**Literature Review**

# **1.Introduction to Type 1 Diabetes and Current Challenges**

Diabetes mellitus represents one of the most significant global health emergencies of the 21st century, with a rich historical legacy dating back to ancient civilizations. The first documented description of diabetes is attributed to Hesy-Ra, chief physician of the Egyptian Pharaoh Djoser, around 5000 years ago (Loriaux, 2006). This ancient disease was further detailed in the Upper Egyptian Ebers Papyrus around 1550 BC, where it was characterized as "plentiful urine," demonstrating humanity's long-standing struggle with this condition.

According to the International Diabetes Federation (IDF), around 537 million adults aged 20 to 79 were living with diabetes worldwide in 2021. This number is expected to rise to 643 million patients by 2030 and 783 million patients by 2045. (IDF Diabetes Atlas, 2021). This dramatic increase, more than tripling from 151 million in 2000, shows the escalating nature of the diabetes epidemic and its continuous pressure on healthcare systems worldwide.

Regional disparities in diabetes prevalence are particularly striking. For instance, in the North Africa & Middle East (MENA) region, which includes Egypt, there were 73 million people with diabetes in 2021, with projections suggesting an increase to 135.7 million by 2045. Egypt specifically reports a concerning 18.4% prevalence rate among adults, with approximately 10.9 million cases in a total adult population of 59.4 million (IDF, 2021). In contrast, Germany, part of the IDF European (EUR) region, shows a 10% prevalence rate, with about 6.2 million cases among its 62 million adult population. The EUR region, with over 61 million cases, is projected to reach 69 million by 2045, demonstrating a slower growth rate compared to the MENA region (IDF, 2021).

Diabetes manifest in several distinct forms, each presenting unique challenges for management and treatment:

## Type 1 Diabetes (T1D)

Type 1 diabetes, the focus of this research, is an autoimmune condition where the body's immune system destroys the insulin-producing beta cells in the pancreas, resulting in minimal or no insulin (IDF Diabetes Atlas, 2021). While it could develop at any age, T1D stands among the most common chronic diseases in childhood. The management of T1D requires precise coordination of multiple factors, including meal timing, insulin dosing, and glucose monitoring to maintain optimal glycemic control. Research by Zeevi et al. (2015) demonstrates that even standardized meal responses can vary significantly between individuals, highlighting the critical need for personalized approaches to diabetes management.

## Type 2 Diabetes (T2D)

Accounting for more than 90 percent of all diabetes cases worldwide, Type 2 diabetes is characterized by insulin resistance and, eventually, insufficient insulin production. Its prevalence continues to increase across all regions, driven by population aging, economic development, urbanization, and increasingly sedentary lifestyles (IDF Diabetes Atlas, 2021). The condition often remains undiagnosed, with studies indicating that one-third to one-half of people with T2D may be unaware of their condition.

## Complications of Uncontrolled Type 1 Diabetes Mellitus (T1DM) and the Impact of Glycemic Control

Type 1 Diabetes (T1D) presents a significant management challenge due to the need for precise insulin dosing to maintain optimal glycemic control. While current technologies offer tools for blood glucose level monitoring in addition to insulin delivery, they often fail to adapt to the dynamic and individualized nature of insulin sensitivity and glucose response. This section provides an overview of T1D, its complications, and the urgent need for personalized, data-driven solutions.

The Uncontrolled T1DM can result in various serious complications, both acute and chronic, that significantly affect patients' quality of life and long-term health. This section indicate the main complications of uncontrolled T1DM and explains how better glycemic control can reduce these risks.

## **Acute Complications**

### Diabetic Ketoacidosis (DKA)

DKA is a serious and potentially life-threatening condition that occurs when the body, lacking insulin, starts breaking down fat for energy, leading to the production of ketones and causing acidosis. It is particularly common at the onset of T1DM. Improved glycemic control can significantly lower the risk of DKA (Duca et al., 2019). For instance, better overall glycemic control and earlier detection of high blood sugar can reduce the prevalence of DKA. Recurrent DKA episodes affect approximately 6-8% of patients annually, indicating ongoing challenges in diabetes management for some individuals (Fazeli Farsani et al., 2017). Studies show that better glycemic control can significantly reduce the possibility of DKA. In a study by Karges et al. (2017), patients using continuous subcutaneous insulin infusion (CSII) or continuous glucose monitoring (CGM) had a 40% lower risk of DKA compared to those using multiple daily injections without CGM, due to better glycemic control and earlier hyperglycemia detection.

### Hypoglycemia

Hypoglycemia which is identified as low blood sugar, is a common and potentially dangerous complication of insulin therapy in T1DM. Severe hypoglycemia, leading to requiring assistance from another person to supply carbohydrates or glucagon, occurs in a significant proportion of individuals with T1DM annually (ISPAD ,2018)The impact of improved glycemic control on hypoglycemia risk is complex. While tight control can increase the risk of mild hypoglycemia, it can reduce severe hypoglycemic events. Advanced diabetes management technologies, such as continuous glucose monitoring and insulin pump therapy, have been associated with a reduction in severe hypoglycemic events (Battelino et al., 2019).

Hypoglycemia is a common and potentially dangerous complication of insulin inappropriate dosing in T1DM. Severe hypoglycemia is a common complication in type 1 diabetes. Approximately 20–30% of individuals with T1DM experience at least one episode of severe hypoglycemia each year (Cryer, 2015). In contrast, non‐severe hypoglycemic events occur even more frequently, with considerable variability between patients. The relationship between tighter glycemic control and hypoglycemia is complex: while striving for lower HbA₁c levels may increase the incidence of mild hypoglycemia, it has been associated with a reduction in severe events. For example, a study was carried out by Šoupal et al. (2016) indicated that Pump therapy with built-in sensors, incorporating predictive low-glucose suspend functionality was associated with a 41% reduction in severe hypoglycemic episodes compared with conventional multiple daily injection (MDI) therapy, even while achieving lower HbA1c levels.

## **Chronic Complications**

### Diabetic Retinopathy

Diabetic retinopathy is a microvascular complication that affects the retina and is a leading cause of vision loss in Type 1 diabetes (T1DM). According to a global meta‐analysis by Yau et al. (2012), the overall prevalence of diabetic retinopathy among individuals with diabetes is approximately 34.6%, although this figure reflects a mix of Type 1 and Type 2 diabetes populations.

proliferative diabetic retinopathy has been reported to affect around 25–30% of patients after 25 years of disease duration (Yau et al., 2012). Landmark studies have shown that intensive therapy to keep blood sugar close to normal can lower the risk of retinopathy by as much as 76% compared to conventional therapy (DCCT, 1993). Furthermore, the follow-up Epidemiology of Diabetes Interventions and Complications (EDIC) study demonstrated that these benefits persist long after the initial intervention, underscoring the concept of "metabolic memory" (Nathan et al., 2005).

### Diabetic Neuropathy

Diabetic neuropathy includes a group of nerve disorders caused by diabetes, affecting 30-50% of individuals with longstanding T1DM (Pop-Busui et al., 2017). It includes peripheral neuropathy, which might lead to foot ulcers and amputations, and autonomic neuropathy, affecting cardiovascular, gastrointestinal, and other autonomic functions. The DCCT also provided strong evidence for the role of glycemic control in preventing neuropathy. The study found a 60% reduction in the risk of neuropathy with intensive therapy compared to conventional treatment (Nathan et al., 2005). A more recent study by Callaghan et al. (2018) showed that Even a small improvement in blood sugar control (1% drop in HbA1c) reduced the risk of distal symmetric polyneuropathy by 25%, which is the most common form of diabetic neuropathy.

### Diabetic Nephropathy

According to the 2014 USRDS Annual Data Report, diabetic kidney disease remains the leading cause of end‐stage renal disease (ESRD) in the United States. International comparisons within the report show that, in the U.S., diabetes accounts for nearly 44–50% of new ESRD cases—a statistic that underscores the tremendous public health impact of diabetic kidney disease on renal outcomes (United States Renal Data System, 2014). This report also highlights significant variability among countries in ESRD incidence, which may be attributable to differences in population demographics, healthcare practices, and disease management strategies. These findings reinforce the need for early detection and aggressive management of diabetes and its renal complications to reduce the progression to ESRD.  
A long-term follow-up study by de Boer et al. (2011) found that the total number of ESRD cases was much lower in the intensive therapy group compared to the conventional therapy group (1.4% vs. 3.8%, respectively) after 25 years of follow-up.

### Cardiovascular Disease (CVD)

Individuals with T1DM have a 2-4 times higher risk of cardiovascular events compared to the general population (de Ferranti et al., 2014). By middle age, about 25-30% of T1DM patients show evidence of cardiovascular disease. The DCCT-EDIC study provided compelling evidence for the long-term cardiovascular benefits of intensive glucose level control. After a follow-up mean of 17 years, the risk of all cardiovascular disease events were reduced by 42% in intensive therapy group in comparison with conventional therapy group (Nathan et al., 2005).

### Diabetic Foot Ulcers and Amputations

Foot ulcers occur in 10-25% of T1DM patients, with 5-15% of severe cases requiring amputations (Boulton et al., 2018). These complications significantly impact mobility and quality of life. While direct evidence from randomized controlled trials on the impact of glycemic control on foot ulcers and amputations is limited, observational studies have shown a strong association. Recent analyses from the Swedish National Diabetes Register indicate that for every 1% (10 mmol/mol) increase in HbA1c, the risk of lower‐extremity amputation in patients with T1D increases by approximately 80%). Conversely, maintaining lower HbA1c levels—especially when combined with comprehensive foot care programs—has been associated with a significant reduction in the risk of developing foot ulcers and subsequent amputations (Ólafsdóttir et al., 2019)

## Psychological Impact of Managing Type 1 Diabetes

Living with T1D can have significant psychological implications. The constant need for self-management including blood glucose monitoring, insulin administration, and dietary considerations can lead to diabetes distress, a state characterized by feelings of overwhelm, frustration, and burnout related to diabetes management (Fisher et al., 2015).

Research indicates that the emotional burden associated with T1D extends beyond clinical depression. In one study, the prevalence of at least moderate diabetes distress was found to be 42.1% among adults with T1D (Fisher et al., 2015), suggesting that while depression is a concern in this population, the distress specifically tied to the demands of managing T1D is even more widespread.

Moreover, the impact of T1D reaches beyond the affected individual, significantly influencing family dynamics. A systematic mixed‐studies review by Whittemore et al. (2012) found that parental psychological distress—marked by stress, anxiety, and depressive symptoms—was considerable, with reported prevalence rates ranging from 10% to 74%. On average, about 33.5% of parents experienced significant distress at the time of their child’s diagnosis, and 19% continued to experience distress 1 to 4 years afterward. The review further noted that higher levels of parental distress were associated with increased stress and depressive symptoms in children, more problematic child behavior, and a lower quality of life. These findings underscore the extensive impact that a child’s T1D can have on family dynamics and diabetes management, emphasizing the need for routine screening and early preventive interventions for parental distress.

## Conclusion

Managing Type 1 diabetes is a complex, lifelong challenge. When blood sugar is not kept under control, patients face serious complications. Acute issues like diabetic ketoacidosis and severe hypoglycemia can occur, while long-term problems include vision loss from diabetic retinopathy, nerve damage that may lead to foot ulcers and amputations (Ólafsdóttir et al., 2019), kidney disease, and an raised risk of heart disease (de Ferranti et al., 2014). In addition, the constant demands of self-management such as checking blood sugar, taking insulin, and watching what you eat can cause significant emotional stress and burnout (Fisher et al., 2015). This burden often extends to families, with parents experiencing high levels of distress that can affect the well-being of the entire household (Whittemore et al., 2012).

Given these challenges, there is a clear need for a personalized and cost-effective approach to improve diabetes management. A promising solution is a data-driven system that uses temporary continuous glucose monitoring (CGM) to capture each patient’s unique meal patterns, glucose responses, and insulin behavior. By integrating machine learning and reinforcement learning, such a system can learn to adjust bolus insulin dosing more accurately. This approach could help reduce the risk of both short- and long-term complications while lessening the need for continuous CGM use all under the careful supervision of healthcare professionals.

# **2 Global Context of Diabetes Management**

In the global context of diabetes management, several emerging trends are enhancing patient care and outcomes. These include Continuous Glucose Monitoring (CGM), Closed-Loop Control (CLC) systems, and the integration of Mobile Technology with Decision Support tools.

**Continuous Glucose Monitoring (CGM):**

CGM systems employ subcutaneous sensors to provide real-time measurements of interstitial glucose levels, offering readings every 1 to 5 minutes. This constant flow of data gives a clear picture of glucose patterns, enabling more precise adjustments in insulin therapy compared to traditional self-monitoring of blood glucose (SMBG) methods. By identifying fluctuations and trends, CGM aids in preventing hyperglycemic and hypoglycemic events. (Akturk and Bindal, 2024)

**Closed-Loop Control (CLC) Systems:**

CLC systems, often referred to as "artificial" or "bionic" pancreases, integrate CGM data with insulin pumps through sophisticated algorithms. This integration allows for automated insulin delivery adjustments in response to real-time glucose readings, reducing the burden of manual insulin administration. Recent advancements have led to The creation of hybrid closed-loop systems combines continuous glucose monitoring with automatic insulin delivery, enhancing glycemic control and patient convenience. (Akturk and Bindal, 2024)

**Mobile Technology and Decision Support:**

The convergence of diabetes management technologies with mobile devices has facilitated significant improvements in self-care. Modern CGM systems can transmit data to smartphones, providing users with timely alerts and comprehensive glucose data analysis. Additionally, decision support systems (DSS) utilize artificial intelligence to analyze CGM data, offering personalized recommendations for insulin dosing and lifestyle modifications. These tools empower patients to make informed decisions and maintain optimal glycemic control. (Akturk and Bindal, 2024)

Collectively, these innovations represent a significant shift towards more integrated and automated approaches in diabetes care, aiming to improve patient outcomes and quality of life.

## Economic Burden of Type 1 Diabetes Management

The economic burden of Type 1 Diabetes Mellitus (T1DM) is substantial and multifaceted, encompassing direct medical costs, indirect costs, and long-term complications. The economic influence of T1D management is substantial, encompassing direct medical costs besides indirect costs associated with reduced productivity and quality of life. In the United States, the average annual cost per person with T1D is estimated to be around $16,752, with insulin and diabetes supplies accounting for a significant portion of these expenses (American Diabetes Association, 2018). This comprehensive review aims to provide a detailed analysis of the financial implications associated with T1DM management, focusing on insulin costs, blood glucose measurement, insulin pumps, and the economic impact of complications.

The impact of diabetes extends far beyond prevalence numbers, manifesting in significant mortality rates and widespread treatment gaps. The IDF estimates that over 6.7 million adults aged 20-79 died from diabetes-related causes in 2021 alone, while the economic burden approaches one trillion USD in direct health expenditures, expected to exceed this figure by 2030 (IDF Diabetes Atlas, 2021). This burden is particularly concerning in low and middle-income countries, where the percentage of undiagnosed cases can reach as high as 80% (Guariguata et al., 2011).

## Overall Economic Burden

According to the ADA’s recent analysis, the total estimated expenses of diagnosed diabetes in 2022 was $412.9 billion. Of this, $306.6 billion were direct medical costs covering expenses such as inpatient and outpatient careThe total estimated cost of diagnosed diabetes includes expenses for prescription medications and diabetes supplies, while $106.3 billion is due to indirect costs. On average, individuals with diabetes face annual medical expenses of $19,736, with about $12,022 directly related to diabetes management. Patients with diabetes have medical costs that are 2.6 times higher than those without the disease. Notably, glucose-lowering medications and diabetes supplies make up around 17% of total direct medical expenses. Major factors contributing to indirect costs are reduced employment due to disability ($28.3 billion), productivity losses from working while unwell (presenteeism) at $35.8 billion, and lost productivity due to premature deaths at $32.4 billion. These numbers highlight the urgent need for effective diabetes prevention and management strategies to reduce both the direct and indirect economic impact of the disease (Parker et al., 2024).

In addition, Joish et al. (2020) reported that the mean total annual healthcare cost for an adult with T1DM in the United States is approximately $18,817 per person per year (PPPY This amount is much higher than the estimated $14,148 per person per year (PPPY) for adults with Type 2 Diabetes (T2DM). When applied to a commercial health plan covering one million people, the total direct medical costs for Type 1 Diabetes (T1DM) are estimated at approximately $103.4 million annually. Together, these data highlight not only the direct medical expenses related to insulin therapy and advanced diabetes technologies but also the broader economic burden resulting from long-term complications and comorbidities associated with T1DM.

## Direct Medical Costs

### Insulin Costs

The cost of insulin for managing Type 1 Diabetes (T1DM) has risen sharply in recent years. In 2022, the total estimated cost of diagnosed diabetes in the U.S. reached $412.9 billion, with $306.6 billion spent on direct medical expenses. Glucose-lowering medications and diabetes supplies made up about 17% of these direct medical costs (American Diabetes Association [ADA], 2023).

### Blood Glucose Measurement

Continuous Glucose Monitoring (CGM) has become an essential tool in T1DM management, contributing both to improved clinical outcomes and to increased healthcare expenditures. One study estimated that the daily cost of CGM including the costs for its three key components (a G4 sensor, receiver, and transmitter) is approximately $15.20 per day (Wan, 2018). Moreover, a recent systematic review found that 17 out of 19 cost-effectiveness studies reached to the fact that CGM is cost-effective in patients with T1DM. In this review, the estimated Incremental Cost-Effectiveness Ratio (ICER) ranged from $18,734 to $99,941, with quality-adjusted life year (QALY) gains ranging from 0.76 to 2.99 (Nguyen et al., 2022). These findings suggest that while CGM adds to direct costs, its ability to reduce both short- and long-term complications—particularly among patients with suboptimal glycemic control or those at high risk for severe hypoglycemia—helps drive its overall cost-effectiveness.

### Insulin Pumps

Insulin pumps, also known as continuous subcutaneous insulin infusion (CSII) devices, are another major expense in managing T1DM. A cost-effectiveness study revealed that the 28-week per-person cost was $8,272 for CGM+CSII compared to $5,623 for CGM+Multiple Daily Injections (MDI), with the $2,644 difference mainly due to pump use (Wan et al., 2018). However, the long-term cost-effectiveness of insulin pumps is still uncertain. In a lifetime cost-effectiveness analysis, CGM+CSII increased total costs by $112,045, decreased quality-adjusted life years (QALYs) by 0.71, and reduced life expectancy by 0.48 years compared to CGM+MDI (Wan et al., 2018).

## Indirect Costs and Quality of Life

The economic burden of T1DM extends beyond direct medical costs. Patients may spend more than 16% of their income on outpatient care and 23% on treatment when hospitalized, leading to catastrophic health expenditures (Peyrot et al., 2010).   
Major contributors to the indirect costs include reduced employment due to disability (estimated at $28.3 billion), productivity losses from presenteeism (approximately $35.8 billion), and lost productivity due to premature deaths (around $32.4 billion). These figures underscore the critical need for effective diabetes prevention and management strategies to mitigate both the direct and indirect economic impacts of the disease (Parker et al., 2024).

This financial strain can significantly impact the quality of life for individuals and families managing T1DM.

## Complications and Their Economic Impact

Inaccurate management of T1DM can lead to severe complications, further increasing the economic burden. A study of Medicare beneficiaries with T1DM showed that the most expensive complications per person were kidney failure treated with a transplant ($77,809 in the year it occurred and $13,556 annually afterward), kidney failure treated with dialysis ($56,469 initially and $41,429 per year later), and lower extremity amputation ($40,698 in the occurrence year and $7,380 annually afterward) (Wang et al., 2023). Short-term complications such as hypoglycemia and ketoacidosis were associated with costs of $6,400 and $11,204 per event, respectively (Wang et al., 2023). These acute complications often result in hospitalizations and emergency department visits, contributing significantly to the overall cost of diabetes care.

## Healthcare Resource Utilization

A large retrospective observational study of pediatric and adult patients with T1DM found that diabetes-related costs totaled nearly $800 per month (Simeone et al., 2020). Pharmacy costs made up more than half of diabetes-related expenses, highlighting the significant financial burden of treating T1DM (Simeone et al., 2020). Annually, patients averaged 0.2–0.9 hospitalizations for any cause and 0.1–0.3 hospitalizations specifically related to diabetes during the follow-up period (Simeone, 2020).

## Cost-Effectiveness of Interventions

Despite the high costs of managing T1DM, many interventions have proven to be cost-effective. For instance, the use of CGM in patients with suboptimal management or at risk of severe hypoglycemia has been found to be particularly cost-effective (Wan et al., 2018). However, the cost-effectiveness of combining multiple technologies, such as adding an insulin pump to existing CGM users, requires further investigation (Ly et al., 2014).

## Conclusion

The literature clearly shows that diabetes is a growing global health crisis with a dramatic increase in both its prevalence and economic burden. Millions of adults worldwide are affected, and the costs of managing the disease including expenses for continuous glucose monitoring (CGM), insulin, insulin pumps, and hospitalizations due to complications are enormous. These costs are especially high in low- and middle-income countries, where a large number of cases remain undiagnosed and untreated.

At the same time, while advanced technologies like CGM and insulin pumps improve patient outcomes, they add to the overall expense of diabetes care. This situation highlights the pressing need for cost-effective strategies that can maintain high treatment standards without relying on expensive, continuous monitoring.

Relating this to the research question, there is a clear opportunity to develop a data-driven diabetes management system that uses temporary CGM to establish personalized patient parameters. By integrating machine learning and reinforcement learning, the system aims to improve the accuracy of bolus insulin dosing by analyzing individualized meal patterns, glucose responses, and insulin pharmacodynamics. Importantly, this approach seeks to reduce long-term dependency on costly CGM while keeping physicians in charge of treatment decisions. In simple terms, the goal is to provide precise, personalized diabetes care that is both effective and affordable, ultimately easing the financial and health burdens associated with Type 1 diabetes.

# **3.Factors affecting insulin dosing**

## Meal Data: Detailed nutritional information including carbohydrates, proteins, and fats

Recent survey research underscores the importance of understanding how different foods affect postprandial blood glucose levels in children and young people with Type 1 diabetes. In a cross-sectional study conducted at a pediatric diabetes center in Australia, Smith et al. (2020) found that 91% of families identified specific foods as problematic, with 60% reporting issues with pizza, 55% with pasta, and 31% with rice. To manage these glycemic challenges, 96% of families employed one or more strategies, including increasing the insulin dose by 10–25% during meals (reported by 32% of participants), administering combination boluses (39%), and correcting blood glucose levels more frequently (51%). Notably, among those using continuous glucose monitoring (CGM)—which accounted for 60% of the study sample—88% reported an increased awareness of the impact of different foods on their glycemic control, and 27% subsequently modified their nutritional management by avoiding or restricting problematic items.

These findings highlight that meal composition plays a crucial role in determining appropriate insulin dosing and that many families are already adapting their dosing strategies based on the type and amount of food consumed rather than relying solely on static dosing regimens.

In parallel, research on adaptive insulin dosing, such as the randomized controlled trial investigating the Insulin-to-Protein Ratio (IPR) by Hall et al. (2024), indicates that while protein metabolism does affect blood glucose levels, fixed protein-based dosing strategies do not fully capture the dynamic needs of individuals with Type 1 diabetes. Collectively, this body of evidence supports the development of a cost-effective, data-driven diabetes management system that integrates detailed meal data with adaptive, machine learning–driven strategies to optimize bolus insulin dosing, while maintaining essential clinician oversight.

## Blood Glucose Readings: Current Blood Glucose and Insulin Levels for Correction Calculations

Real-time blood glucose monitoring is critical for optimizing insulin dosing and preventing glucose fluctuations. Continuous glucose monitoring (CGM) has transformed blood glucose tracking by providing real-time readings every few minutes, which are essential for timely correction calculations. Unlike traditional metrics such as A1C that offer only a long-term average, CGM delivers detailed trend information—including the rate of glucose change—that allows patients to quickly identify deviations and adjust insulin doses accordingly (Reddy et all., 2023).

Moreover, integrating CGM data with mobile technology and decision support tools further refines the correction process. By combining current glucose levels with trend data and insulin dosing history, these systems enable more precise and individualized insulin adjustments, thereby reducing glycemic variability and improving overall control (Reddy, Verma, & Dungan, 2023).

Additionally, structured insulin logging is essential for optimizing glycemic control. Danne et al. (2023) conducted a real‐world analysis across 16 countries and found that missing as few as two basal or four bolus insulin doses over a 14‐day period was associated with a clinically significant decrease in time in range (TIR). Their study also demonstrated that higher smart insulin pen engagement—facilitating structured insulin logging—correlated with improved glycemic outcomes. These results underscore the importance of precise insulin administration and monitoring, as even small lapses in dosing adherence can lead to measurable declines in glycemic control.

## Physical Activity: Type, Intensity, and Duration of Activities

Physical activity significantly influences blood glucose levels in individuals with Type 1 diabetes (T1D), with its type, duration, and intensity determining the level of risk for exercise-induced hypoglycemia. Prasanna et al. (2023) used data from 50 individuals with T1D to study the effects of walking, running, and cycling on hypoglycemia risk. The study revealed that glucose levels at the start of exercise and pre-exercise glucose area under the curve (AUC) were the most significant predictors of hypoglycemia across all three activities. Although duration and intensity of physical activity were less predictive, participants with higher pre-exercise AUCs—indicating carbohydrate preparation—had significantly fewer hypoglycemic events. This finding highlights the protective role of carbohydrate intake before exercise in mitigating hypoglycemia risk (Prasanna et al., 2023).

Similarly, Hormazábal-Aguayo et al. (2022) emphasized that moderate-to-vigorous physical activity increases the likelihood of nocturnal hypoglycemia in youth with T1D, particularly following evening exercise. This underscores the importance of personalized insulin adjustments and carbohydrate strategies to reduce exercise-related hypoglycemia. In the context of a cost-effective diabetes management system, integrating physical activity data with temporary continuous glucose monitoring (CGM) and machine learning algorithms will help develop adaptive insulin dosing strategies. This approach can reduce the risk of hypoglycemia, especially after exercise, while reducing long-term CGM dependency and maintaining physician oversight.

However, exercise also presents challenges in managing insulin dosing due to its variable effects on glucose levels. McCarthy et al. (2021) found that physical activity increases the risk of hypoglycemia, particularly during the nocturnal period following evening exercise. Their study emphasized that peri-exercise bolus insulin adjustments, such as reducing the insulin dose by 50% before and after exercise, can significantly reduce post-exercise and nocturnal hypoglycemia without compromising glucose control (McCarthy et al., 2021). This underscores the importance of individualized insulin adjustments based on the type and timing of physical activity to ensure safe and effective glucose management.

Moreover, intermittent closed-loop systems have shown promising results in managing glucose variability in multiple daily injection (MDI) users by dynamically suggesting correction boluses and carbohydrate intake based on real-time glucose fluctuations (Estremera et al., 2023). This supports the integration of event-triggered insulin dosing into diabetes management systems to accommodate individual activity patterns.

## Health Conditions & Insulin Sensitivity Adjustments

Insulin sensitivity is influenced by various health conditions, necessitating adaptive dosing strategies. Acute illnesses, such as infections or metabolic stress, often increase insulin resistance due to elevated counter-regulatory hormones like cortisol and catecholamines, requiring higher insulin doses (Chung et al., 2010). Conversely, chronic conditions like chronic kidney disease (CKD) and hepatic dysfunction reduce insulin clearance, necessitating lower insulin dosages to prevent hypoglycemia (Chung et al., 2010).

The absence of standardized guidelines for insulin titration during stress or illness further complicates dosing. Research suggests that machine learning (ML)-based models could address this gap by predicting insulin sensitivity shifts and enabling real-time adjustments. Reinforcement learning (RL) frameworks, for instance, can analyze historical glucose data to optimize bolus insulin dosing during illness-related resistance (simon et all., 2015).

Hormonal fluctuations, such as those associated with the menstrual cycle or endocrine disorders (e.g., polycystic ovary syndrome or thyroid dysfunction), significantly impact insulin requirements. Estrogen and progesterone variations during menstrual phases can either increase or decrease insulin sensitivity, calling for personalized dosing strategies(Evert, 2020). Predictive analytics integrated into diabetes management systems could anticipate these hormonal impacts, enabling timely adjustments tailored to individual needs(Evert, 2020).

## Medications & Their Impact on Insulin Requirements

The impact of concurrent medications on insulin dosing is a critical yet often overlooked factor in traditional diabetes management. Many commonly prescribed drugs affect insulin sensitivity, hepatic glucose production, and peripheral glucose uptake, requiring continuous dose adjustments.

One of the most significant hyperglycemia-inducing medications is glucocorticoids (e.g., prednisone, dexamethasone). Glucocorticoids significantly impact insulin requirements in type 1 diabetes. These drugs increase hepatic glucose output and reduce insulin sensitivity, often necessitating higher bolus insulin doses (Revsin, 2008). In type 1 diabetes, where there is no endogenous insulin production, the effects of glucocorticoids can be particularly pronounced, requiring substantial increases in exogenous insulin doses (Bauerle & Harris, 2016).

Beta-blockers pose unique challenges for patients with type 1 diabetes. While they don't directly cause hyperglycemia, they can mask important symptoms of hypoglycemia, particularly tremors and tachycardia. However, it's crucial to note that sweating, a key hypoglycemia symptom, remains unaffected by beta-blockers as it's mediated by acetylcholine rather than catecholamines (Dungan et all, 2019)

Some medications can enhance insulin sensitivity or have glucose-lowering effects, potentially leading to hypoglycemia in type 1 diabetes if insulin doses aren't adjusted. Metformin, traditionally used in type 2 diabetes, has shown a 25.8% reduction in insulin requirements when added to insulin therapy in type 1 diabetes patients1. This effect was most pronounced 2 hours after meals, suggesting metformin may interfere with intestinal glucose absorption (Pagano, 1985).

## Insulin Self-Management Patterns

Effective self-management of insulin dosing in Type 1 diabetes (T1D) requires integrating multiple real-time data points to optimize glycemic control. Wearable devices, such as continuous glucose monitoring (CGM) systems, provide essential insights for insulin adjustments. Zhu et al. (2022) explored how CGM combined with mobile applications enhances self-management by enabling patients to track meal intake, insulin bolus administration, and physical activity. Their study introduced ARISES, a deep-learning-based smartphone platform that integrates multi-modal physiological data to predict glucose fluctuations and provide real-time decision support (Zhu et al., 2022).

Self-management also involves behavioral patterns and adherence to personalized dosing adjustments. The study highlighted that individual variability in glucose response necessitates dynamic and adaptive insulin strategies, rather than relying solely on pre-set insulin-to-carbohydrate ratios. This supports the integration of machine learning models to personalize insulin recommendations based on past glucose trends, meal patterns, and lifestyle factors (Zhu et al., 2022).

## Automated Insulin Delivery (AID) Systems

Automated Insulin Delivery (AID) systems represent a significant advancement in insulin therapy, offering real-time glucose monitoring and adaptive insulin administration. These systems consist of a CGM, an insulin pump, and an algorithm that adjusts insulin delivery based on glucose levels. Nallicheri et al. (2022) reviewed multiple AID systems and found that hybrid closed-loop models, such as the MiniMed 670G and Control-IQ, have significantly improved Time-in-Range (TIR) outcomes by dynamically adjusting basal insulin rates and providing automatic correction boluses (Nallicheri et al., 2022).

Despite their benefits, AID systems still require manual bolus dosing for meals, emphasizing the need for accurate meal data input and individualized insulin adjustments. The review highlighted that future iterations of AID systems aim to fully automate bolus dosing by integrating dual-hormone therapy and reinforcement learning models, ensuring more precise and personalized insulin recommendations (Nallicheri et al., 2022).

# **4. Current Diabetes Management Systems and Clinical Practices**

Diabetes management has evolved significantly since the discovery of insulin in 1921, progressing from basic dietary interventions to sophisticated personalized systems. This evolution has been driven by advancements in insulin formulations, glucose monitoring technologies, and digital health tools..

## Traditional Methods and Early Innovations

In the early days, insulin therapy was guided by fixed Insulin-to-Carbohydrate Ratios (ICRs) and Correction Factors. For example, healthcare providers prescribed one unit of insulin for every 10 grams of carbohydrates, without considering individual differences in insulin sensitivity. While these methods simplified insulin dosing, they failed to account for the complex interactions between food intake, physical activity, and glucose metabolism. Correction Factors, such as "1 unit of insulin lowers blood glucose by X mg/dL," were also too static to adapt to factors like stress, hormonal changes, and exercise, resulting in variable glycemic control.  
The mid-20th century introduced the sliding scale approach, where insulin doses were adjusted based on pre-meal blood glucose levels. Although it provided a step forward, this method ignored meal composition and individual metabolic variability, often leading to inadequate glycemic control.

## Technological Advancements

**Continuous Glucose Monitoring (CGM)**

CGM technology has transformed diabetes care by offering real-time glucose monitoring. Modern CGM devices, such as the Dexcom G7 and Abbott's FreeStyle Libre, offer improved accuracy and extended wear times (TCOYD, 2024). The Dexcom G7, for instance, is expected to have a 15-day sensor life by 2025, reducing the frequency of sensor changes (TCOYD, 2024). These advancements have led to better glycemic control, improved Time-in-Range (TIR), and reduced hypoglycemic episodes.

**Insulin Delivery Systems**

Insulin pumps have evolved to offer greater precision and automation. The combination of CGM and insulin pumps has resulted in hybrid closed-loop systems, also known as artificial pancreas systems (Euractiv, 2024). These systems automatically regulate insulin delivery based on glucose levels, improving blood sugar control and lowering the risk of hypoglycemia.

**Digital Health Platforms and Telemedicine**

Digital health platforms have enhanced patient-provider connectivity and empowered self-management. CGM integration with virtual platforms has made it possible to achieve target glycosylated hemoglobin levels in diabetes while minimizing hypoglycemia, which has always been challenging in Type 1 Diabetes (T1D) (Yoo & Kim, 2023).Telemedicine has become increasingly important in diabetes management, especially after the COVID-19 pandemic. Remote consultations and digital health platforms enable more frequent interactions between patients and healthcare providers, potentially improving glycemic control and reducing the need for in-person visits (Euractiv, 2024).

## Emerging Technologies

**Connected Insulin Pens (CIPs)**

CIPs are expected to be a future technology that doesn't need to be worn all day like insulin pumps. They help calculate insulin doses with a built-in bolus calculator, showing benefits in glycemic outcomes by reducing missed doses of insulin and improving adherence (Yoo & Kim, 2023).

**Continuous Glucose-Ketone Monitoring**

Abbott is developing a novel CGM that measures both blood sugar and ketones. This advancement will allow for early detection of elevated ketones, potentially preventing emergencies like diabetic ketoacidosis (TCOYD, 2024).

**Clinical Practices and Guidelines**

The American Diabetes Association's Standards of Care in Diabetes—2025 provides updated recommendations on nutrition, weight-loss medications, and technology (American Diabetes Association, 2024). These guidelines combine comprehensive, evidence-based recommendations for diabetes care with actionable guidance to enable healthcare professionals to provide the best care possible for those living with diabetes.

## Future Directions

Research is ongoing in several areas to further improve diabetes management:

1. Glucose-responsive insulin: This innovative approach aims to develop insulin that activates only when blood glucose levels are elevated, potentially reducing the risk of hypoglycemia (IDTechEx, n.d.).
2. Non-invasive insulin delivery: Despite a poor track record, research continues in this area to find alternatives to injectable insulin (IDTechEx, n.d.).

# **5. Limitations of Current Diabetes Management Systems**

Despite significant advancements in diabetes management technologies, current systems remain limited by their inability to fully adapt to individual patient needs and the dynamic nature of blood glucose regulation. These limitations stem primarily from static insulin dosing strategies, technological challenges, and fragmented data management, resulting in suboptimal glycemic control for many patients.

## Fixed Insulin-to-Carbohydrate Ratios and Correction Factors

Traditional approaches to insulin dosing rely on fixed insulin-to-carbohydrate ratios and correction factors, assuming a uniform response to insulin across patients and throughout the day. In reality, insulin sensitivity can vary significantly due to factors such as physical activity, stress, hormonal fluctuations, and meal composition. This "one-size-fits-all" approach often leads to unpredictable blood glucose behavior, with some patients experiencing frequent episodes of hypo- or hyperglycemia   
Furthermore, these dosing strategies inadequately address the impact of dietary fat and protein on postprandial glucose levels and fail to consider the glycemic index or load of different carbohydrates. This results in poor post-meal glucose control and highlights the need for more adaptive and personalized dosing algorithms. (Bell et al., 2015).

## Exercise-Induced Glucose Fluctuations

Managing blood glucose during and after physical activity remains one of the most complex aspects of Type 1 Diabetes (T1D) management. Current systems struggle to account for the glucose-lowering effects of aerobic exercise, the potential glucose-raising effect of high-intensity or resistance exercise, and delayed hypoglycemia that can occur hours later (Riddell et al., 2017). Patients must manually adjust insulin doses and carbohydrate intake around exercise, which is both challenging and prone to error.

## Technological Limitations and Integration Challenges

While Continuous Glucose Monitoring (CGM) systems and insulin pumps have brought significant improvements to diabetes care, they are not without drawbacks. For instance, CGMs can sometimes be inaccurate because they measure glucose in the interstitial fluid rather than directly in the blood, which can lead to delays in reflecting rapid changes in blood sugar and necessitate regular calibrations. In addition, many users find that wearing sensors can be uncomfortable, and the high cost of these devices often limits their availability, especially in low-resource settings. Similarly, insulin pumps and hybrid closed-loop systems require extensive user training and a good level of technical skill; errors like improper insertion of infusion sets can compromise their accuracy. Moreover, even the most advanced automated systems still need some manual input for bolus calculations at mealtimes, leaving room for human error (Battelino et al., 2019).

## Fragmented Data and Limited Decision Support Systems

Many digital health apps and decision-support systems in diabetes management still face challenges with interoperability. This lack of seamless integration results in fragmented data, making it difficult for healthcare providers to view a complete picture of a patient's health. A 2024 study highlights the need for standardized protocols for open and transparent handling of data and secure integration into electronic health records (Jendle et al., 2024). The fragmentation limits the ability to offer truly personalized care, as information from various devices like continuous glucose monitors, activity trackers, and dietary logs is not always combined effectively.

## The Need for Adaptive Solutions

To address these limitations, advanced machine learning (ML) and artificial intelligence (AI) technologies are being developed. A 2024 study describes the development of a Digital Twin (DT) technology that uses machine learning algorithms to predict personalized postprandial glucose responses (PPGRs) and generate real-time dietary recommendations (Paramesh et al., 2024). This approach aims to minimize glucose fluctuations by integrating continuous glucose monitoring data, dietary logs, physical activity, and other physiological inputs.

## Future Directions: Towards Personalized and Adaptive Care

The future of diabetes management is moving towards more personalized and adaptive care. A 2025 study on personalized nutrition in type 2 diabetes remission demonstrates the potential of ML-powered platforms to provide individualized dietary recommendations based on predicted glucose responses3. These technologies offer the promise of dynamic insulin recommendations that account for daily variations in insulin sensitivity, potentially improving glycemic outcomes while reducing the burden on patients and healthcare providers. (Paramesh et al., 2024)

In summary, while current diabetes management systems have made significant advancements, challenges remain in achieving fully integrated, real-time adaptive solutions. The integration of advanced machine learning and AI technologies is showing promise in bridging the gap between current capabilities and the goal of optimized, personalized glycemic control in real-time. (Paramesh et al., 2024)

# **6. The Role of Artificial Intelligence and Machine Learning in Advancing Diabetes Management**

The integration of artificial intelligence (AI) in diabetes management is transforming traditional approaches by addressing critical limitations of static dosing algorithms through adaptive learning capabilities. AI-powered systems analyze complex patterns in continuous glucose monitoring (CGM) data, nutritional intake, and insulin pharmacodynamics—patterns that static models often fail to capture (Battelino et al., 2019). This ability to process large datasets and identify hidden relationships makes AI particularly suited for managing a condition as complex as diabetes.

## Predictive Analytics for Glucose Forecasting

One of the most impactful applications of AI in diabetes management is predictive modeling for glucose trends. Machine learning models, particularly Long Short-Term Memory (LSTM) networks, have demonstrated an 18–23% improvement in prediction accuracy compared to conventional methods when analyzing 72-hour CGM data. These models can help anticipate postprandial glucose excursions by incorporating factors such as meal composition, activity levels, and time-dependent insulin sensitivity (Zhu, Fan, & Wang, 2020).

Commercial implementations like DreaMed Advisor Pro™ utilize similar architectures by combining random forest classifiers with physiological models to optimize basal rates and correction factors in closed-loop systems control (Moon et al., 2021). Predictive tools such as IBM Watson Health also apply historical glucose data to anticipate fluctuations, offering actionable insights to help prevent hyperglycemia through pre-emptive insulin administration.

## AI for Automated Dietary Analysis

AI extends beyond glucose prediction to improve dietary management, which is a crucial aspect of diabetes care. Computer vision systems such as GoCARB (Pölsterl et al., 2021) use smartphone images to automatically estimate carbohydrate content with approximately 85% accuracy. This capability helps reduce dosing errors caused by inaccurate carbohydrate counting, a common source of insulin dosing inaccuracy. Integrating such a feature into a nutritional logging module could significantly enhance user accuracy and overall diabetes management.

## AI-Driven Decision Support Systems

AI has also revolutionized insulin dosing with decision-support systems that provide individually tailored recommendations. Systems like DreaMed Advisor Pro™ fine-tune insulin therapy using data from CGMs, insulin pumps, and patient-reported information, leading to significant improvements in glycemic control (Moon et al., 2021). These decision-support systems reduce reliance on static parameters and help patients avoid hypo- and hyperglycemia by dynamically adjusting recommendations based on real-time data.

## Economic and Clinical Impact

Economic and clinical data suggest that AI-optimized systems can have a significant impact on diabetes management. For example, one study reported that such systems reduce severe hypoglycemia events by 40%, yielding an estimated annual savings of approximately $2,800 per patient in acute care costs (American Diabetes Association, 2018).

When these AI-based approaches are integrated with an automated titration layer that dynamically adjusts for factors like physical activity and metabolic responses, the potential cost savings could be even greater. This is particularly relevant given that the average annual cost of Type 1 diabetes management has been reported to be around $16,752 by the American Diabetes Association (2018).

## Enhancing Patient Engagement

AI technologies are reshaping patient engagement in diabetes care by providing personalized guidance and education. Digital tools, such as conversational agents and virtual assistants, offer real-time support; for instance, the AI-driven chatbot Bluestar Diabetes provides tailored recommendations regarding diet, exercise, and medication adherence. This kind of personalized, on-demand support helps reduce the cognitive burden on patients and promotes more effective self-management. (Bluestar Diabetes)

## Summary

In simple terms, artificial intelligence is transforming how we manage diabetes. AI-powered systems can learn from vast amounts of data such as continuous glucose readings, meal details, and activity levels to predict blood sugar trends more accurately than traditional methods (Zhu, Fan, & Wang, 2020). For example, advanced models like LSTM networks can foresee post-meal blood sugar spikes, allowing for timely adjustments in insulin doses. Additionally, tools like computer vision systems automatically count carbohydrates from food images, reducing common errors in insulin dosing (Pölsterl et al., 2021). AI also drives decision-support systems that offer personalized insulin recommendations by continuously analyzing real-time data from various sources. These innovations not only improve glycemic control but also help lower healthcare costs by preventing severe episodes of low blood sugar. Overall, AI is making diabetes management more precise and personalized—an approach that is central to our project, which uses temporary CGM data and machine learning to optimize insulin dosing while keeping physicians involved in the decision-making process.

# **7. Reinforcement Learning for Personalized Medicine and Adaptive Insulin Therapy in Diabetes**

Reinforcement learning (RL) represents a transformative approach in diabetes management, moving from population-based strategies to personalized care. Unlike supervised learning, RL relies on continuous interaction with the environment to learn optimal strategies, making it particularly suited for managing the significant inter-individual variability in insulin sensitivity. Recent studies highlight RL's potential to tailor insulin therapy dynamically, improving glycemic outcomes while minimizing patient burden. (Dénes‑Fazakas et al., 2024)

## Applications of Reinforcement Learning in Diabetes Management

1. **Deep Q-Learning for Time-in-Range Optimization**  
   Deep Q-learning has shown significant promise in optimizing time-in-range (TIR) metrics. For example, a study demonstrated that RL algorithms achieved a 73% TIR compared to traditional methods, which averaged around 58% (Dénes‑Fazakas et al., 2024). These RL models can analyze continuous glucose monitoring (CGM) data and macronutrient-level meal logs to dynamically adjust insulin dosing strategies, reducing postprandial glucose spikes and improving overall glycemic control.
2. **Managing Exercise-Induced Variability**  
   Adjusting insulin dosing during and after physical activity remains one of the most challenging aspects of diabetes management due to rapid changes in insulin sensitivity. RL-based systems have been shown to outperform traditional methods by incorporating real-time CGM data and reinforcement signals. For instance, multi-step RL algorithms have demonstrated improved TIR during exercise-induced variability by dynamically adapting to changing physiological states (Cakiroglu et al., 2024). These systems could further reduce risks such as delayed hypoglycemia by learning from patient-specific responses.
3. **Dual-Hormone Systems with RL Integration**  
   Dual-hormone systems delivering both insulin and glucagon represent a promising frontier for RL integration. Studies have shown that RL-driven dual-hormone systems can significantly reduce hypoglycemia by up to 68% in experimental models(Dénes‑Fazakas et al., 2024). While current systems primarily focus on insulin delivery, future expansions could incorporate glucagon delivery for enhanced blood glucose stability.

## Clinical Validation and Safety Considerations

Clinical validation is critical for implementing RL-based solutions safely. A phased approach, starting with retrospective data analysis and progressing to controlled clinical trials, has proven effective in ensuring safety and efficacy (Wang et al., 2023). For example, RL-based frameworks like RL-DITR have undergone stepwise validation, demonstrating superior performance compared to standard clinical methods in managing hospitalized patients with type 2 diabetes (Wang et al., 2023). Simulated environments using digital twins provide an additional layer of safety by allowing RL models to be tested and refined before deployment.

## Future Directions

Reinforcement learning offers immense potential for adaptive insulin therapy by continuously evolving with new data inputs from CGMs, activity monitors, and dietary logs. The future lies in integrating RL into fully autonomous systems that provide real-time, patient-centered recommendations. Expanding beyond single-hormone therapies to dual-hormone systems and incorporating advanced safety protocols could set a new standard in diabetes management (Jafar et al., 2024).

**8. Maintaining Physician Oversight in AI-Driven Systems**

Integrating artificial intelligence (AI) in diabetes management requires a delicate balance between automation and clinical judgment. The "clinician-in-the-loop" approach, endorsed by medical associations, ensures that human expertise remains central to decision-making while AI assists physicians (Evans, 2024). This is particularly crucial given the significant annual prevalence of severe hypoglycemia in diabetic patients.

## Dashboard Design and Decision Transparency

Effective physician dashboards are critical for improving oversight and decision acceptance. Key features that enhance transparency and physician confidence include:

1. Model confidence intervals, indicating prediction reliability
2. Feature importance rankings, explaining factors influencing recommendations
3. Longitudinal outcome comparisons between AI-driven decisions and standard care

Incorporating these elements can significantly improve physician acceptance of AI recommendations. Additionally, adaptive safety thresholds have been shown to reduce false hypoglycemia alerts by up to 42%, further enhancing accuracy and trust in AI-driven systems (Mackenzie, Sainsbury, & Wake, 2024).

## Adaptive Safety Parameters and Alerts

Implementing adaptive safety parameters allows for dynamic alerts based on evolving patient data. This approach minimizes unnecessary warnings while ensuring timely intervention for critical events, effectively reducing alert fatigue and increasing the accuracy of clinical decision support. (Evans, 2024).

## Ethical and Legal Considerations

Addressing ethical implementation requires careful consideration of liability distribution and accountability. Recent reports highlight the complexity of assigning responsibility in AI-assisted clinical decisions (Evans, 2024). . Implementing robust audit trail protocols that log model versions, decision overrides, and clinician rationales aligns with current "explainable AI" standards and enhances accountability while building trust in AI-driven systems (Mackenzie, Sainsbury, & Wake, 2024).

## Summary and Practical Implementation

Incorporating physician oversight in AI systems is crucial for safe and effective diabetes management. By integrating adaptive thresholds, transparent dashboards, and robust audit trails, your system can bridge the gap between AI’s technical capabilities and clinical practice. This hybrid decision-making model ensures that AI serves as an augmentation of clinical expertise, not a replacement, maintaining both safety and personalization.

# **9. Summary**

Type 1 diabetes (T1D) is a chronic condition requiring continuous monitoring and precise insulin dosing to maintain glycemic control and prevent both acute complications, such as diabetic ketoacidosis and severe hypoglycemia, and chronic issues like cardiovascular disease, neuropathy, and kidney failure. Although advances in diabetes technology such as continuous glucose monitoring (CGM) and insulin pumps have improved patient outcomes, current management systems remain limited by static insulin dosing strategies, high costs, and fragmented data management. These limitations create an urgent need for more adaptive, cost-effective solutions that can personalize care based on each patient’s unique physiological responses.

Recent innovations in diabetes care have focused on integrating digital health tools, decision support systems, and artificial intelligence (AI) to optimize insulin therapy. AI-driven systems, particularly those using machine learning (ML) and reinforcement learning (RL), offer the ability to predict blood glucose trends, analyze meal composition, and dynamically adjust insulin recommendations. Predictive analytics can significantly reduce hypoglycemia and improve overall glycemic control by learning from continuous glucose data and real-life meal patterns. Reinforcement learning, in particular, has shown great potential for adapting to the variability in insulin sensitivity, especially during exercise and illness

However, despite these technological advancements, maintaining physician oversight and ensuring patient safety remains critical. The "clinician-in-the-loop" approach ensures that automation supports, rather than replaces, clinical expertise, improving both physician trust and patient outcomes.

Economically, the growing cost burden of T1D management highlights the importance of developing affordable solutions that reduce long-term dependency on expensive technologies like CGM. A system that utilizes temporary CGM for initial parameter identification, combined with ML and RL for continuous learning and optimization, could provide a more sustainable model for personalized diabetes care. This approach could help reduce costs while improving dosing accuracy, minimizing complications, and enhancing quality of life for patients.

The opportunity to create a cost-effective, AI-driven diabetes management system lies at the intersection of clinical medicine and technology. This project bridges that gap by structuring patient data—covering meals, activity, medications, and health conditions—into a scalable framework. Machine learning will optimize dosing, while reinforcement learning personalizes it in real time. By reducing CGM reliance and empowering physicians with actionable insights, this system could set a new standard for personalized diabetes care.

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