic data [18], as well as the onset of diabetic complications like retinopathy using ML models [19], underscoring AI's expanding role across the diabetes care continuum. In diabetes management, the application of AI can be divided into two aspects: those relevant to healthcare providers and those pertinent to people with diabetes. For clinicians, AI

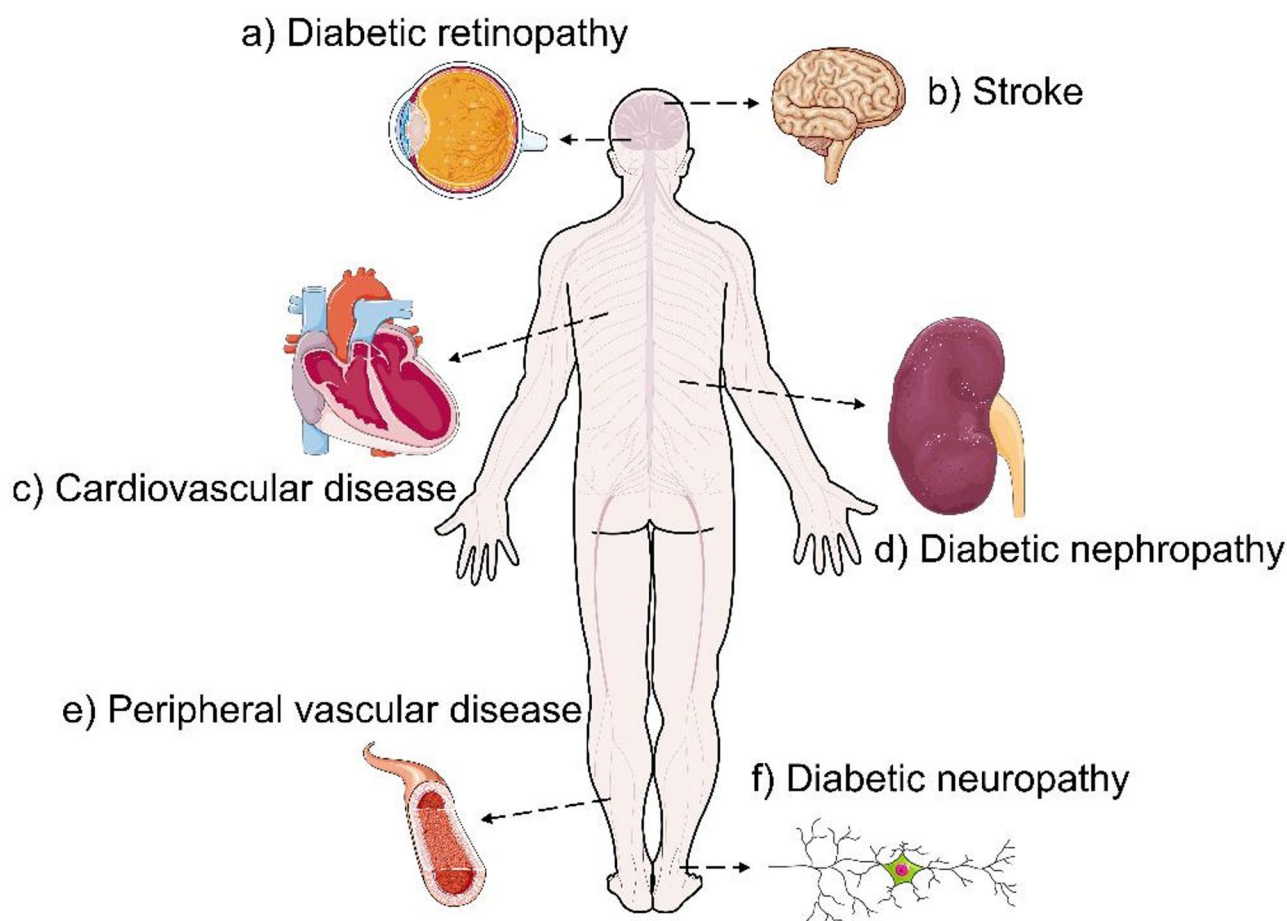


Fig. 1 Serious hazards with diabetes can lead to various complications. **(a)** Diabetic retinopathy is the leading cause of blindness in adults. **(b)** Diabetes doubles the risk of stroke. **(c)** 80% of deaths in people with diabetes are due to cardiovascular events. **(d)** Diabetic nephropathy is the primary cause of end-stage renal disease. **(e-f)** Peripheral vascular disease and diabetic neuropathy are the main reasons for non-traumatic lower limb amputation surgeries

can analyze large-scale subject datasets, generating retrospective insights that assist in optimizing treatment strategies [20, 21]. These insights include trends in glucose fluctuations and individualized treatment effect analyses, thereby enhancing the accuracy and efficiency of interventions [22–25]. For people with diabetes, AI integrated into continuous monitoring systems can provide real-time decision support, aiding them in daily self-management [10, 11, 26–28]. The application of AI algorithms in automated insulin delivery (AID) and CGM systems [29–31] has created closed-loop systems resembling an artificial pancreas [32, 33]. This system can make instantaneous insulin dosing decisions based on real-time data analysis from CGM sensors, thereby reducing the need for continuous people with diabetes monitoring [34, 35]. Specifically, the establishment of closed-loop systems relies on the integration of CGM systems (such as Dexcom G6 or Freestyle Libre) with insulin pumps (such as Medtronic or Tandem). The role of AI algorithms is to optimize data processing to adjust insulin delivery strategies in real time [32, 36]. For instance, AI can analyze historical glucose data alongside current CGM readings to predict trends in glucose fluctuations and adjust insulin delivery accordingly, maintaining glucose within target ranges. This intelligent regulation helps mitigate the risks of hyperglycemia and hypoglycemia, thereby improving overall glycemic management [29, 31, 37–39]. This innovative approach not only enhances the quality of life for people with diabetes but also opens new avenues for the future of diabetes treatment. By combining AI algorithms with AID systems, people with diabetes can benefit from more efficient and personalized treatment plans, significantly improving their disease management outcomes.

Here, we aim to conduct a systematic meta-analysis of the included studies, such as randomized controlled trials (RCTs) and crossover trials, to assess the effectiveness and safety of AI in diabetes management. Our search databases include PubMed, Cochrane Library, and ClinicalTrials.gov, with keywords encompassing diabetes, AI, and closed-loop systems. We analyzed two categories of AI-based interventions such as CGM and AID. Effectiveness will be evaluated by changes in the time spent in the target glucose range (70–180 mg/dL) [40, 41], while safety assessments will focus on the incidence of severe hypoglycemic events and diabetic ketoacidosis (DKA) [42–45], time below range (TBR) < 70 mg/dL and < 54 mg/dL may also be considered. This meta-analysis will help identify the optimal treatment regimen by comparing the efficacy outcomes of different treatment modalities, such as sensor-based and traditional care. The integrated evidence will elucidate the role of AI in improving glucose and insulin communication, potentially providing insights for regulatory guidelines for AI-based diabetes devices and guiding future research directions.

Methods

Study design

This review was based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines [46]. The protocol was prospectively registered in the PROSPERO platform (CRD42024592213).

Search methodology

A comprehensive literature review was conducted to identify relevant studies focused on AI-driven closed-loop systems for diabetes management. The databases systematically searched included PubMed, the Cochrane Library, and ClinicalTrials.gov. This search was performed on July 20, 2024, and covered studies published from January 2000 to July 2024. The review was limited to articles published in English and the detailed search strategy is outlined below:

“type 1 diabetes” OR “type 2 diabetes” OR “diabetes mellitus”) AND (“artificial intelligence” OR “machine learning” OR “AI”) AND (“wearable devices” OR “continuous glucose monitor” OR “artificial pancreas” OR “automated insulin delivery” OR “closed loop” OR “automated insulin delivery (AID)”).

Criteria for selection

The selection criteria for this review were explicitly limited to studies that met the following requirements:

- (1) Studies are designed such as RCTs, parallel or crossover trials.
- (2) Data compares closed-loop systems with a control group.
- (3) Participants have been treated with insulin for at least six months before enrollment.
- (4) Studies report all the relevant outcomes we mentioned, including safety-related issues.

The primary outcome was the percentage of time during which glucose levels were maintained within the target range (time in range, TIR, 70–180 mg/dL). Secondary outcomes included: the percentage of time spent above the target range (time above range, TAR, subdivided into > 250 mg/dL and > 180 mg/dL), and below the target range (TBR, subdivided into < 70 mg/dL and < 54 mg/dL), mean glucose level, glycated hemoglobin (HbA1c) level, as well as the incidence of severe hypoglycemia and DKA. Severe hypoglycemia and DKA were reported regarding the number of individuals affected and the total number of events.

Data extraction

The information extracted included various study characteristics, such as the author, year of publication, study design, type of closed-loop device, therapy administered

to the control group, and duration of the intervention. Additionally, subjects' demographics were recorded, encompassing age, type of diabetes, average duration of diabetes, and baseline HbA1c level. Clinical outcomes were also extracted, including the percentage of TIR, percentage of TAR, percentage of TBR, mean glucose level, HbA1c level, and the cases related to severe hypoglycemia and DKA [47–50]. For data presented as median values with interquartile ranges (IQR), we estimated the mean and standard deviation using validated methods for skewed distributions [51, 52]. These approaches are used for meta-analysis when individual participant data are unavailable and have been applied to metabolic parameters, including glucose levels [53]. To facilitate comparisons across studies, the standard deviation (SD) was calculated using the formula $SD = IQR/1.35$, as recommended [52]. While this approach allows for a more uniform representation of glucose data across studies, it is acknowledged that inherent variability and potential skewness in the original data may limit the robustness of these assumptions.

Risk of bias assessment

The risk of bias in the included studies was assessed using the Cochrane Collaboration tool [54]. Each study underwent a comprehensive examination of various potential sources of bias, including selection bias, performance bias, detection bias, attrition bias, and reporting bias. Studies were categorized as having a low, high, or unclear risk of bias.

Meta-analysis

A random-effects meta-analysis was performed with Review Manager 5.4 (RevMan 5.4) software. A meta-analysis was conducted to systematically evaluate the aggregated impact of AI-driven closed-loop systems on significant clinical outcomes in diabetes management. The standardized mean difference (SMD) between AI-based wearables subjects and controls was calculated for all data, with 95% confidence intervals (95% CIs). The degree of heterogeneity among the included studies was assessed using the I^2 statistics, and a random-effects model was applied where appropriate. $SMD > 0.8$ was classified as a large effect size, $p < 0.05$ was considered statistically significant, and $I^2 \geq 75\%$ was considered to indicate high heterogeneity [55]. The presence of publication bias was evaluated through funnel plots.

Results

Study selection and characteristics

We conducted a systematic literature search, identifying 3,344 records. After excluding 1,345 duplicates and 1,929 irrelevant articles based on titles/abstracts, we evaluated 70 full texts for eligibility, ultimately selecting 8 studies

for meta-analysis (Fig. 2). These studies enrolled 1,156 subjects and compared closed-loop therapy with conventional diabetes management (sensor-augmented pumps or multiple daily injections). The included trials exhibited methodological diversity, seven focused on type 1 diabetes (T1D) and one on type 2 diabetes (T2D), with participant ages spanning 3.8–69.3 years and follow-up durations ranging from 72 h to 6 months, baseline characteristics were generally balanced across groups. The closed-loop systems employed heterogeneous algorithmic approaches (such as DIAS USS, Cambridge hybrid, MPC, Control-IQ) and device configurations (such as t: slim X2, iLet bionic pancreas, Omnipod 5). Notably, while all systems utilized CGM, the specific CGM models and their integration with insulin pumps were not uniformly reported across studies. For instance, some trials explicitly mentioned Dexcom G6 or FreeStyle Navigator II use, whereas others provided limited technical details. This lack of standardization in reporting CGM-pump communication may influence the interpretation of system efficacy, particularly regarding real-time glucose data accuracy and algorithmic responsiveness. Control arms predominantly used conventional therapy with CGM, though the level of integration (such as sensor-augmented pumps vs. standalone CGM) varied. Importantly, the role of AI in these systems ranging from basic threshold alerts to advanced predictive hypoglycemia prevention was seldom explicitly discussed, despite its potential to enhance closed-loop performance through adaptive learning and personalized insulin dosing. Study designs included RCTs ($n=7$) and single-arm prospective studies ($n=1$), with sample sizes varying from 20 to 256 participants. Notably, Brown, S. A. stratified results by age (children [6.0–13.9 years] and adults [14.0–70.0 years]) [56], requiring separate data extraction (Table 1 and Table S1). This clinical, technological, and reporting heterogeneity, particularly in CGM specifications and AI integration, underscores the need for cautious interpretation of pooled outcomes.

Risk of bias assessment

We assessed the quality and the risk of bias in the included studies. The results showed that 75% of the studies had a low risk of bias in random sequence generation. In comparison, 25% had uncertainties, and no studies showed a high risk of bias, indicating that most studies employed appropriate randomization methods. In evaluating allocation concealment, 62.5% of the studies exhibited a low risk of bias, 25% had uncertainties, and 12.5% showed a high risk of bias. Regarding participant and personnel blinding, 25% of the studies had a low risk of bias, 25% had uncertainties, and 50% faced high risk. This high proportion of bias risk related to blinding may impact the objectivity of the results. In the assessment of

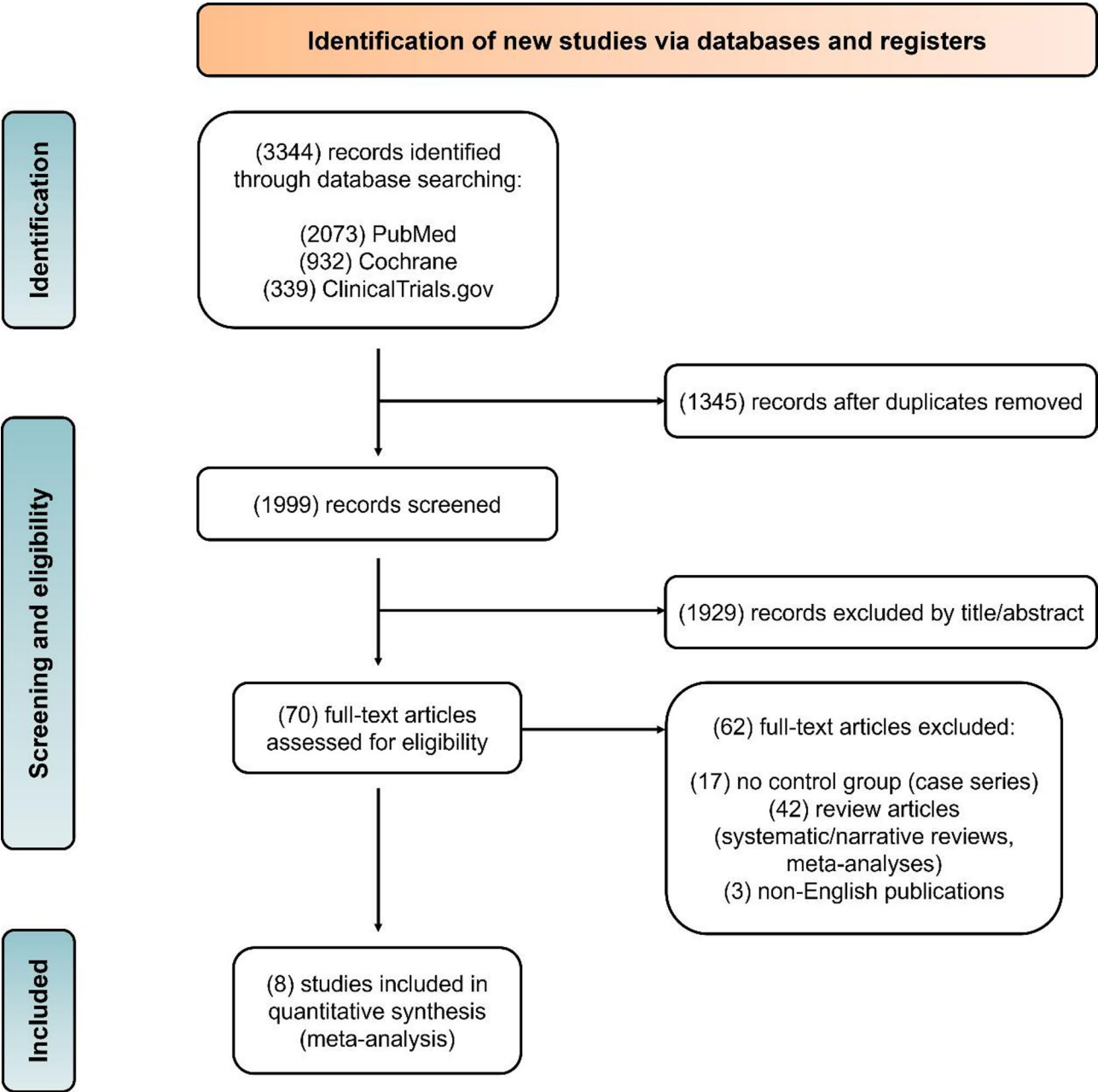


Fig. 2 Flow chart of the screening process for the database studies

outcome blinding, 25% of the studies showed a low risk of bias, 50% had uncertainties, and 25% had a high risk. Notably, all studies reported no issues with missing outcome data due to a high loss rate to follow-up or withdrawal, resulting in a 100% low loss bias risk assessment. Furthermore, all studies performed well in reporting bias, with 100% showing a low risk of reporting bias, indicating that researchers did not selectively report specific outcome measures, ensuring transparency of results. However, 12.5% of potential biases may still need to be

explicitly listed, which could stem from shortcomings in study design (Fig. S1-2).

Primary outcome: glucose level in the range of 70–180 mg/dL

Eight studies investigated the TIR between AI-driven wearables and standard care, with TIR reflecting the percentage of time glucose is in the target range in subjects (Table S2). All studies defined the range as 70–180 mg/dL, except for the study by Thabit, H., which used a target range of 5.6–10.0 mmol/L (approximately 100–180 mg/

Table 1 Characteristics of the included studies

Algorithm	Closed-loop device type	Control device type	Inter- vention duration	Study design	Sam- ple size	Type of diabetes	Study ID
DIAS USS algorithm	The t: slim X2 insulin pump with Control-IQ Technology system	Insulin pump or multiple daily injections with CGM	16 weeks	Randomized, controlled trial	102	1	Wadwa, R. P. 2023 [57]
Cambridge hybrid closed-loop algorithm	The iLet bionic pancreas system	Insulin pump or multiple daily injections with CGM	13 weeks	Multicenter randomized trial	165	1	Messer, L. H. 2022 [58]
Cambridge hybrid closed-loop algorithm	FlorenceM configuration or CamAPS FX configuration with Cambridge closed-loop algorithm running on a smartphone	Insulin pump therapy with or without sensor (standard)	6 months	Multicenter randomized controlled trial	123	1	Ware, J. 2022 [59]
Model Predictive Control (MPC) algorithm	FlorenceD2W-T2 with a model predictive control algorithm (version 0.3.65) residing on a control algorithm device (Dell Latitude 10 Tablet, Dell, TX, USA) linked by a USB cable to the CGM receiver (FreeStyle Navigator II)	Continued usual insulin and other antihyperglycemic therapy with CGM receiver (Freestyle Navigator II)	72 h	Randomized, parallel-group trial	40	2	Thabit, H. 2017 [60]
Control-IQ	The t: slim X2 insulin pump with Control-IQ Technology and a continuous glucose monitor (Dexcom G6, Dexcom)	Dexcom G6 sensors Sensor-augmented insulin pump	16 weeks	Multicenter, randomized, open-label, parallel-group trial	100	1	Breton, M. D. 2020 [61]
Zone Model Predictive Control (MPC) algorithm	Tandem t: AP insulin pump and Dexcom G6 CGM wirelessly connected to the interoperable artificial pancreas system (iAPS) running on the unlocked Google Pixel 2 smartphone	Personal pump and study Dexcom G6 CGM in the SAP/PLGS conventional therapy	2 weeks	Randomized, crossover	20	1	Deshpande, S. 2020 [62]
DBLG1 regulation algorithm	Hybrid DiabeLoop Generation 1 (DBLG1) system Cellnovo insulin patch-pump managed by the DiabeLoop application installed on an android smartphone and connected to the Dexcom G5 CGM system using Bluetooth Low Energy technology.	Sensor-assisted pump therapy Usual treatment with their pump, with a Dexcom G5 Mobile CGM system	12 weeks	Multicenter, open-label, randomized controlled crossover trial	126	1	Benhamou, P.Y. 2019 [63]
Omnipod 5 algorithm	Tubeless insulin pump (Pod) with an embedded AID algorithm (Omnipod 5), an interoperable glucose sensor (Dexcom G6), and a mobile app (Omnipod 5 app) on a locked-down Android phone.	Standard therapy (usual insulin regimen)	3-month AID phase compared with the 2-week standard therapy phase	Single-arm, multicenter, prospective clinical study	224	1	Brown, S. A. 2021 (Child) [56]
Omnipod 5 algorithm	Tubeless insulin pump (Pod) with an embedded AID algorithm (Omnipod 5), an interoperable glucose sensor (Dexcom G6), and a mobile app (Omnipod 5 app) on a locked-down Android phone.	Standard therapy (usual insulin regimen)	3-month AID phase compared with the 2-week standard therapy phase	Single-arm, multicenter, prospective clinical study	256	1	Brown, S. A. 2021 (Adult) [56]

dL) [60]. A higher proportion of time spent in the target range indicates glucose management that reduces symptoms of diabetes and helps to avoid complications. Glucose levels below 70 mg/dL can lead to acute symptoms such as dizziness, fatigue, and loss of consciousness, while persistent levels above 180 mg/dL increase the risk of long-term diabetes complications, including neuropathy,

retinopathy, and cardiovascular disease. Although DKA can occur with severe hyperglycemia, chronic exposure to elevated glucose levels primarily contributes to progressive organ damage over time. The combined results showed that compared to conventional therapy, closed-loop therapy maintained a longer duration in the target glucose range, with no high heterogeneity present but a

significant difference (SMD = 0.90, 95% CI = 0.69 to 1.10, $I^2 = 58\%$, $P < 0.001$), highlighting the greater effectiveness of closed-loop systems in glucose management (Fig. 3).

3.4 Secondary Outcomes: Glucose level > 250 mg/dL, Glucose level > 180 mg/dL, Glucose level < 70 mg/dL, and Glucose level < 54 mg/dL.

TAR > 250 mg/dL typically indicates a hyperglycemic state, which can lead to acute complications such as hyperglycemic hyperosmolar state (HHS), with symptoms including polyuria, thirst, and fatigue [64, 65]. A higher proportion of TAR indicates more time above the glucose goals. The combined results showed that for TAR, closed-loop therapy demonstrated a lower percentage of time than standard care (SMD = -0.74, 95% CI = -0.94 to -0.53, $I^2 = 60\%$, $P < 0.001$). The studies had no high heterogeneity, but significant differences were observed (Fig. 4a). TAR > 180 mg/dL is often due to postprandial hyperglycemia, and prolonged levels at this threshold increase the risk of cardiovascular disease [66–68]. The meta-analysis also showed similar results, with closed-loop therapy exhibiting a significantly lower percentage of time (SMD = -0.74, 95% CI = -0.95 to -0.52, $I^2 = 57\%$, $P < 0.001$), with no heterogeneity but significant differences, indicating statistical significance (Fig. 4b).

TBR < 70 mg/dL indicates hypoglycemic events that may lead to dizziness, palpitations, sweating, and hunger [69]. Closed-loop therapy significantly reduced the time below the target glucose range compared to conventional treatment (SMD = -0.33, 95% CI = -0.57 to -0.09, $I^2 = 71\%$, $P < 0.01$), with no high heterogeneity but significant differences observed. The combined results show less time below 70 mg/dL, indicating a more effective reduction in hypoglycemia (Fig. 4c). TBR < 54 mg/dL represents very low glucose levels, which may lead to seizures and loss of consciousness. If the person is conscious and able to swallow, rapidly absorbable carbohydrates should be administered. In cases of unconsciousness, glucagon (available in subcutaneous injectable or intra-nasal formulations) should be given. Although the combined results indicated that subjects using closed-loop therapy

spent more time below the target glucose level than those receiving standard care, this difference was not statistically significant (SMD = -0.20, 95% CI = -0.46 to 0.07, $I^2 = 77\%$, $P > 0.05$) and exhibited considerable high heterogeneity (Fig. 4d). A possible reason for this is that the studies employed a stratified approach, where the TBR < 70 mg/dL showed statistical significance but with a slightly lower effect size. Consequently, formal testing was not conducted for TBR < 54 mg/dL.

Secondary outcomes: mean glucose level and HbA1c level

To comprehensively observe the overall profile of glucose management, we also extracted average glucose data. Mean glucose level refers to the average glucose measurements over a specific period (the past few days or weeks), obtained through frequent monitoring. While the mean glucose provides an estimate of overall glycemic exposure, it does not reflect glycemic variability, SD of glucose measurements is a more appropriate indicator of fluctuations in glucose levels [70]. Elevated mean glucose level is associated with increased risk of diabetes-related complications [71]. The combined results demonstrated significantly lower mean glucose levels in the closed-loop group compared to controls (SMD = -0.58, 95% CI = -0.79 to -0.37, $I^2 = 61\%$, $P < 0.001$), with moderate heterogeneity (Fig. 5a).

HbA1c is the form of hemoglobin bound to glucose, reflecting mean glucose levels over the preceding 2–3 months [72, 73]. It serves as an essential indicator for assessing overall glycemic management, with a target typically below 7% for most subjects with diabetes to mitigate complication risks. In the included studies, HbA1c levels were measured through standard laboratory assays. An elevation of 1% in HbA1c corresponds to an approximate 28–30 mg/dL increase in mean glucose levels. While the intervention duration in this meta-analysis (up to 6 months) demonstrates short-term glycemic improvement, sustained HbA1c reduction is required for long-term risk reduction. Thus, the closed-loop therapy group produced lower HbA1c level compared to the

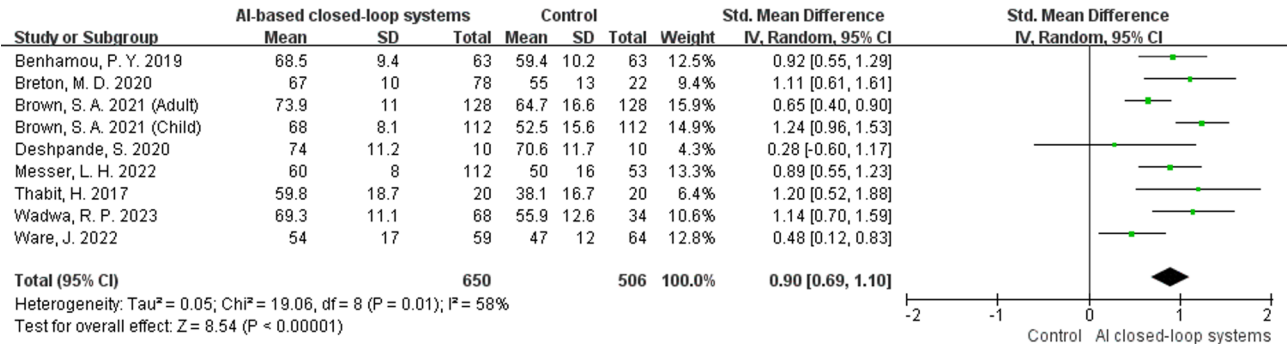


Fig. 3 Comparison of AI-based closed-loop systems and control groups in managing TIR in people with diabetes. Positive SMD indicates a higher proportion of time in the target glucose range of 70–180 mg/dL, reflecting higher attainment of this glycemic goal

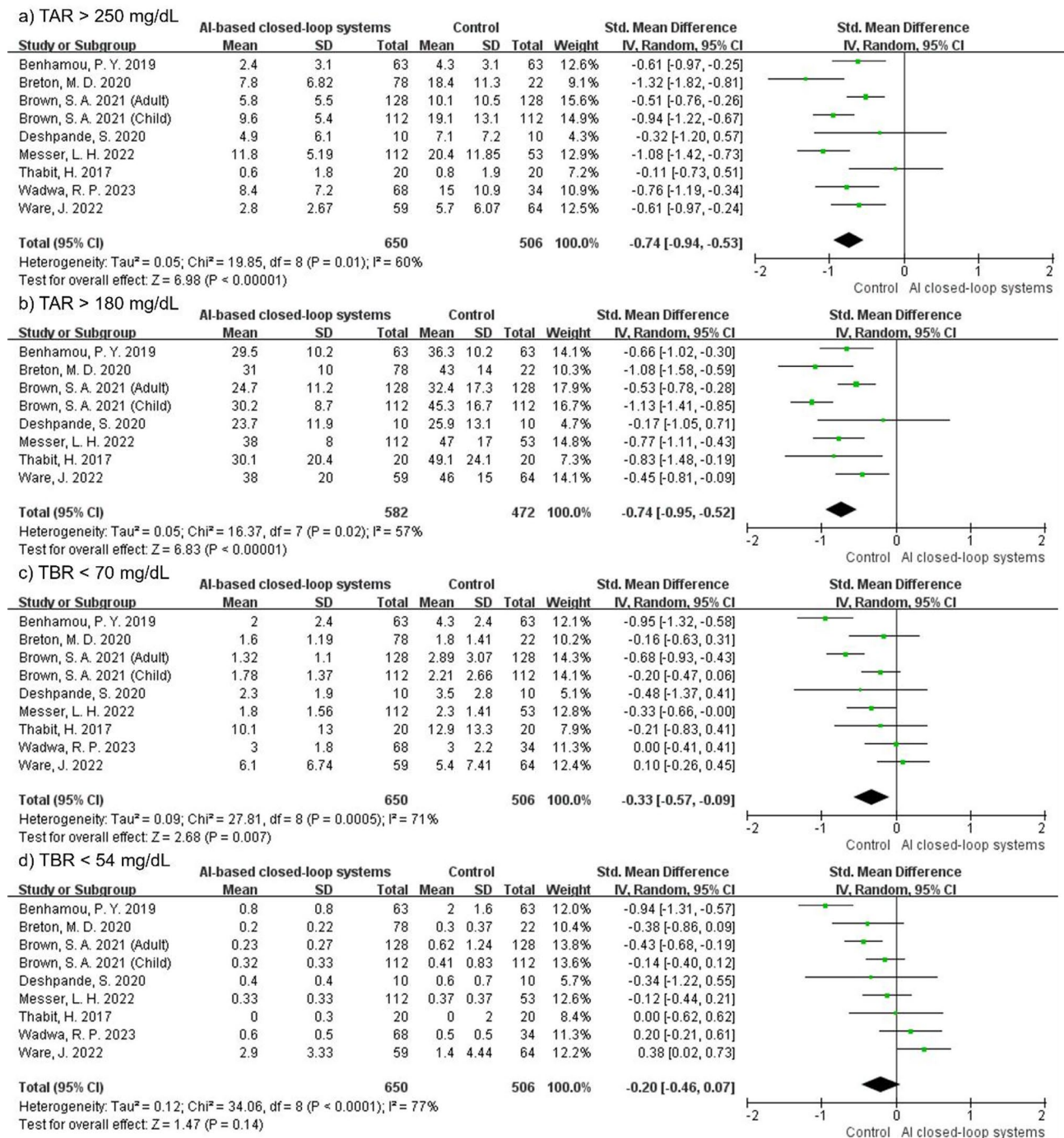


Fig. 4 Comparison of the performance of AI-based closed-loop systems versus standard care in managing people with diabetes. **(a)** Percent TAR > 250 mg/dL. **(b)** Percent TAR > 180 mg/dL. **(c)** Percent TBR < 70 mg/dL. **(d)** Percent TBR < 54 mg/dL. A negative SMD indicates that subjects in the closed-loop group spent less time in hyperglycemia or hypoglycemia than those in the standard care group

control group (SMD = -0.58, 95% CI = -0.73 to -0.43, $I^2 = 21\%$, $P < 0.001$), demonstrating improved HbA1c outcomes with AI-based closed-loop systems (Fig. 5b).

Additionally, we examined publication bias and conducted a sensitivity analysis. The funnel plot results showed a relatively symmetrical distribution of the

included studies [74], indicating a high reliability of the findings (Fig. S3-S5). This symmetry suggests that our conclusions are less likely to be affected by publication bias, enhancing confidence in the effectiveness of closed-loop systems for diabetes management.

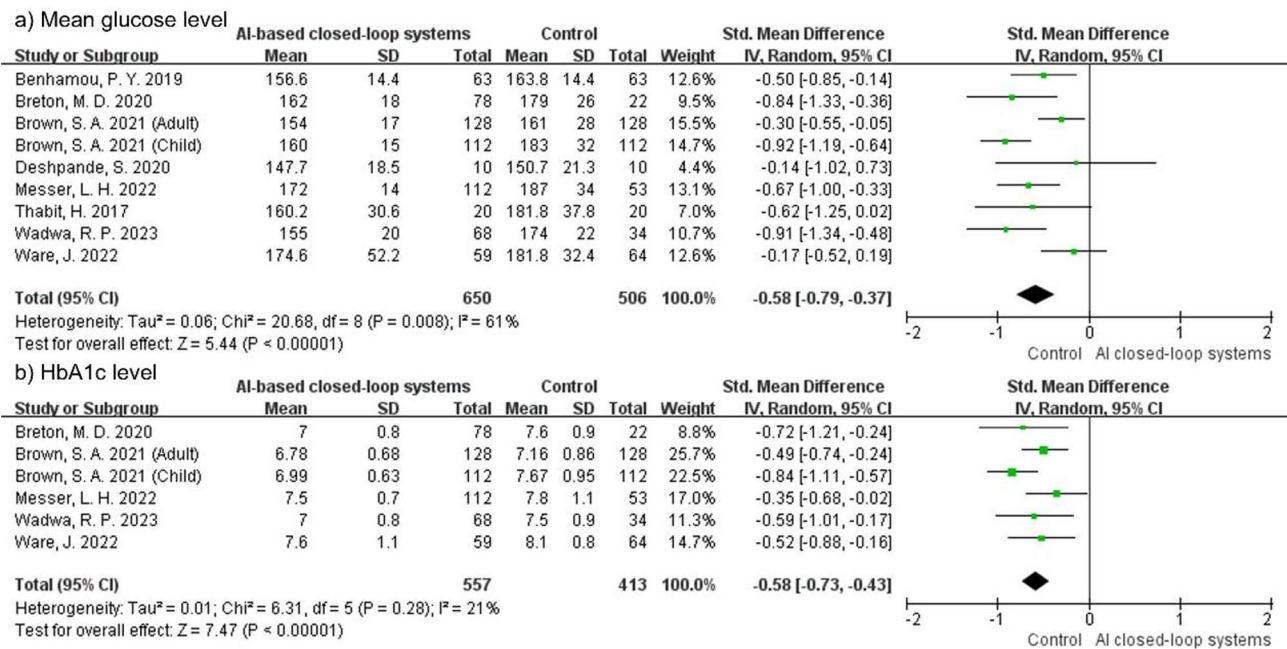


Fig. 5 Comparison of the performance of AI-based closed-loop systems versus standard care in managing people with diabetes. (a) Mean glucose level. (b) HbA1c level. A negative SMD indicates that subjects in the closed-loop group had lower mean glucose or HbA1c levels than those in the standard care group

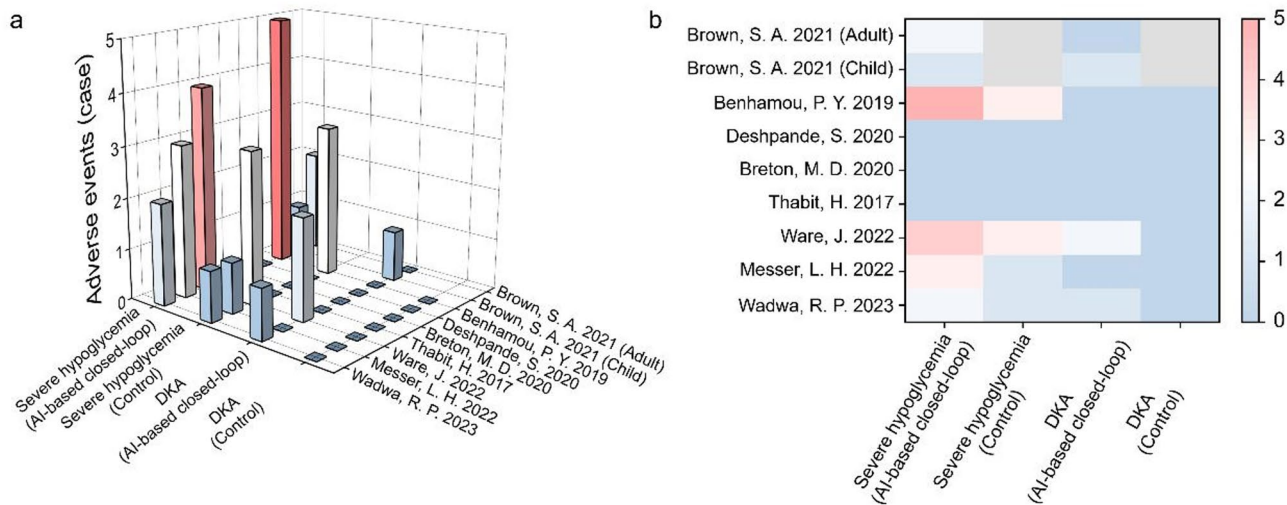


Fig. 6 (a) The incidence of severe hypoglycemia and DKA. (b) The distribution heatmap of severe hypoglycemia and DKA. This indicates a higher frequency of safety-related events with AI-based closed-loop systems compared to standard care

Safety outcomes: severe hypoglycemia and DKA

To assess treatment effects and safety of closed-loop systems versus standard care [75–77], we analyzed adverse events (severe hypoglycemia and DKA) across studies (Table S3-S4). In pooled analyses, severe hypoglycemia occurred in 17 cases (closed-loop) vs. 8 cases (control), while DKA was reported in 4 cases (closed-loop) vs. 0 cases (control) (Fig. 6a). Notably, 4 studies had unequal group sizes, which may influence incidence rates. The complete safety profile is presented in Fig. 6b, while

AI-based closed-loop systems showed greater reduction in hyperglycemia duration and HbA1c levels, the incidence of adverse events was higher.

Discussion

In this meta-analysis, we compared the effectiveness of AI-based closed-loop systems with traditional therapies in diabetes management. The primary outcomes indicated that closed-loop therapy significantly improved glucose management, with participants maintaining

glucose levels within the target range for longer durations. Secondary outcomes showed reductions in both TAR and TBR, strongly supporting the efficacy of this approach. Additionally, the closed-loop group demonstrated lower mean glucose levels and HbA1c levels compared to traditional therapy. However, our analysis revealed higher absolute counts of adverse events in closed-loop systems (severe hypoglycemia: 17 vs. 8, DKA: 4 vs. 0), though the overall rates remained low (3.2% vs. 1.6%). These observations may be influenced by: (1) larger closed-loop group sizes in four trials, (2) enhanced hypoglycemia detection sensitivity through continuous monitoring, (3) algorithm adaptation phases in AID. The DKA cases, while limited, suggest potential interactions between system parameters and subject behaviors (such as sensor failures) requiring further characterization.

To optimize the safety profile of closed-loop systems, we recommend three key implementation strategies: First, risk-stratified safety protocols could mitigate hypoglycemia risks during algorithm adaptation periods. Second, targeted subject education on DKA prevention (such as proper sensor use) may reduce system-related risks. Third, dynamic algorithm adjustments during initial treatment phases could balance glycemic management and safety, particularly for clinically diverse populations. These measures should be systematically evaluated in future trials.

Despite these positive findings, several limitations warrant consideration. Significant heterogeneity existed across studies in participant demographics, methodologies, and intervention protocols, potentially affecting result generalizability. One study failed to report adverse events in the control group [56], limiting comprehensive safety comparisons. The use of averaged glucose metrics in studies lacking HbA1c data may introduce interpretation bias. Furthermore, most studies showed high risk of performance bias due to unblinded designs, a methodological constraint inherent to comparative diabetes technology trials where blinding would require impractical 24/7 caregiver involvement and raise ethical concerns regarding safety monitoring. While our results align with previous evidence supporting closed-loop efficacy, variations in system architectures, algorithm models, and population characteristics likely contributed to outcome diversity.

Future research should focus on three priority areas: (1) development of advanced AI algorithms with improved glucose fluctuation prediction and personalized lifestyle recommendations, (2) carefully designed clinician alert systems that balance clinical benefits with healthcare provider workload considerations, (3) standardized reporting of safety outcomes across studies to facilitate robust meta-analyses. With continued technological refinements, AI-based closed-loop systems have

significant potential to enhance both clinical outcomes and quality of life for people with diabetes.

Conclusion

In summary, this meta-analysis indicates that AI-driven closed-loop systems can effectively maintain glucose levels within target ranges while demonstrating acceptable safety. Compared to traditional therapies, closed-loop systems exhibit superior glycemic management outcomes in the studied populations, primarily among subjects with T1D under clinical trial conditions. However, the evidence is predominantly derived from high-income western countries, which may not adequately represent variations in system performance or accessibility on a global scale.

Future application strategies should be stratified based on subject characteristics (such as age, type of diabetes, and socioeconomic background) to ensure equitable implementation. It is noteworthy that the included studies employed heterogeneous AI methodologies (such as model predictive control and rule-based algorithms), suggesting that system design may influence outcomes, warranting further exploration in practical applications. Recent advancements, such as the FDA-approved Omnipod 5 and iAPS systems, reinforce the efficacy of closed-loop systems in trials but also underscore the need for more real-world evidence to align with current regulatory and clinical trends. Future implementations should prioritize system adaptability, individualized monitoring, and real-world safety data to optimize efficacy.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s13098-025-01819-0>.

Supplementary Material 1

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None.

Author contributions

X.Y. supervised and planned the project. X.W. conducted the study of design, literature selection, quality assessment, and statistical analysis. J.Y.S., Y.L., and P.T. performed the literature selection and quality assessment. G.Z., X.J.W., and J.R., carried out the literature search and data collection. J.X., J.C.S., and X.Y. supervised the literature search, collected data, assessed quality, and reviewed the manuscript. X.W. and X.Y. wrote the original manuscript. All the authors discussed the analysis of the results and commented on the manuscript.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

All authors have approved this manuscript for publication. This manuscript has not been published previously and is not awaiting publication elsewhere.

Competing interests

The authors declare no competing interests.

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