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Diabetes and Technology: The Role of Artificial Intelligence, Continuous Glucose Monitors, and Insulin Pumps in Modern Care

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Abstract

The increasing global prevalence of diabetes and the substantial burden it places on individuals and healthcare systems underscore the urgent need for advanced technological solutions. This review highlights the transformative role of artificial intelligence (AI), continuous glucose monitors (CGMs), and insulin pumps in modern diabetes care, addressing gaps in accessibility, integration, and long-term efficacy. By synthesizing recent advancements and challenges, this review aims to provide a comprehensive perspective on how these technologies can revolutionize diabetes management. The review explores the precision of AI-driven algorithms in insulin dosing and glucose prediction, the benefits of CGMs in real-time glycemic monitoring, and the advancements in insulin pump technology, including hybrid closed-loop systems. It also examines the integration of these technologies into cohesive ecosystems, their impact on patient outcomes, and the disparities in access that hinder widespread adoption. Key topics include AI's role in personalized treatment, the clinical efficacy of CGMs, and the convergence of pumps and sensors for automated insulin delivery (AID). Additionally, the review addresses ethical considerations, data privacy concerns, and the psychosocial effects of technology adoption. Insights from clinical trials and real-world studies demonstrate significant improvements in glycemic control, quality of life, and patient engagement, while also identifying persistent challenges such as cost, interoperability, and user adherence. Future research should prioritize large-scale, diverse clinical trials to validate AI models and ensure equitable access to these technologies across populations. Innovations in multimodal data integration, fully AID systems, and emerging wearable technologies hold promises for further personalizing diabetes care. Collaborative efforts among clinicians, researchers, and policymakers will be essential to overcome existing barriers and fully realize the potential of AI, CGMs, and insulin pumps in transforming diabetes worldwide.

Keywords: Artificial intelligence, Continuous glucose monitors, Diabetes management, Glycemic control, Insulin pumps, Personalized medicine, Telehealth, Wearable technology

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Introduction

Research on diabetes and technology has emerged as a critical area of inquiry due to the increasing global prevalence of diabetes and the substantial burden it places on individuals and healthcare systems [1-4]. Over the past decades, diabetes management has evolved from traditional insulin injections and self-monitoring of blood glucose (type 1 diabetes (T1D) and type 2 diabetes (T2D)) to advanced digital ecosystems integrating CGMs, insulin pumps, and AI algorithms [5-8] (Table 1). These technological advancements have demonstrated improvements in glycemic control, reduction in hypoglycemia, and enhanced quality of life for patients [14, 27]. With over 463 million people affected worldwide and healthcare costs exceeding hundreds of billions annually, the integration of technology in diabetes care is both a practical necessity and a promising frontier [1, 32].

Recent literature underscores the rapid development and application of these tools in improving patient outcomes and personalizing care. AI has emerged as a transformative force in diabetes management, leveraging big data analysis to enable precise sub-typing and tailored treatment strategies [42]. Its capabilities extend to early detection of complications such as diabetic retinopathy, thereby facilitating timely interventions [42]. When combined with CGM technology, AI supports remote monitoring and the development of novel glucose metrics and algorithms, enhancing the accuracy and responsiveness of glucose control [42]. Notably, AI-driven closed-loop insulin pumps can automatically adjust insulin infusion rates, thereby increasing the time blood glucose levels remain within target ranges and reducing hypoglycemia risks [42, 43].

Technological advancements in glucose monitoring devices, particularly CGMs, have been instrumental in data-driven diabetes management [44-48]. The integration of CGMs with insulin pumps has led to the development of closed-loop systems, often referred to

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Table 1: Descriptive summary of the few selective studies reported. The reviewed studies vary in methodology, including randomized controlled trials, observational studies, and narrative reviews, with a predominant focus on T1D and emerging applications in T2D. Geographic and disciplinary diversity is evident, with contributions from clinical medicine, biomedical engineering, and computer science, reflecting the interdisciplinary nature of this field. This comparative analysis is crucial for addressing research questions related to AI efficacy, device integration, clinical outcomes, patient experiences, and ethical considerations in diabetes technology.

Algorithm performance	Clinical outcomes	Technology integration level	Patient-reported outcomes	Ethical and accessibility considerations	Ref.
Moderate AI use in insulin dosing algorithms	Improved glycemic control and reduced burden	High integration of CGM and insulin pumps	Enhanced adherence and self-management support	Discusses user choice and device accessibility	[5]
Adaptive AI algorithms with real-time insulin adjustment	Reduced hypoglycemia and improved glycemic control	Full AI-driven insulin delivery system	Positive user feedback on quality of life	Notes safety mechanisms and personalization challenges	[9]
Algorithmic insulin delivery with CGM data	Improved glycated hemoglobin (HbA1c) and quality of life in T1D	Advanced AID systems	Quality of life benefits reported	Highlights limitations in connectivity and future opportunities	[10]
AI and machine learning for glucose prediction	Clinical effectiveness of closed-loop systems	Integration of AI with CGM and insulin pumps	Improved patient engagement and self-management	Addresses privacy and ethical concerns in data use	[11]
AI supports individualized nutrition and monitoring	Benefits in glucose control and education	Use of wearable devices and internet of things (IoT) integration	Mixed patient acceptance due to cost and complexity	Discusses cost barriers and data privacy issues	[12]
AI and IoT for predictive analytics in chronic care	Enhanced glycemic control and reduced hospitalizations	Remote monitoring with AI-enabled devices	Improved patient empowerment	Highlights data security and cost challenges	[13]
AI-enhanced decision support tools	Improved HbA1c, time in range, and reduced hypoglycemia	Hybrid closed loop and CGM integration	Positive or neutral impact on self-care burden	Notes lack of diversity and equity issues	[14]
AI in pediatric diabetes technology	Improved glycemic control and reduced diabetic ketoacidosis	Automated delivery systems with CGM and pumps	Patient-centered care with telemedicine	Notes, access inequalities and burden of care	[15]
AI algorithms for glucose prediction and safety	Enhanced safety in closed-loop systems	Wearable CGM with AI-driven insulin delivery	Improved patient safety perceptions	Emphasizes algorithm optimization and security	[16]
Large sensor AI models for glucose prediction	High accuracy in glucose forecasting	Integration with CGM data	Not specifically addressed	Discusses model generalizability and robustness	[1]
RL for artificial pancreas control	Promising patient-specific glycemic control	AI-based closed-loop insulin delivery	Not detailed	Highlights need for further optimization and validation	[17]
AI for personalized diabetes diagnosis and treatment	Potential for precision medicine	Integration of multi-omics and patient data	Not specifically addressed	Ethical and data privacy considerations discussed	[18]
AI with physical activity data for insulin dosing	Improved glucose prediction accuracy	Cloud-based CGM and activity integration	Positive user feedback	Notes scalability and data security	[19]
AI for therapy personalization and algorithm optimization	Enhanced individualized treatment outcomes	AI-driven insulin pump and CGM integration	Not specifically addressed	Identifies gaps in multimodal data and interpretability	[20]
AI biosensors for CGM calibration and control	Improved glucose prediction and closed-loop control	AI-enhanced CGM biosensors	Not detailed	Discusses challenges in AI implementation	[21]
AI-driven neuroevolution for insulin dosing	Reduced glucose variability and injections	AI-guided insulin pump control	Improved quality of life	Emphasizes ease of adoption and interface design	[22]
AI-enabled closed-loop systems for T1D	Improved glycemic control and reduced hypoglycemia	Hybrid closed loop and CGM integration	Positive patient satisfaction	Notes, data privacy and long-term use challenges	[23]
AI-based dietary management with CGM	HbA1c reduction in T2D patients	Digital platform integrating CGM and AI	Enhanced self-management support	Addresses app usage and engagement issues	[24]
AI prediction for insulin dosing in pumps	Effective hypoglycemia and hyperglycemia avoidance	Integration of AI with insulin pump and CGM	Patient notifications and data sharing	Not specifically addressed	[25]
Deep learning for glucose prediction with IoT	High prediction accuracy with cloud computing	Wearable CGM is integrated with cloud AI	Not detailed	Discusses technological feasibility and accuracy	[26]
Clinical guidelines based on recent AI and CGM studies	Supports CGM and AID	High integration recommended in guidelines	Not detailed	Notes guideline-driven accessibility improvements	[27]
Review of AID systems	Proven safety and efficacy in trials	Algorithm-driven pump and CGM integration	User knowledge critical for success	Addresses regulatory and access challenges	[28]
Role of pharmacists in diabetes technology	CGM reduces HbA1c and hypoglycemia	Use of RT-CGM and insulin pumps	Improved patient education and satisfaction	Emphasizes pharmacist involvement and training	[29]
AI decision support with CGM sensors	Personalized insulin bolus and glucose prediction	Integration of AI with CGM data	Not detailed	Discusses AI potential in advanced management	[30]
AI models for basal insulin estimation	Random forest models highly accurate	AI integrated with insulin pump data	Not detailed	Notes need for validation in diverse populations	[31]
Wearable glucose sensors and implantable delivery	Emerging closed-loop wearable and implantable systems	Integration of sensors with drug delivery	Not detailed	Highlights unmet challenges and future directions	[32]
Evolution of insulin pumps	Advances in pump technology and integration	From continuous subcutaneous insulin infusion to hybrid closed-loop systems	Not detailed	Calls for further research into artificial pancreas	[33]
Review of artificial pancreas systems	Improved glycemic control and reduced distress	Hybrid and fully closed-loop systems	Better physiological and psychosocial outcomes	Discusses access and adoption barriers	[34]
AI in diabetes care continuum	Personalized treatment and complication prediction	AI-enhanced screening and management	Empowers patients and providers	Addresses bias, ethics, and equitable deployment	[35]
AI trends in diabetes care	Predictive analytics and personalized regimens	Integration with other technologies	Emphasizes patient empowerment	Discusses regulatory and ethical frameworks	[36]

AI enhancing prevention and management	AI impacts multiple diabetes care domains	AI integrated with health monitoring systems	Improves patient engagement and outcomes	Highlights need for data security and collaboration	[2]
AI and wearables for diabetic foot ulcer	Predictive analytics and real-time monitoring	Wearables integrated with AI for prevention	Personalized care and patient participation	Notes adherence and socioeconomic barriers	[37]
Pediatric study on pumps and CGM	CGM lowers HbA1c; pumps less impact	Moderate integration of devices	No difference in acute complications	Highlights disparities in device use	[38]
Digital health in India	Adoption of CGM, pumps, and apps	Growing integration in Indian healthcare	Challenges in acceptance and training	Addresses digital divide and policy needs	[39]
Review of mobile apps and devices	Mobile tech aids insulin dosing and monitoring	CGM and pump therapy reviewed	Enhance patient self-care	Notes challenges in technology adoption	[40]
Review of DIY artificial pancreas systems	Open-source AI algorithms for insulin delivery	Integration of CGM, pumps, and smartphones	Improved time in range and quality of life	Regulatory and safety concerns highlighted	[41]

as artificial pancreas systems, which automate insulin delivery based on real-time glucose readings [5, 49]. These systems exemplify the convergence of sensor technology and AID, representing a significant leap toward personalized and autonomous diabetes care [5, 49]. Insulin pumps themselves have seen innovations aimed at enhancing their functionality and user understanding. Efforts to demystify pump mechanics and control principles through cost-effective, modular platforms aim to improve clinician and patient familiarity with these devices [50]. Additionally, the connectivity between insulin pumps and CGMs, although promising, faces current limitations that hinder seamless integration [10]. Despite these challenges, the potential for AID systems to revolutionize care remains substantial, with ongoing research focusing on overcoming connectivity barriers [10, 51].

The role of telehealth and smart devices further complements these technological advances [52-55]. Telehealth platforms incorporate devices such as glucose meters, CGMs, insulin pumps, and smartphones to facilitate remote monitoring and management [56]. This integration supports continuous oversight and timely adjustments, aligning with the broader trend toward digital and personalized diabetes care [49]. Overall, the literature highlights a trajectory toward increasingly automated, data-driven, and personalized diabetes management systems. AI enhances diagnostic and treatment precision, while innovations in CGMs and insulin pumps-particularly their integration into closed-loop systems—are central to this evolution. Despite existing challenges, these technological advancements collectively aim to improve glycemic control, reduce complications, and enhance quality of life for individuals with diabetes [5, 42, 49, 51].

Diabetes management has undergone a significant transformation in recent years, largely due to advancements in technology. The integration of AI, CGMs, and insulin pumps has revolutionized the way healthcare providers and patients manage diabetes. This article explores the role of these technologies in modern diabetes care, highlighting their benefits, challenges, and implications for patient outcomes.

AI in Diabetes Management

AI is increasingly being utilized in diabetes care to enhance decision-making and improve patient outcomes [57-60]. AI algorithms can analyze vast amounts of data from electronic medical records and glucose monitoring systems to identify patterns and predict future glucose levels. This capability allows for personalized treatment plans that can adapt to individual patient needs, potentially improving glycemic control and reducing the risk of complications associated with diabetes [42, 61]. AI-driven systems can also assist in the management of diabetes by providing real-time feedback and recommendations for insulin dosing. For instance, AID systems that incorporate AI can adjust insulin delivery based on CGM readings, thereby optimizing blood glucose levels and minimizing the risk of hypoglycemia [42, 62]. However, challenges such as data privacy concern and the need for clinical validation of AI algorithms remain significant barriers to widespread adoption [42].

AI in diabetes diagnosis and prediction

- AI models, particularly machine learning and deep learning techniques, have demonstrated high accuracy in diagnosing diabetes and predicting its onset. Techniques such as support vector machines, random forests, and convolutional neural networks are effective in analyzing medical data for early detection of diabetes [63, 64].
- Ensemble learning methods, like Gradient Boosting, have been identified as superior in predictive performance, providing reliable risk assessments for diabetes [64].
- AI's ability to process large datasets and identify patterns aids in the development of predictive models that can forecast diabetes complications, thereby facilitating timely interventions [2].

Personalized diabetes management

- AI-driven systems are capable of tailoring treatment plans to individual patient needs, optimizing medication dosages, and providing personalized dietary recommendations. For instance, the Nutrition Diet Expert System uses AI to offer dietary advice with high accuracy, supporting stable blood glucose levels [65].
- AI applications in wearable devices and mobile health apps enhance real-time monitoring and glycemic control, bridging the gap between technological advancements and practical healthcare solutions [2, 64].

Enhancing patient engagement and self-management

- AI technologies empower patients by providing tools for self-management and engagement. These include AI-enhanced glucose monitoring systems that offer predictive insights into blood sugar fluctuations, helping patients manage their condition more effectively [66].
- Social media and internet forums, supported by AI, increase patient participation in diabetes care, fostering a community-driven approach to disease management [67].

While AI holds significant promise in revolutionizing diabetes management, it is crucial to address the challenges associated with its implementation. Continued research, interdisciplinary collaboration, and a focus on patient-centered solutions are necessary to harness AI's full potential in diabetes care. Additionally, regulatory frameworks and education for healthcare professionals are vital to ensure the responsible and effective use of AI technologies in managing this global health challenge.

CGMs

CGMs have become a cornerstone of diabetes management, particularly for individuals with T1D. CGMs provide real-time data on glucose levels, allowing patients to make informed decisions about their insulin use and dietary choices. Studies have shown that the use of CGMs is associated with improved glycemic control, as evidenced by lower HbA1c levels [68]. The integration of CGMs with insulin pumps has led to the development of hybrid closed-loop systems, which automate insulin delivery based on CGM data. These systems have demonstrated efficacy in maintaining glucose levels within the target range, thereby reducing the burden of diabetes management on patients [69]. However, disparities in access to CGMs persist, particularly among racial and ethnic minorities, highlighting the need for targeted interventions to ensure equitable access to diabetes technology [70].

Benefits

- Improved glycemic control: CGMs have been shown to significantly reduce HbA1c levels, with studies reporting an average decrease of 0.85% in diverse patient cohorts [71]. They also help in maintaining time in range, a critical parameter for diabetes management, by providing continuous data on glucose levels [72].

- Enhanced self-management: Patients using CGMs report improved self-care and a better understanding of how lifestyle choices affect glucose levels. This real-time feedback encourages dietary improvements and stress management, which are crucial for glycemic control [73, 74].

- Quality of life improvements: CGMs offer convenience and peace of mind by reducing the need for frequent fingerstick tests and allowing early responses to glucose fluctuations. This can lead to a better quality of life and increased social participation for patients [73, 74].

Technological advancements and usage

- Device variants: There are different types of CGMs, including real-time and intermittently scanned monitors. These devices have evolved to become more user-friendly and accurate, with major brands like Medtronic, Dexcom, and freestyle leading the market [72, 75].

- Integration with insulin pumps: CGMs are particularly effective when integrated with insulin pump systems, allowing for AID based on glucose trends. This integration is especially beneficial for adults, although challenges remain in pediatric applications [76].

Challenges and barriers

- Cost and accessibility: The high cost of CGMs and limited insurance coverage pose significant barriers to widespread adoption, particularly in low-resource settings [73, 74, 77].

- Technical and logistical issues: Users often face challenges related to device complexity, data management, and occasional inaccuracies in reading. These issues can be overwhelming and may deter consistent use [74, 77].

- Regulatory and systemic barriers: The deployment of CGMs, especially in hospital settings, is hindered by regulatory, logistical, and staffing challenges. Addressing these barriers is crucial for optimizing CGM usage [77].

While CGMs offer numerous benefits in diabetes management, they are not without challenges. The cost and complexity of these devices can limit their accessibility and usability, particularly in resource-constrained environments. Moreover, while CGMs provide valuable data, the need for proper interpretation and integration into treatment plans remains critical. Future research and policy efforts should focus on making CGMs more affordable and user-friendly, as well as on improving healthcare provider training to maximize the potential of this technology in diabetes care.

Insulin Pumps

Insulin pumps have revolutionized insulin delivery for individuals with diabetes, providing a more flexible and precise method of managing blood glucose levels. These devices can deliver both basal and bolus insulin, allowing for better control of blood sugar fluctuations throughout the day. Recent advancements in insulin pump technology, including AID systems, have further enhanced their effectiveness [62, 78]. Research indicates that the use of insulin pumps, particularly when combined with CGMs, can lead to significant improvements in glycemic control and quality of life for patients with diabetes [68, 79]. However, challenges such as the cost of these devices and the need for proper training and education on their use remain critical issues that must be addressed to maximize their benefits [80].

Benefits

- Improved glycemic control: Insulin pumps deliver insulin in a manner that closely resembles the body's natural insulin production, which can lead to better glycemic control and reduced HbA1c levels. This is particularly beneficial for patients transitioning from multiple daily injections to pump therapy, as it reduces hyperglycemic events and the risk of hypoglycemia [81, 82].

- Enhanced quality of life: The use of insulin pumps allows for greater flexibility in lifestyle, including meal timing and physical activity, which can significantly improve the quality of life for patients. The reduced need for frequent injections and the ability to adjust insulin delivery based on real-time glucose readings contribute to this improvement [83].

- Convenience and flexibility: Insulin pumps offer a programmable and physiological method of insulin delivery, which is more convenient and lifestyle friendly. This flexibility is particularly advantageous for patients with variable daily routines and dietary habits [84].

Technological advancements

- Integration with CGM: The combination of insulin pumps with CGM systems allows for sensor-augmented pump therapy, which can further reduce HbA1c levels and the incidence of hypoglycemia. This integration represents a significant advancement in diabetes management technology [81, 85].

- AID: Advances in pump technology have led to the development of systems that can automatically adjust insulin delivery based on glucose sensor readings, moving closer to an artificial pancreas. These systems aim to provide a more natural state of glucose control [86].

- Diverse pump designs: Insulin pumps are available in various designs, including traditional pumps with tubing and tubeless patch pumps, offering patients options that best suit their preferences and lifestyle needs [83, 87].

Considerations and challenges

- Patient education and support: Successful insulin pump therapy requires comprehensive education and support from healthcare professionals. Patients must be knowledgeable and motivated to manage their therapy effectively, and regular updates and education are essential for safe practice [85, 87].

- Individualized assessment: The decision to use an insulin pump should be based on an individualized assessment of the patient's needs and lifestyle. This is particularly important for patients with T2D, where pump use is less common but can still be beneficial [85].

While insulin pumps offer numerous benefits, it is important to consider the challenges and limitations associated with their use. Not all patients may be suitable candidates for pump therapy, and the initial cost and complexity of managing the device can be barriers. Additionally, while observational studies have shown improvements in glycemic control, randomized controlled trials have not consistently demonstrated substantial reductions in HbA1c, highlighting the need for further research to optimize pump therapy outcomes [82].

Clinical Trials and Case Studies

The integration of technology in diabetes care, particularly through AI, CGMs, and insulin pumps, has significantly transformed the management of diabetes, especially T1D. These technologies have been shown to improve glycemic control, reduce the risk of hypoglycemia, and enhance the quality of life for patients. Randomized controlled trials have provided evidence supporting the efficacy and safety of these technologies, highlighting their role in modern diabetes care.

A randomized controlled trial (NCT05081011) study by Nayak et al. [88] investigated the effectiveness of a voice-based conversational AI (VBAI) application for managing basal insulin titration in patients with T2D, comparing it against standard of care. Participants using the VBAI application achieved their optimal insulin dose significantly faster than those receiving standard care. The median time for the VBAI group was 15 days (interquartile range (IQR) 6 to 27 days), while for the standard of care group, it exceeded 56 days (IQR >29.5 to >56 days). This difference was statistically significant ($p = 0.006$). Fewer than half of the standard of care participants achieved optimal insulin dosing within 8 weeks. The VBAI group demonstrated better insulin adherence, with a mean (standard deviation (SD)) of 82.9% (20.6%) compared to 50.2% (43.0%) in the standard of care group. This resulted in a significant difference of 32.7% (95% confidence interval (CI): 8.0% to 57.4%; $p = 0.01$). A higher proportion of participants in the VBAI group achieved glycemic control (fasting blood glucose (FBG) level <130 mg/dL) by 8 weeks, with 81.3% (13 of 16 participants) reaching this goal, compared to 25.0% (4 of 16 participants) in the standard of care group. This difference of 56.3% (95% CI: 21.4% to 91.1%) was highly significant ($p = 0.005$). Glycemic improvement, measured by the change in mean FBG level, also showed a significant difference. The VBAI group experienced a mean decrease of 45.9 (45.9) mg/dL (95% CI: −70.4 to −21.5 mg/dL), whereas the standard of care group had a mean increase of 23.0 (54.7) mg/dL (95% CI: −8.6 to 54.6 mg/dL). The overall difference between groups was -68.9 mg/dL (95% CI: −107.1 to −30.7 mg/dL; $p = 0.001$). There was a significant difference in the change in composite survey scores measuring diabetes-related emotional distress. The VBAI group's scores decreased by 1.9 points, while the standard of care group's scores increased by 1.7 points, leading to a difference of -3.6 points (95% CI, −6.8 to −0.4 points; $p = 0.03$). The VBAI group had a mean (SD) of 7.3 (4.2) automated insulin dose adjustments, significantly more than the 1.6 (3.2) adjustments in the standard of care group. Participants in the VBAI group logged data on 50 of the 56 days they were followed up (89.3%). There were no adverse events requiring clinician intervention or participant withdrawal. All 11 episodes of nonsevere hypoglycemia in the VBAI group were autonomously handled by the AI with insulin dose reductions. In summary, the randomized clinical trial demonstrated that a VBAI application significantly improved basal insulin dose optimization, insulin adherence, glycemic control, and reduced diabetes-related emotional distress in adults with T2D compared to standard of care. These findings suggest that such digital health solutions can be highly effective for medication titration and patient engagement.

A study (NCT05409391) by Wang et al. [89] presents the results of a proof-of-concept trial and evaluations of an AI-based reinforcement learning (RL) framework, called RL-based dynamic insulin titration regimen for T2D (RL-DITR), designed for personalized insulin titration in patients with T2D. RL-DITR achieved superior insulin titration optimization with a mean absolute error (MAE) of 1.10 ± 0.03 U. This performance was better than other deep learning models and standard clinical methods. The AI model was able to accurately predict patient glucose trajectories, with predicted glucose values closely following actual trends in both internal and external test sets. The model's accuracy improved with more information input over time. The AI model demonstrated good performance in predicting 'within target range' for glucose values, achieving an area under the curve of 0.830 for preprandial and 0.808 for postprandial blood glucose values in the internal test set. The patient model's evaluation was highly correlated with clinical outcomes, indicating its utility as an interaction environment for the RL model. In retrospective studies, RL-DITR showed better performance in glycemic control compared to junior and intermediate-level physicians, with an MAE of 1.18 ± 0.09 U. While slightly inferior to senior physicians in terms of MAE (0.95 U), the AI system's overall treatment regimen acceptability, hyperglycemia, and hypoglycemia control were superior to junior physicians and similar to experienced physicians. A blinded review indicated that the AI model's performance in glycemic control was better than junior and intermediate-level physicians. The perceived effectiveness, safety, and acceptability of the AI model were higher than junior and intermediate physician groups and slightly lower than senior physician groups. The percentage of 'clinical agreement' (same direction, dose difference ≤20%) with the AI model was 81.42%, which was higher than junior physicians and slightly lower than senior physicians (Figure 1). In a single-arm, patient-blinded proof-of-concept feasibility trial involving 16 T2D patients, the mean daily capillary blood glucose significantly decreased from 11.1 (±3.6) mmol/L to 8.6 (±2.4) mmol/L ($p < 0.01$), meeting the pre-specified endpoint. The percentage of glucose concentration in TIR (3.9 to 10.0 mmol/L) consistently improved, from 61.4% in the first 24 h to 85.5% in the last 24 hours ($p = 0.03$). Time spent above 13.9 mmol/L decreased from 10.6% to 0.9%, and time spent above 10.0 mmol/L decreased from 37.5% to 13.6%. No episodes of severe hypoglycemia or hyperglycemia with ketosis occurred during the trial. Physicians reported high satisfaction with the AI system, finding its interface understandable (4.57/5.00), timesaving (4.50/5.00), effective (4.00/5.00), and safe (4.29/5.00) in routine clinical practice, with an overall satisfaction score of 4.14/5.00. The AI regimen adoption rate increased from 70% at initial review to 77.5% at retest, indicating growing trust and adoption by physicians. Overall, the results indicate that the RL-DITR system is a promising and feasible tool for optimizing glycemic control in hospitalized T2D patients, demonstrating superior performance in insulin titration and positive clinical outcomes, while also gaining physician acceptance and trust over time. These preliminary findings support further investigation in larger, more diverse clinical studies.

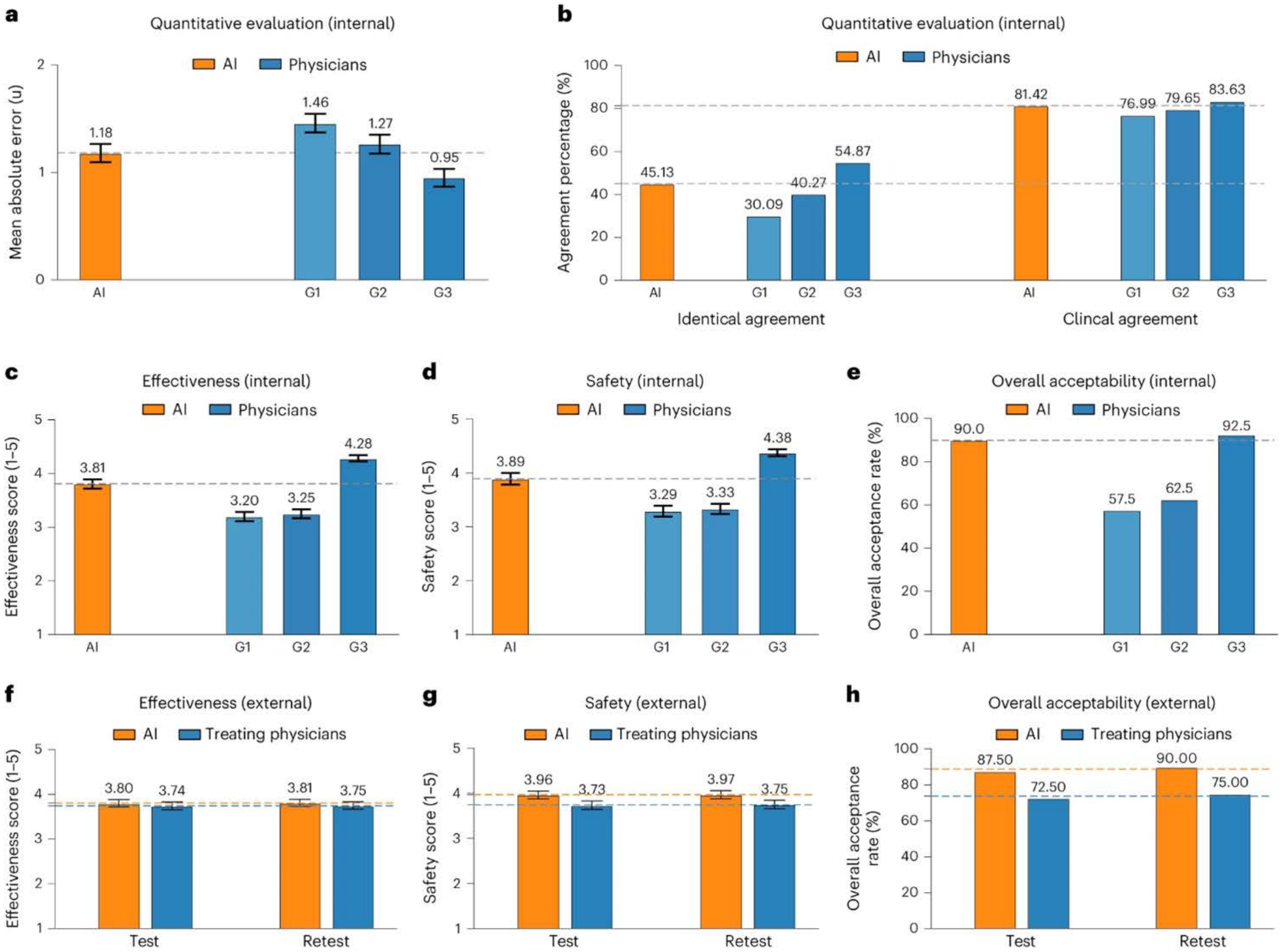

Figure 1: Performance evaluation between the AI model and human physicians in retrospective studies. **(a-e)** Comparison of AI and physician performance in insulin titration (internal cohort, n = 40 T2D patients). The AI model's insulin titration regimens were evaluated against those of three physician groups with varying experience levels: junior (n = 5), intermediate (n = 5), and senior (n = 5) physicians. **(a-b)** Quantitative assessment (expert consensus reference, n = 226 insulin data points). **(a)** MAE in dosage predictions for AI and physicians. **(b)** Agreement in dosage adjustments, measured by identical agreement (same direction and dosage) and clinical agreement (same direction, ≤20% dose difference). **(c-e)** Qualitative expert panel evaluation (n = 40 regimens). Clinical performance was assessed for effectiveness **(c)**, safety **(d)**, and overall acceptability **(e)**. **(f-h)** External cohort test–retest comparison (n = 40 regimens). Expert panel review compared AI-generated regimens with prior physician-prescribed regimens in effectiveness **(f)**, safety **(g)**, and overall acceptability **(h)**. The orange dashed line indicates AI's average performance, while the blue line represents physicians' average performance [89].

A study by Nimri et al. [90] compared insulin dose adjustments recommended by multinational physicians and an automated decision support system (ED-DSS) for individuals with T1D using multiple daily injections. The proportion of agreement and disagreement in the direction of insulin dose adjustment among physicians was statistically non-inferior to that observed between the ED-DSS and physicians. This non-inferiority was observed for basal rate, carbohydrate-to-insulin ratio, and correction factor. The statistical significance for agreement and disagreement across these three parameters was $p < 0.001$ and $p \leq 0.004$, respectively. The ED-DSS consistently proposed a lower magnitude of insulin dose change compared to the physicians. In summary, the study concluded that the recommendations for insulin dose adjustments made by the automated ED-DSS did not significantly differ from those given by expert physicians concerning the direction of change, although the magnitude of change was generally lower than the ED-DSS. These results suggest the potential utility of ED-DSS as a clinical tool for managing insulin titration and adjustments.

A randomized clinical trial (NCT03566693) study by Martens et al. [91] investigated the effectiveness of CGM compared to traditional blood glucose meter (BGM) monitoring in adults with T2D treated with basal insulin without prandial insulin. The mean HbA1c level in the CGM group decreased from 9.1% at baseline to 8.0% in 8 months. In the BGM group, the mean HbA1c level decreased from 9.0% at baseline to 8.4% in 8 months. The adjusted difference between the groups was −0.4% (95% CI: −0.8% to −0.1%), with a $p = 0.02$, indicating a statistically significant lower HbA1c level in the CGM group. The mean percentage of CGM measured time in the target glucose range (70 to 180 mg/dL) was 59% for the CGM group vs 43% for the BGM group. The adjusted difference was 15% (95% CI: 8% to 23%), with $p < 0.001$, showing significantly more time in range for the CGM group. The mean percentage of time with glucose levels exceeding 250 mg/dL was 11% for the CGM group compared to 22% for the BGM group. The adjusted difference was −11% (95% CI: −16% to −7%), with $p < 0.001$, indicating less time in hyperglycemia for the CGM group. The mean glucose level was 172 mg/dL for the CGM group vs 192 mg/dL for the BGM group. The adjusted difference was −20 mg/dL (95% CI: −29 to −11 mg/dL), with $p < 0.001$, demonstrating a significantly lower mean glucose level in the CGM group. Out of 175 randomized participants, 165 (94%) completed the trial. The mean age of participants was 57 years (SD, 9 years), with 88 women (50%) and 92 racial/ethnic minority individuals (53%). The mean baseline HbA1c level was 9.1% (SD, 0.9%). In conclusion, the study found that CGM significantly improved glycemic control, as evidenced by lower HbA1c levels and better time in target glucose range, in adults with poorly controlled T2D using basal insulin without prandial insulin, compared to traditional BGM monitoring.

A randomized clinical trial (NCT03877068) study by Spanakis et al. [92] evaluated the efficacy and safety of CGM in guiding insulin therapy for hospitalized patients with diabetes, comparing it to standard point-of-care glucose testing. The study included 185 general medicine and surgery patients with T1D and T2D receiving a basal-bolus insulin regimen. The study found no significant differences in time in range (70 to 180 mg/dL) between the CGM-guided group (54.51% ± 27.72) and the point-of-care group (48.64% ± 24.25; p = 0.14). Similarly, mean daily glucose levels were comparable: 183.2 ± 40 mg/dL for CGM and 186.8 ± 39 mg/dL for point-of-care (p = 0.36). There were also no significant differences in the percentage of patients with CGM values below 70 mg/dL (36% vs 39%; p = 0.68) or below 54 mg/dL (14% vs 24%; p = 0.12) between the two groups. Non-statistically significant reductions were observed in time below range for <70 mg/dL and <54 mg/dL in the CGM group compared to the point-of-care group. Among patients who experienced at least one hypoglycemic event, the CGM group showed a significant reduction in hypoglycemia reoccurrence (1.80 ± 1.54 events/patient) compared to the point-of-care group (2.94 ± 2.76 events/patient; p = 0.03). This reduction was also reflected in a lower percentage of time below range <70 mg/dL (1.89% ± 3.27 vs 5.47% ± 8.49; p = 0.02). The incidence rate ratio for inpatient hypoglycemia <70 mg/dL was estimated at 0.53 (95% CI: 0.31 to 0.92). The CGM group also experienced less nocturnal recurrent hypoglycemic events <70 mg/dL (1.21 ± 0.43 vs 1.93 ± 0.92 events/patient; P = 0.02) and a lower percentage of nocturnal time below range <70 mg/dL (1.30% ± 1.71 vs 4.27% ± 5.15; P = 0.004) compared to the point-of-care group. For hypoglycemia <54 mg/dL, real time-CGM (RT-CGM) intervention led to less frequent hypoglycemic events, with an estimated incidence rate ratio of 0.37 (95% CI: 0.17 to 0.83). There were no significant differences in glycemic variability between the point-of-care and CGM groups. The study found no statistically significant difference in the entire hospital length of stay between the CGM and point-of-care groups (median 8.0 days for both; p = 0.79). Additionally, there were no significant differences in hospital-related complications, mortality, or adverse events related to sensor insertion between the groups. Minor bleeding and sensor applicator malfunctions were observed in a small number of participants in both groups. In summary, the inpatient use of real-time Dexcom G6 CGM is both safe and effective for guiding insulin therapy. While it resulted in similar overall glycemic control and time in range compared to point-of-care guided adjustment, a significant benefit was observed in the reduction of recurrent hypoglycemic events, particularly during nocturnal hours. This suggests that CGM can be a valuable tool for managing insulin in hospitalized patients with diabetes, especially in preventing repeated hypoglycemic episodes.

Comparing continuous with flash glucose monitoring in adults with T1D (ALERTT1) trial (NCT03772600) study by Visser et al. [93] investigated the sustained impact of switching from intermittently scanned CGM (IS-CGM) to RT-CGM in adults with T1D. The study's key findings highlight improvements across several critical metrics, sustained over a 24-month period. Participants in the trial were, on average, 42.9 years old. The mean HbA1c at the start of the study was 7.4%. A minority of participants (n = 49) used an insulin pump. A minority of participants (n = 44) reported being hypo unaware. Time in range increased significantly from 51.8% to 63.5% on month 12, showing an increase of 11.7% (95% CI: 9.6 to 13.8; p < 0.0001). This improvement remained stable up to month 24, with a sustained increase of 11.7% (95% CI: 9.4 to 14.0; p < 0.0001). Time in range increased from 52.5% to 63.0% on month 12, an increase of 10.6% (95% CI: 8.4 to 12.8; p < 0.0001). The increase remained stable up to month 24, at 10.5% (95% CI: 8.2 to 12.8; p < 0.0001). HbA1c decreased to 6.9% in month 24, representing a reduction of −0.54% (p < 0.0001) (Figure 2). HbA1c decreased to 7.0% on month 24, representing a reduction of −0.43% (p < 0.0001). Former IS-CGM group, Hypoglycemia Fear Survey Worry score decreased by −2.67 points (p = 0.0008). Former RT-CGM group, Hypoglycemia Fear Survey Worry score decreased by −5.17 points (p < 0.0001). No significant reduction in time <54 mg/dL was observed after month 12 in either group. Former IS-CGM group, the percentage of people achieving the time in range consensus target increased from 14.9% to 37.8% (p < 0.0001). Former RT-CGM group, the percentage of people achieving the time in range consensus target increased from 13.4% to 41.4% (p < 0001). In summary, the ALERTT1 trial demonstrated that switching from IS-CGM to RT-CGM provides sustained benefits over 24 months for adults with T1D, including significant improvements in time in range, HbA1c, and reduced fear of hypoglycemia, reinforcing the superiority of RT-CGM with alerts over IS-CGM without alerts.

A study by Bergenstal et al. [94] compared the effectiveness of structured self-monitored BGM and RT-CGM in optimizing glucose control in individuals with T2D. Both CGM and BGM groups showed significant reductions in A1c levels. The CGM group (n = 59) experienced a decrease from 8.19% to 7.07%, representing a 1.12% difference. The BGM group (n = 55) saw a decrease from 7.85% to 7.03%, a 0.82% difference (p <0.001). This indicates that consistent use of glucose data, regardless of the device, leads to improvements in A1c control in T2D. Both BGM and CGM groups demonstrated significant improvements in time in range and glucose variability. There was no significant difference observed between the two groups regarding these metrics. Clinically important hypoglycemia (defined as <50 mg/dL) was significantly reduced in the CGM group compared to the BGM group (p < 0.01). This benefit was particularly notable in subjects' receiving insulin or other therapies associated with a higher risk of hypoglycemia, such as sulfonylurea. CGM proved more effective than BGM in minimizing hypoglycemia, especially for those on higher hypoglycemic risk therapies. In summary, while both structured BGM and RT-CGM effectively improved A1c control, time in range, and glucose variability in T2D patients, CGM demonstrated a superior ability to minimize clinically significant hypoglycemia, particularly for individuals on higher-risk medications.

A REACT project (ISRCTN12793535) by Beardsall et al. [95], which included a feasibility study, a multicenter randomized controlled trial, and a pilot of 'closed loop' CGM, yielded several significant results regarding glucose control in extremely preterm infants. Infants in the CGM group showed a 9% higher mean percentage of time with sensor glucose levels within the target range of 2.6 to 10 mmol/L (95% CI: 3% to 14%; p = 0.002). The amount spent on the tighter target range of 4 to 8 mmol/L was 12% higher in the CGM group (95% CI: 4% to 19%; p = 0.004). There was no observed difference in the number of episodes of hypoglycemia between the groups. Exploratory outcomes indicated a reduced risk of necrotizing enterocolitis in the intervention arm, with an odds ratio of 0.33 (95% CI: 0.13 to 0.78; p = 0.01). The health economic analyses demonstrated that CGM was cost-effective when

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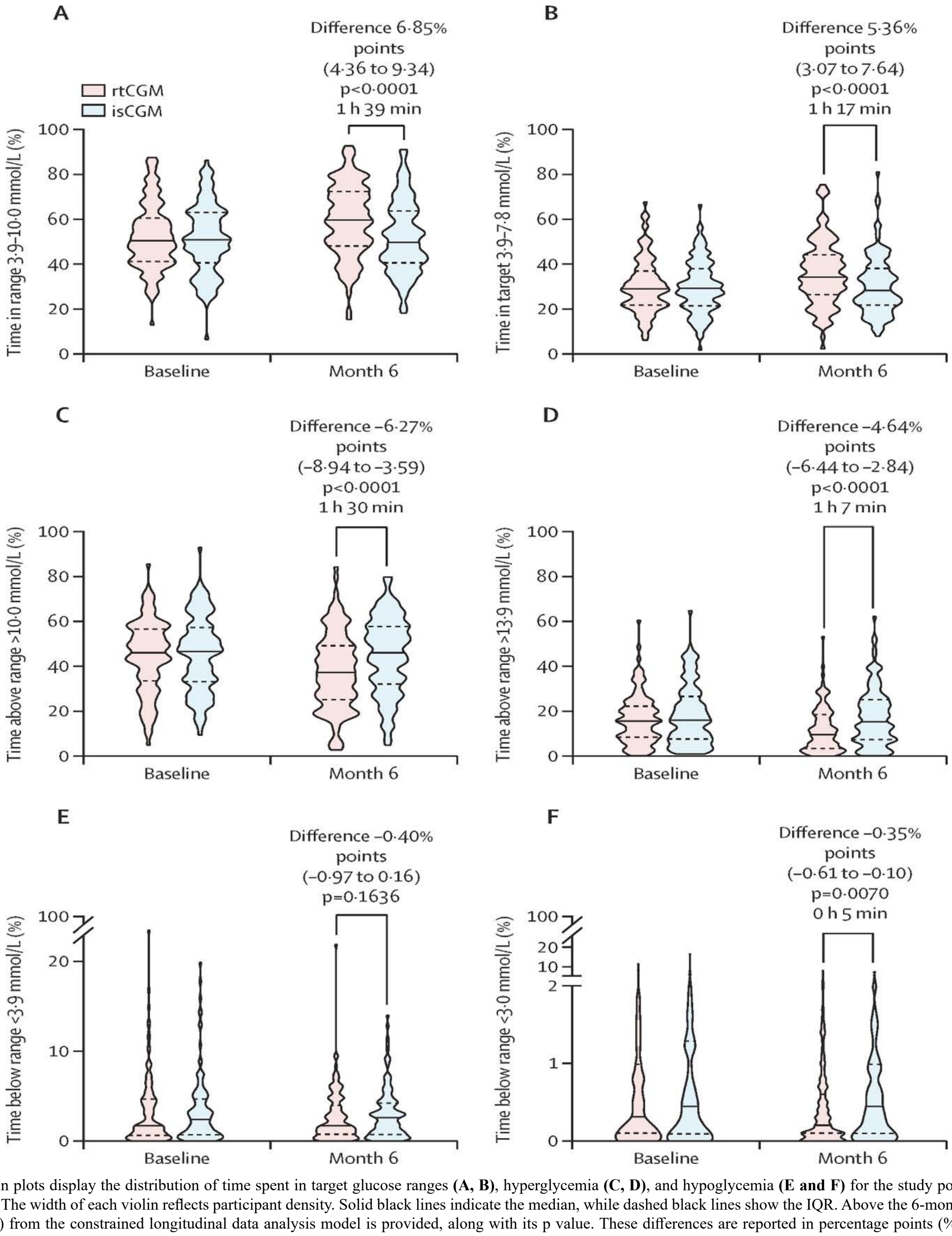

Figure 2: The violin plots display the distribution of time spent in target glucose ranges **(A, B)**, hyperglycemia **(C, D)**, and hypoglycemia **(E and F)** for the study population at baseline and after 6 months. The width of each violin reflects participant density. Solid black lines indicate the median, while dashed black lines show the IQR. Above the 6-month violins, the mean difference (95% CI) from the constrained longitudinal data analysis model is provided, along with its p value. These differences are reported in percentage points (% points) and hours/minutes. The comparison involves RT-CGM and IS-CGM [93].

considering the cost per additional case of adequate glucose control between 2.6 and 10 mmol/L. The primary outcome of percentage of time in the target range (sensor glucose 4 to 8 mmol/L) significantly increased during closed-loop insulin delivery. It rose from a median of 26% (IQR 6 to 64%) to 91% (IQR 78 to 99%) ($p < 0.001$). Both staff and parents perceived that the use of CGM improved care. The studies did not define optimal glucose control targets or the best strategies to achieve them. Future research is needed to evaluate the longer-term impact of targeting glucose control on clinical outcomes. In summary, the study's results indicated that CGM can improve glucose control in extremely preterm infants, with closed-loop insulin delivery showing even greater potential. CGM was also found to be cost-effective and was positively received by staff and parents, alongside a potential reduction in necrotizing enterocolitis risk.

A study (NCT04266379) by Renard et al. [96] aimed to assess the safety and efficacy of AID in adults with T1D who are at high risk for hypoglycemia. The results demonstrate significant benefits of AID compared to sensor and pump therapy, particularly in managing hypoglycemia and improving glycemic control. AID significantly reduced the time spent on hypoglycemia (glucose levels <70 mg/dL) by −3.7 percentage points compared to sensor and pump therapy. This reduction was observed rapidly after AID initiation and was sustained over 24 weeks. The study also found a significant decrease in the percentage of time with sensor glucose levels <54 mg/dL by −0.8 percentage points. AID led to an 8.6% increase in the time spent within the target glycemic range (70 to 180 mg/dL). This improvement in time in range was sustained throughout the 12-week randomized trial and the subsequent 12-week extension phase. The percentage of time spent in hyperglycemia (glucose levels >180 mg/dL) decreased by −5.3% with AID. This is considered a favorable outcome due to its link with severe hypoglycemia and the restoration of hypoglycemia awareness. AID significantly reduced the number of hypoglycemic events (defined as ≥15 consecutive minutes at <70 mg/dL). While AID significantly reduced the risk of hypoglycemia, two severe hypoglycemic events occurred in participants using AID during the randomized phase. These events were interpreted within the context of the participants' very high risk for severe hypoglycemia. Two additional severe hypoglycemic events occurred during the run-in period before randomization. Two ketoacidosis events and one hyperglycemia event occurred while AID was in use, all of which were related to infusion-catheter occlusions. These issues are considered preventable through reinforced education. The benefits of AID, including reduced time below range and increased time in range, were sustained during the 12-week extension period, demonstrating the long-term effectiveness of the system. Participants who moved from sensor and pump to AID during the extension phase experienced similar positive results as the initial AID group, indicating the reproducibility of AID's effects. The Clarke score, a measure of hypoglycemia awareness, tended to improve in the AID group, particularly during the extension phase. Scores on hypoglycemia confidence and INSPIRE surveys also showed improvement. In conclusion, the study strongly recommends AID as a potentially effective treatment for adults with T1D who are at high risk for hypoglycemia, as it significantly reduces hypoglycemia, improves time in range, and decreases hyperglycemia, with sustained benefits over time.

An older adult closed loop (ORACL) trial, a randomized, crossover study by McAuley et al. [97], investigated the efficacy and safety of closed-loop insulin delivery compared to sensor-augmented pump therapy in older adults with T1D. The study's results demonstrated significant improvements in glycemic control with the closed-loop system, particularly regarding time in range and reduction of hypoglycemia, without identifying significant safety concerns. The primary outcome, mean time in range (3.9 to 10.0 mmol/L), was significantly higher during the closed-loop stage at 75.2% (SD 6.3) compared to 69.0% (SD 9.1) during the sensor-augmented pump stage. This represents a difference of 6.2 percentage points (95% CI: 4.4 to 8.0; p < 0.0001), equating to an additional 90 min per day spent in the target range. Time spent above 10.0 mmol/L was 5.4 percentage points lower in the closed-loop stage (p < 0.0001), which means 78 fewer minutes per day in hyperglycemia. All prespecified CGM metrics favored the closed-loop system. Closed-loop therapy significantly reduced time below 3.9 mmol/L by 0.5 percentage points (p = 0.0005) and time below 3.0 mmol/L by 0.11 percentage points (p = 0.0078). The benefits were most pronounced overnight, with a fourfold reduction in time spent below all hypoglycemia thresholds. There was no significant difference in HbA1c between the closed-loop (7.3% (IQR 7.1 to 7.5)) and sensor-augmented pump stages (7.5% (7.1 to 7.9)) (p = 0.13). The study notes that the group's baseline HbA1c levels did not have much room for improvement. Three severe hypoglycemia events occurred during the closed-loop stage and two during the sensor-augmented pump stage. None of these events required hospitalization. The paper noted that participants had high levels of severe hypoglycemia prior to enrollment, which may explain the higher rates observed. One episode of diabetic ketoacidosis occurred during the sensor-augmented pump stage. No serious adverse events occurred during the closed-loop stage. Participants generally had a positive view of closed-loop therapy, both at baseline and at the end of the closed-loop stage, although the degree of positivity was higher before starting the closed-loop system. The trial showed high levels of adherence to the protocol, with similar durations for both closed-loop and sensor-augmented pump stages (approximately 123 days each) and high sensor use (over 96%). Automated basal insulin delivery was operational for 93.3% of the total time during the closed-loop stage. In summary, the ORACL trial provides compelling evidence that closed-loop insulin delivery is a safe and effective treatment option for older adults with long-duration T1D, leading to significantly better glucose control, particularly in terms of increased time in range and reduced time in hypoglycemia, especially overnight. These benefits were achieved without significant safety concerns or an increase in HbA1c, and with high participant adherence to the technology. The findings support the use of closed-loop systems in this population, suggesting that older age is not a barrier to its implementation.

While the advancements in diabetes technology have shown promising results, there are challenges and limitations to consider. The clinical adoption of these technologies is still in its early stages, with barriers such as equitable access, cost, and the need for substantial support from healthcare professionals and family members to ensure effective use. Additionally, the trials often have small sample sizes and lack detailed analyses of sub-populations, which limits the generalizability of the findings. Despite these challenges, the potential of these technologies to revolutionize diabetes care is significant, and ongoing research and development are crucial to overcoming these barriers and optimizing patient outcomes.

Challenges and Future Directions

Despite these advances, challenges remain in optimizing diabetes management through technology. Current gaps include limited accessibility, variability in patient adherence, and the need for more personalized and adaptive systems [12, 38, 98]. While AI-powered closed-loop systems and hybrid artificial pancreas devices have shown efficacy in improving glycemic outcomes, controversies persist regarding their long-term effectiveness, user burden, and equitable access [17, 34, 40]. Moreover, the integration of AI raises ethical and privacy concerns that require careful consideration [36, 98]. The consequences of these gaps are significant, as suboptimal diabetes control continues to contribute to morbidity and healthcare costs [2]. Access to these technologies is often limited by socioeconomic factors, with individuals from lower-income backgrounds facing barriers to obtaining necessary devices and medications [70, 99]. Additionally, the integration of technology into clinical practice requires ongoing education and support for both healthcare providers and patients to ensure effective use [79, 80].

Looking ahead, the future of diabetes management will likely involve further integration of AI, CGMs, and insulin pumps into a cohesive system that prioritizes personalized care (Table 2). As technology continues to evolve, it is essential to address the disparities in access and ensure that all individuals with diabetes can benefit from these

Table 2: Gaps and future research directions.

Gap area	Description	Future research directions	Justification	Research Priority	Ref.
AI model generalizability and diversity	Current AI algorithms for insulin dosing and glucose prediction often lack validation across diverse populations, including different ages, ethnicities, and diabetes types	Conduct large-scale, multi-center studies to validate AI models in heterogeneous populations; develop adaptive algorithms that account for demographic and clinical variability	Limited generalizability restricts clinical adoption and may exacerbate health disparities	High	[14, 31, 38]
Multimodal data integration in AI systems	Most AI models rely primarily on glucose data, with insufficient integration of multimodal inputs such as physical activity, diet, stress, and comorbidities	Develop AI frameworks that incorporate multimodal patient data (e.g., wearable sensors, dietary logs, activity trackers) to enhance prediction accuracy and personalization	Multimodal integration can improve insulin dosing precision and patient outcomes but remains underexplored	High	[19, 20, 31]
Long-term real-world effectiveness and adherence	There is a scarcity of longitudinal real-world studies assessing sustained clinical outcomes and patient adherence to AI-driven diabetes technologies	Design prospective cohort studies and registries to monitor long-term effectiveness, adherence patterns, and psychosocial impacts of AI-integrated devices in routine care	Understanding durability of benefits and adherence is critical for optimizing technology deployment	High	[14, 38, 100]
Full automation in insulin delivery systems	Current AID systems require user input for meal announcements and bolus dosing, limiting full automation	Research and develop fully closed-loop systems that autonomously manage basal and bolus insulin delivery without manual inputs, including dual-hormone approaches	Full automation could reduce patient burden and improve glycemic control but faces technical and safety challenges	High	[10, 28, 34]
Pediatric and high-risk population inclusion	Pediatric, elderly, and high-risk patients are underrepresented in clinical trials of AI and diabetes technologies	Prioritize inclusion of these subgroups in clinical trials and real-world studies; tailor AI algorithms to address age-specific physiological and behavioral factors	These populations have unique needs and may benefit differently from technology	High	[15, 23, 38]
Ethical, privacy, and equity challenges	Data privacy, algorithmic bias, and equitable access remain inadequately addressed in AI and diabetes technology deployment	Develop transparent AI governance frameworks; implement bias mitigation strategies; design policies to improve affordability and access in underserved populations	Ethical and equity issues can hinder trust, adoption, and widen health	High	[35, 39, 98]
Interoperability and integration barriers	Device interoperability and seamless integration of CGM, insulin pumps, AI algorithms, and health records are limited by technical and regulatory hurdles	Standardize communication protocols; foster collaboration among device manufacturers, software developers, and regulators to enable integrated diabetes management ecosystems	Integration is essential for real-time data sharing and optimized therapy but remains fragmented	Medium	[28]
Psychological and behavioral impact assessment	Psychosocial effects of diabetes technologies, including technology-related distress and behavioral barriers, are inconsistently measured and understood	Incorporate standardized patient-reported outcome measures in trials; study behavioral interventions to support sustained technology use and reduce burden	Psychosocial factors influence adherence and clinical outcomes but are underexplored	Medium	[14, 100]
Validation of emerging wearable and implantable technologies	Novel wearable glucose sensors and implantable drug delivery systems show promise but lack extensive clinical validation and usability data	Conduct rigorous clinical trials assessing safety, efficacy, and patient acceptance of emerging non-invasive and implantable devices integrated with AI	These technologies could revolutionize care but require evidence for widespread	Medium	[32, 101]
AI interpretability and clinical trust	Many AI models lack transparency and interpretability, limiting clinician trust and regulatory approval	Develop explainable AI models with user-friendly interfaces; involve clinicians in AI design to enhance trust and facilitate clinical decision-making	Interpretability is crucial for clinical integration and patient safety	Medium	[20, 35]

advancements [68, 102]. In summary, the role of AI, CGMs, and insulin pumps in modern diabetes care is transformative. These technologies not only enhance glycemic control but also empower patients to take an active role in managing their health. Continued research and innovation, coupled with efforts to address access disparities, will be crucial in shaping the future of diabetes management.

Conclusions

The literature reveals that the integration of AI, CGMs, and insulin pumps has substantially transformed modern diabetes care, offering improved glycemic control, enhanced patient quality of life, and advancing personalized treatment paradigms. AI-driven technologies, particularly those employing adaptive algorithms and RL, have demonstrated notable precision in insulin dosing and glucose prediction, enabling real-time adjustments that reduce hypoglycemia and hyperglycemia events. CGM systems provide critical, continuous data that empower both patients and clinicians to make informed decisions, contributing to significant reductions in HbA1c levels and increased time within target glucose ranges. The convergence of CGM with insulin pumps through AID systems, especially hybrid closed-loop configurations, represents the current pinnacle of technology integration, alleviating patient burden and improving metabolic outcomes.

Despite these advancements, challenges remain in achieving fully automated and user-independent therapy due to requirements for manual inputs such as meal announcements and limitations in AI model interpretability and generalizability across diverse patient populations. Moreover, psychosocial and behavioral dimensions are pivotal, with many patients reporting improved adherence and reduced distress, yet others encountering increased complexities and technology-related burdens affecting sustained usage. Patient education and support infrastructures emerge as vital components to maximize positive outcomes. Equity and accessibility issues permeate the technological landscape, with cost barriers, insurance limitations, and digital literacy gaps restricting widespread adoption, particularly among underserved and minority populations. Ethical considerations surrounding data privacy, algorithmic bias, and regulatory oversight demand ongoing attention to ensure safe, transparent, and equitable deployment. While the promise of AI and integrated diabetes technologies is substantial, literature underscores the need for rigorous long-term real-world studies, broader inclusivity in research cohorts, and comprehensive frameworks that address ethical, social, and practical challenges.

Looking forward, emerging trends in multi-omics integration, cloud-based platforms, wearable biosensors, and advanced AI models hold the potential to further personalize and optimize diabetes management. However, their clinical translation will require harmonized efforts among clinicians, researchers, policymakers, and technology developers to balance innovation with patient-centered care, accessibility, and ethical integrity. Overall, the synthesis highlights a dynamic and evolving field where technological progress offers transformative opportunities, tempered by the imperative to ensure that such advances translate into tangible, inclusive, and sustainable benefits for people living with diabetes worldwide.

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None.

Conflict of Interest

None.

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