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ARTIFICIAL INTELLIGENCE FOR PREDICTION OF EXERCISE-ASSOCIATED HYPOGLYCEMIA IN PHYSICALLY ACTIVE PEOPLE WITH TYPE 1 DIABETES

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ABSTRACT

Research objectives. Physical activity continues to be a major barrier to achieving ideal blood glucose control in individuals with type 1 diabetes due to the ongoing threat of hypoglycemia. Traditional alerts from Continuous Glucose Monitoring (CGM) systems are mostly reactive as they fail to consider the specific context of physical activity. The purpose of this project is to provide a critical overview of evidence regarding AI and ML techniques for identifying when exercise will cause low blood glucose in individuals who are physically active and have type 1 diabetes.
Methods. The primary databases searched for this narrative review with a structured literature search were PubMed/MEDLINE and PubMed Central.
Key findings. Exercise-specific models based on repeated-measures random forest and logistic regression achieved AUROC values around 0.83, while broader explainable XGBoost models using CGM data showed excellent short-term predictive performance. The use of simple translation of clinical knowledge into tool-based formats such as GlucoseGO has been shown to retain high levels of performance when only using limited number of easily obtained variables.
Conclusions. AI will allow for a meaningful integration with traditional monitoring in order to shift clinical practice from detecting problems after they occur toward predicting the level of risk each patient has when participating in an activity. The direction in which this will be clinically beneficial will be through developing cost-effective, interpretable, validated tools for use within the current CGM and automated insulin delivery systems.

KEYWORDS

Artificial Intelligence, Machine Learning, Continuous Glucose Monitoring, Type 1 Diabetes, Physical Activity

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1. Introduction

Regular physical activity is a good idea for all individuals who have type 1 diabetes as it increases cardiovascular health, insulin sensitivity and improves general health and wellness. On the other hand, there is no doubt that the challenges associated with daily diabetes management are at least as much a result of how an individual's blood glucose levels respond to different types of exercises performed at varying intensities, times during the day and at various times before the exercise, how much circulating insulin they have and their current level of fitness (Adolfsson et al., 2022; Gaszynska et al., 2025; Parent et al., 2023; Riddell & Peters, 2023).

Physiologic complexity exists when considering exercise-associated dysglycemia in individuals with type 1 diabetes. Generally, aerobic exercises are associated with declining blood glucose levels due to increased glucose uptake by skeletal muscle along with continued elevated levels of exogenously administered insulin. On the other hand, resistance training and high intensity interval training have been shown to lead to greater variability in blood glucose levels in response to exercise such as an acute decrease in blood glucose concentration smaller than expected at the time of exercise, a transient increase in blood glucose levels at some point during the time of exercise or even later onset post-exercise hypoglycemia. Thus, exercise-associated dysglycemia can occur outside of the actual time frame of the individual's exercise and may also occur immediately after the conclusion of their physical activity session potentially extending well into the subsequent night (Adolfsson et al., 2022; Helleputte et al., 2023; McClure et al., 2023; Murillo et al., 2022; Riddell & Peters, 2023).

In recent years, improvements in diabetes technology have greatly increased the safe practice of physical activity for those with type 1 diabetes. Continuous Glucose Monitoring Systems provide users real time interstitial glucose levels as well as threshold-based alarms to alert patients of impending hyperglycemia. Automated Insulin Delivery (AID) systems now also enable personalized treatment options for each patient. While advancements in technology continue to improve exercise management for individuals with type one diabetes, there still exists some limitations of traditional management strategies. Traditional alarm settings on AID devices tend to trigger an alarm once the blood glucose level is low or declining rapidly at which point it may be too late to prevent an episode of hypoglycemia from occurring. These limitations can be particularly problematic in the context of athletic training where many important carbohydrate intake and insulin dosing decisions regarding what foods to consume, how much insulin to reduce prior to training, when to train and post-training monitoring must frequently be made by athletes before significant biochemical changes occur (American Diabetes Association Professional Practice Committee, 2025; Moser et al., 2025; Perkins et al., 2024; Schubert-Olesen et al., 2022).

Threshold-based alerts are relatively poor at determining the likelihood that an individual will experience hypoglycemic events. Artificial Intelligence (AI), machine learning (ML) methods offer potential solutions for filling these gaps. The predictive model used in AI/ML methods would use all relevant information such as current CGM values, change rates of blood glucose levels over time, how much insulin was administered, how many hours BG levels were less than desired, type and duration of physical activity, and individual responses to those factors. A wide variety of techniques have been studied recently; examples include logistic regression, repeated measures random forests, explainable ML using mixed effects, ensemble methods and XGBoost using SHAP based explanations (Bergford et al., 2023; Denes-Fazakas et al., 2022; Duckworth et al., 2024; Katsarou et al., 2025; Ma et al., 2025; Mosquera-Lopez et al., 2023; Russon et al., 2026; Tsichlaki et al., 2022; Tyler et al., 2022; Zhang et al., 2023).

While there are increasing data to suggest models that will offer the best clinical utility as well as minimize user burden (through the use of easily accessible data from CGMs) and have minimal input requirements (e.g., few if any food entries, no need for detailed descriptions of insulin dosages or exercise patterns, no wearable device required), there remain many challenges in this area. These include very small sample sizes of subjects with type 1 diabetes, heterogeneity among the different outcomes being studied, limited numbers of studies that can provide some degree of external validation and a lack of clarity regarding how an individual's predictive algorithm output should be integrated into decisions to engage in physical activity using the patient's CGM system or AID system (Katsarou et al., 2025; Ma et al., 2025; Russon et al., 2026; Tsichlaki et al., 2022; Zhang et al., 2023).

This systematic literature review aims to critically assess research on the use of AI and ML models for predicting exercise associated hypoglycemia in physically active individuals with type 1 diabetes. Emphasis will be placed on comparing different model families, as well as identifying specific exercise related factors, including CGM data used as input for these models, methods to improve model interpretability and their potential for immediate application in a clinical or sporting setting. Additionally, we will evaluate how accurately an AI supported prediction system predicts hypoglycemic events compared to a traditional CGM based monitoring systems. Lastly, we will identify potential barriers to widespread implementation of AI supported predictive systems in both clinical and sporting environments (Tsichlaki et al., 2022; Zhang et al., 2023).

2. Methodology

This article has been developed as a narrative review with a structured literature search. A structured literature search was utilized in order to synthesize the heterogeneity of this body of research (study design, participants, type of exercise, effect on blood glucose levels, models used for analysis) that have emerged from a variety of sources including narrative/systematic reviews, original ML model development articles, real-world observational studies, randomized technology trials and clinical guidelines.

The literature search was primarily conducted in MEDLINE/PubMed and PubMed Central.

Type 1 diabetes was a core term in addition to the other terms for hypoglycemia, CGM, machine learning, artificial intelligence, prediction, automated insulin delivery, exercise, sport, and physical activity. Search strategies used supplementary searches using tighter combinations of these core terms. For example, "type 1 diabetes AND exercise AND hypoglycemia AND CGM," "type 1 diabetes AND physical activity AND prediction," and "exercise-associated hypoglycemia type 1 diabetes machine learning."

Studies that met inclusion criteria were: Clinical Practice Guidelines/Position Statements (e.g. ADA); Narrative or Systematic Reviews (of all types); Original Human Observational Studies or Interventional Studies (involving participants diagnosed with T1D); Studies of Continuous Glucose Monitoring (CGM) and/or Automated Insulin Delivery Systems (AIDs), which occur prior to/during/ex post-physical activity; Any study(s) assessing Artificial Intelligence (AI), Machine Learning (ML), Explainable Machine Learning (XLM), Predictive Models for Hypoglycemia/Exercise-induced Glycemic Events. Priority was given to papers which utilized exercise-specific predictor variables; Real world physical activity data collection; Clinically interpretable outcome measures; Direct Relevance to Preventing Hypoglycemia in Active Individuals Diagnosed with Type 1 Diabetes.

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The evidence base used to create the final analysis consisted of five major areas or "domains" which included: (1) what is known about how exercise-induced changes can cause a decrease in blood glucose levels among people who have type 1 diabetes; (2) the strength and limitations of current continuous glucose monitoring (CGM) alert systems to predict drops in blood sugar during physical activity; (3) the potential of using artificial intelligence (AI), machine learning (ML) techniques to predict low blood sugar episodes; (4) what factors are most predictive of low blood sugar episodes when individuals are physically active and/or exercising, and how these predictive factors can be combined from different sources ("multimodal") for improved predictions; and (5) what are the barriers and opportunities to translating this research into real-world practice. Table 1 presents the search strategy and eligibility criteria, while Figure 1 illustrates the conceptual pathway from exercise physiology to AI-supported hypoglycemia prediction.

Table 1. Search strategy and eligibility criteria

Element	Final version for the manuscript
Review type	Narrative review with a structured literature search
Time window	2022 - 2026
Core databases	PubMed/MEDLINE, PubMed Central
Main concepts	type 1 diabetes, exercise, physical activity, sport, hypoglycemia, CGM, machine learning, artificial intelligence, predictive alert, automated insulin delivery
Inclusion criteria	English-language guidelines, reviews, original human studies, exercise-related CGM/AID studies, ML/XAI/prediction papers relevant to hypoglycemia or exercise-associated dysglycemia in T1D
Exclusion criteria	Studies outside 2022–2026, exclusively T2D populations, engineering-only reports without meaningful clinical interpretation, non-peer-reviewed sources when peer-reviewed versions were available
Final reference set	30 references selected for the review, including 27 core evidence-based sources and 3 contextual APCZ sources requested for the target journal ecosystem

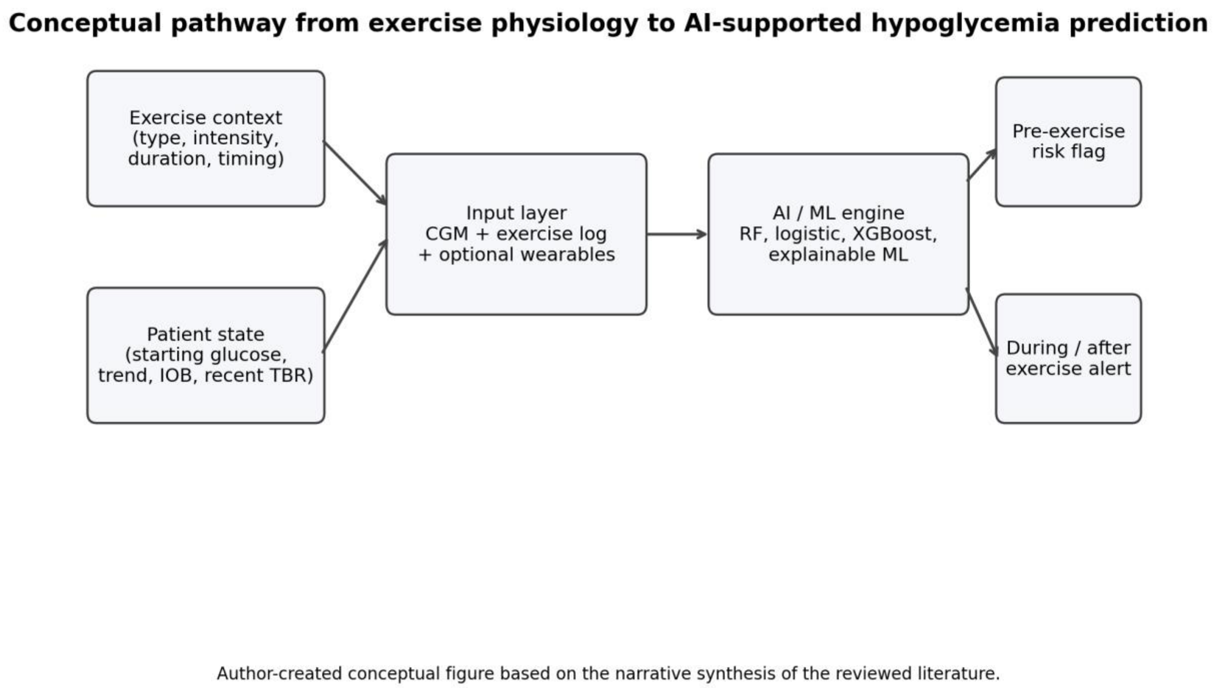

Fig. 1. *Conceptual pathway from exercise physiology to AI-supported hypoglycemia prediction.*

3. Results

3.1. Exercise-associated dysglycemia in type 1 diabetes

The effects of a single exercise session will be influenced by multiple variables which interact with one another to affect the overall effect of the physical activity: the type of physical activity being performed, the length/duration/intensity of the physical activity, the time of day/night the individual chooses to begin their physical activity, the initial glucose levels, the amount of circulating insulin at the beginning of the activity, consumption of carbohydrate prior to initiating physical activity, history of experiencing hypoglycemia prior to this current event, whether or not the individual has habituated themselves to perform this particular form of physical activity (Adolfsson et al., 2022; Cavallo et al., 2024; Riddell & Peters, 2023; Schubert-Olesen et al., 2022).

The risk of hypoglycemia can increase significantly during long-term aerobic physical activity. Aerobic activity increases the amount of glucose taken up by muscles, whereas during the same time frame the liver does not produce enough glucose to compensate for this increased glucose use due to the continued presence of higher-than-normal circulating exogenous insulin levels. People who have type 1 diabetes are unable to naturally decrease their peripheral insulin levels immediately after initiating an episode of physical activity. As a result, there will typically be a significant mismatch between the body's utilization of glucose and its availability. This is likely one reason that mild, prolonged aerobic activity causes progressive decreases in blood glucose levels as well as potentially lead to late-onset post-exercise hypoglycemia (Adolfsson et al., 2022; Helleputte et al., 2023; Riddell & Peters, 2023).

In addition to that, resistance training (RT), sprinting, and High-Intensity Interval Training (HIIT) likely cause varied responses in terms of blood glucose levels. The response of counter-regulatory hormones to intense or anoxic activity could blunt or completely neutralize the immediate decrease in blood glucose levels or create transient hyperglycemia. Although there is no guarantee for safety from hypoglycemia with either RT or HIIT the likelihood of hypoglycemia occurring after a bout of exercise will be delayed until the late post-exercise period or overnight (Helleputte et al., 2023; McClure et al., 2023; Murillo et al., 2022).

Recent real-world research has also documented similar patterns as well. Adults participating in the T1DEXI study demonstrated the greatest average glucose reduction when using aerobic-type exercises. Aerobic was followed by those that used interval type exercises and then those who used resistance-type exercise. Time in range for participants who performed some form of exercise increased over their baseline, yet there was a small increase in time spent below range. The findings support the continued balance between metabolic benefits and increased risk of low blood sugar events (Riddell et al., 2023). Similar variability was observed in adolescent subjects. Exercise related glucose drop magnitude were positively correlated to lower HbA1c values, longer disease durations, lower body mass index, reduced fears of hypoglycemic episodes, increased levels of "insulin on-board" during the episode as well as pre-existing trends in decreasing glucose values over time and higher percentage of time spent within target blood glucose ranges for the 24 hours prior to this episode (Bergford et al., 2024; Riddell et al., 2024).

Pre-exercise factors that predict blood glucose levels during and after exercise have been shown to be highly predictive in previous studies. Modeling studies have shown that low initial glycemic levels, an increasing trend from high to low before exercise, more time spent below target previously and increased pre-exercise basal insulin on board are major contributors to the occurrence of hypoglycemia during exercise (Bergford et al., 2023). Studies have also shown that in adolescents, active youths may want to begin their exercise when interstitial blood-glucose levels are in range between 130mg% and 160 mg% and have a flat or declining trend prior to the beginning of their activity to reduce the risk of dysglycemia (Bergford et al., 2024).

Although modern technologies for managing diabetes are improving control at both planned and unplanned times they do not eliminate the issues with using technology to manage blood glucose levels during exercise. Glucose dynamics can vary rapidly, even within an individual, can vary depending upon the type of exercise being done and can be unpredictable across different individuals. This is why the 2025 EASD/ISPAD position statement on AID and physical activity identifies that "exercise requires tailored technological strategies" and does not view it simply as an extension of how to manage blood glucose levels while resting (Moser et al., 2025; Perkins et al., 2024).

Thus, exercise-related hypoglycemia in T1D can be considered an individually variable, time-variable and possibly predictable clinical condition. Therefore, it is no longer just about measuring blood-glucose levels while exercising but also predicting which direction future blood-glucose changes are most likely to occur and if there exists a clinically significant risk of hypoglycemic episodes associated with exercise, after early recovery from exercise or over night. Thus, this problem lends itself very well to artificial intelligence supported predictive modeling systems. These types of modeling systems will include physiological factors when making predictions rather than relying solely on threshold values (Bergford et al., 2023; Ma et al., 2025; Mosquera-Lopez et al., 2023; Russon et al., 2026; Tyler et al., 2022).

A significant implication of these physiological changes in a practical sense is that the "same" exercise recommendation can result in quite varying levels of glycemia depending upon the conditions. For example, the amount of decrease in blood sugar for an individual performing morning aerobic type activity may vary significantly compared to one who performs postprandial aerobic-type activity under the influence of a substantial amount of circulating bolus insulin and therefore has increased risk for hypoglycemia (Helleputte et al., 2023; Riddell & Peters, 2023).

3.2. Why conventional cgm alerts are often insufficient during exercise

The development of CGMs has improved the ability of individuals with T1D to manage their disease through continuous monitoring of blood glucose level, arrow trend indicators, and alarm notifications when low or high blood glucose levels occur. Physically active diabetics utilize CGM devices extensively for a variety of reasons including, making informed food selections prior to engaging in physical activity (pre-exercise), consuming carbohydrate containing foods within minutes after completion of physical activity, assessing alterations in glucose levels post-physical activity. While there are numerous applications for the use of CGMs during periods of physical activity, a major drawback for utilizing traditional threshold-based alert systems during routine physical activity is the inability to effectively mitigate potentially harmful events caused by delays associated with user reaction time (American Diabetes Association Professional Practice Committee, 2025; Perkins et al., 2024; Schubert-Olesen et al., 2022).

The limits of this technology become even more evident when there are large changes in blood glucose levels. Exercise also has an influence on how fast your body uses glucose. It influences where blood flow is going to various tissues and organs as well as what the relationship is between blood glucose and the level of glucose present in other areas such as muscle or fat as well as the temperature at the site of placement of the sensor. All of these factors will have an effect on how sensors behave and how quickly they reflect actual changes in plasma glucose. A 2024 clamp study was conducted by researchers to assess the effects that physical activity would have on two CGMs: Dexcom G6 and FreeStyle Libre 1 (specifically relating to their ability to accurately detect hypoglycemic episodes). Physical activity resulted in clinically significant reductions in the accuracy of both CGM systems' ability to detect hypoglycemia. Therefore, any predictive models developed using CGM data need to be viewed through the lens of the limitations associated with sensor use during physical activity (Maytham et al., 2024).

A third restriction of traditional alerts is they depend on blood glucose levels at the time and the near-future direction of glucose trends. Therefore, they will have limited impact in terms of integration with other factors related to an individual's exercise session. Alerts don't inherently take into consideration how much insulin remains active, how long the user has been below their target range recently, what kind of exercise the user anticipates doing, the way a person typically responds to activities of this type or specific sensitivities that a particular person has to physical exertion (Bergford et al., 2023; Bergford et al., 2024; Ma et al., 2025; Mosquera-Lopez et al., 2023; Russon et al., 2026).

The amount of alarm burden as well as the amount of time spent with an alarm system will also matter. The ADA Standards of Care have emphasized the need for educating patients on how to set their alert/alarm settings so they are able to avoid alarm overloads and alarm fatigue when starting CGMs. During exercise where many users are experiencing rapid physiological responses along with background noise from the environment and high levels of mental stress having too many alarms especially if those alarms are either unnecessary or poorly focused can actually decrease the protective benefits provided by using a CGM. One example of this is why improving relevance in addition to providing additional alerts should be a top priority when developing artificial intelligence-based CGM alerting systems (American Diabetes Association Professional Practice Committee, 2025; Duckworth et al., 2024).

Limitations of current systems are not arguments against developing CGMs technology. They indicate that the use of cgms alone is often insufficient when the task is not only to detect low blood glucose levels but also to forecast which exercise session will become unsafe before biochemical changes have occurred. This means that in most cases of exercising, a decision needs to be made prior to activity: whether to take carbohydrates, reduce insulin dosage, delay activities, alter intensity or increase monitoring during recovery. Threshold alerts for low blood glucose can be helpful once risk has been initiated and now we must provide next generation of tools to estimate risk prior to crossing the threshold (Moser et al., 2025; Perkins et al., 2024; Rilstone et al., 2024).

The most reasonable approach for future use will then be augmentation rather than replacement. Systems that are based on AI and/or machine learning could also be thought of as an additional analytic layer, layered over CGM. This would take data in the form of trends along with other forms of data related to the exercise being conducted, prior responses, insulin levels and possible wearable derived physiological measures. Essentially, it would mean moving from “low blood sugar is shown by the sensor” to “this person may experience hypoglycemia during some portion of their current phase of exercise or recovery” (Bergford et al., 2023; Ma et al., 2025; Mosquera-Lopez et al., 2023; Russon et al., 2026; Tyler et al., 2022).

3.3. Artificial intelligence and machine-learning models for hypoglycemia prediction

Recent research into artificial intelligence (AI) and machine learning (ML) has seen researchers apply these techniques to better predict a person's glycemic risk when living with type 1 diabetes. While traditional threshold based alert systems notify users about an impending low blood sugar event using thresholds established during clinical trials AI/ML use predictive modeling to forecast future risk based on historical trends of blood glucose values and for some models incorporate additional contextual variables such as insulin dosage, physical activity level and past glycemic variability. In 2022 a systematic review was conducted regarding hypoglycemia prediction algorithms used in individuals diagnosed with T1D. The authors concluded that the field is growing rapidly. However, due to the variety of data sources being utilized, varying lengths of forecasting horizon, different model development strategies employed and variable methods of evaluating model performance. It will likely be years before we have a uniform approach (Tsichlaki et al., 2022). A 2023 narrative review similarly emphasized that hypoglycemia prediction is clinically important but still limited by inconsistency in inputs, outcome definitions and validation strategy (Zhang et al., 2023).

Among a larger number of CGM based methods, explainable (XAI) machine learning has become an increasingly popular method. Using CGM derived features and demographic data from over 28,000 days of CGM usage by 153 young people with type 1 diabetes. Duckworth et al. (2024) built models to predict episodes of hypoglycemia (blood glucose < 70 mg/dl) and hyperglycemia (> 270 mg/dl) within the next sixty minutes. The authors used an XGBoost algorithm to train their predictive models and provided SHAP-based explanations of the predicted values generated for each participant. This is particularly important as the explanation of why a patient's blood glucose level will go high or low in the future can provide an action plan for how to avoid those highs or lows. A technically robust model may be no more effective at reducing episodes of high/low blood glucose levels if it does not provide explanations about what factors are driving the predictions for a particular user.

Since 2022 there have been significant advancements in modeling for specific exercises. Tyler et al. (2022) demonstrated that an adaptive, individualized machine learning algorithm could predict the exercise related glucose changes such as the lowest point of blood glucose during and immediately following the exercise and individuals who had a higher aerobic capacity may have experienced greater drops in glucose levels and lower nadir glucose values from their baseline during aerobic-type exercise. Not only does this research address the issue of exercise but also shows that responses to exercise are well enough organized to be modeled prior to exercise instead of being seen as random variation.

The idea of this model was supported by later studies conducted to determine its use in clinical settings. Using the data from T1DEXI the researchers created two different types of regression models (Repeated Measures Logistic Regression and Repeated Measures Random Forest) to assess how well each could predict hypoglycemic episodes associated with exercise. Both methods produced very similar results for discriminating against non-hypoglycemic events as indicated by an Area Under Receiver Operator Curve (AUROC) of 0.833 for the logistic regression method and 0.825 for the random forest method as well as balance accuracy of 77% (Bergford et al., 2023). Risk for hypoglycemia during exercise increased as a result of being at a low level of blood glucose before starting physical activity, having a negative rate of decline in blood glucose concentration immediately before beginning the physical activity, spending more total minutes below 70 mg/dl within the previous 24 hr and having a larger dose of pre-exercise bolus insulin on board.

A second area of research that is developing has been through the use of explainable or mixed-effects frameworks. Mosquera-Lopez et al. (2023) used an explainable mixed-effects machine learning model to identify hypoglycemic risk associated with the timing and intensity of the physical activity as well as the amount of insulin administered prior to exercise and the glucose burden at the start of each episode. This type of modeling provides several benefits when compared to traditional methods. For example, it can take into consideration both the characteristics of individual events as well as the characteristics of individuals across a series of events.

Ma et al. (2025) created and tested models utilizing the adult T1D Exchange Insulin Database (T1DEXI) to identify glycemic events throughout an individual's exercise session and in the hour immediately post-exercise, specifically: ≤54 mg/dL, ≤70 mg/dL, ≥200 mg/dL and ≥250 mg/dL. The models used four different types of information: Demographic/Clinical Data, Continuous Glucose Monitoring (CGM) Features, Carbohydrate/Insulin Data and Exercise Characteristics (Type, Duration, Intensity). Notably, Ma et al. determined that a model based solely on CGM would be suitable for implementation due to its comparable accuracy to those using multiple modality data but less complex data collection.

Targeted optimization of the hypoglycemic region is supported by research from domains other than just exercise. In addition to evaluating an ensemble approach that combined "basis" models, Katsarou et al. (2025) demonstrated that the ensemble performed better (lower error rates) at a 30 minute prediction time frame within the hypoglycemic range.

One of the most clear examples of translation towards usability in terms of an individual's specific use of an application demonstrates that using information collected through four different groups and over sixteen thousand recorded exercise events the authors used their data to develop an XGBoost model for predicting when exercise would cause hypoglycemia as well as develop a user-friendly heatmap with only three variables: starting blood glucose level, length of time exercising, and glucose trend arrow direction. With only the variable of initial glucose levels being inputted into the model produced a ROC AUC of 0.780 by inputting both the variable of length of time exercising and the variable of glucose trend arrow direction in addition to starting blood glucose levels resulted in the overall ROC AUC to be 0.851. By inputting all three variables of the final simplified model resulted in a ROC AUC of 0.87, sensitivity of 0.77 and specificity of 0.78 which was only slightly less than the full and very complex model (Russon et al., 2026).

The overall body of research from 2022 to 2026 indicates that making predictions about the occurrence of exercise associated hypoglycemia using machine learning algorithms is no longer simply a theoretical concept. There have been many studies which demonstrate that it is possible to estimate future risk based on an individual's CGM data alone or in conjunction with their insulin regimen, exercise history, and historical glucose levels. However, the research has been conducted within a heterogenous environment. The horizon for predicting when these events may occur varies greatly as do the definitions used to determine what constitutes a "hypoglycemic event" and the size of most of the study groups. Because of this variability there are few direct head-to-head comparisons of different types of predictive models. While the current body of evidence provides support for cautious optimism regarding whether or not machine learning based predictive models can provide superior performance compared to standard diabetes technologies, it does not yet support assertions of superiority by all machine learning predictive models (Katsarou et al., 2025; Ma et al., 2025; Russon et al., 2026; Tsichlaki et al., 2022; Zhang et al., 2023).

Another important differentiation exists between predicting blood glucose levels as a continuous value and predicting clinically significant events. The majority of past classical glucose prediction methods forecast future glucose values at some time horizon (15 minutes, 30 minutes, 1 hour). Although this type of question does not have much relevance in clinical practice with regard to making decisions about exercise. More directly related to an exercise decision would be determining if the individual is going to exceed a specific threshold where they will need to take action (Tsichlaki et al., 2022; Zhang et al., 2023). Table 2 summarizes the key studies supporting the core argument of the review, Table 3 compares AI/ML approaches relevant to exercise-associated hypoglycemia and Figure 2 illustrates the qualitative translational profile of model classes used in exercise-risk prediction.

Table 2. Key studies that carry the core argument of the review

Study	Design / population	Model / technology	Main contribution to this review
Adolfsson et al., 2022	ISPAD guideline	Exercise recommendations in youth with diabetes	Defines the clinical background and continuing relevance of hypoglycemia prevention during exercise.
Riddell et al., 2023 (T1DEXI)	Real-world adult study	CGM during aerobic, interval, and resistance exercise	Shows the largest acute glucose decline with aerobic exercise and the trade-off between improved TIR and increased TBR.
Riddell et al., 2024 (T1DEXIP)	Real-world adolescent study	CGM plus activity logging	Demonstrates that glucose change during activity depends on both event-level and person-level factors.
Bergford et al., 2023	Adults with T1D	Repeated-measures RF and logistic regression	Identifies lower starting glucose, falling trend, prior TBR, and IOB as key risk factors for exercise-related hypoglycemia.
Mosquera-Lopez et al., 2023	People with T1D during and after activity	Explainable mixed-effects ML	Supports interpretable prediction of both intraworkout and post-exercise hypoglycemia.
Ma et al., 2025	Adult T1DEXI dataset	Multimodal and CGM-only peri-exercise models	Shows that CGM-only prediction may perform similarly to more complex multimodal approaches.
Russon et al., 2026	Four-cohort exercise dataset	XGBoost plus simplified heatmap	Strong translational example: simple input variables retained good performance and high usability.

Table 3. Comparison of AI/ML approaches relevant to exercise-associated hypoglycemia

Model class	Typical inputs	Typical horizon	Strengths	Main limitation	Value
Repeated-measures logistic regression	Starting glucose, trend, prior TBR, IOB	During exercise	Simple and intuitive	May miss nonlinear relationships	High
Repeated-measures random forest	Same plus nonlinear interactions	During exercise	Good discrimination in real-world exercise data	Less intuitive than logistic models	High
Explainable mixed-effects ML	CGM, insulin, activity context, repeated observations	During and after exercise	Captures within-person structure	More complex deployment	Moderate to high
XGBoost + SHAP	CGM features and demographics	Up to 60 min ahead	Strong performance and explanation	Not exercise-specific in all studies	High
Multimodal peri-exercise models	CGM, exercise, insulin, carbohydrates, demographics	During and 1 h post-exercise	Broad physiologic context	Higher input burden	Moderate
CGM-only translational tools	Current CGM values, trend, summary metrics	During and 1 h post-exercise	Low burden and automatic data capture	May miss richer physiology	Very high

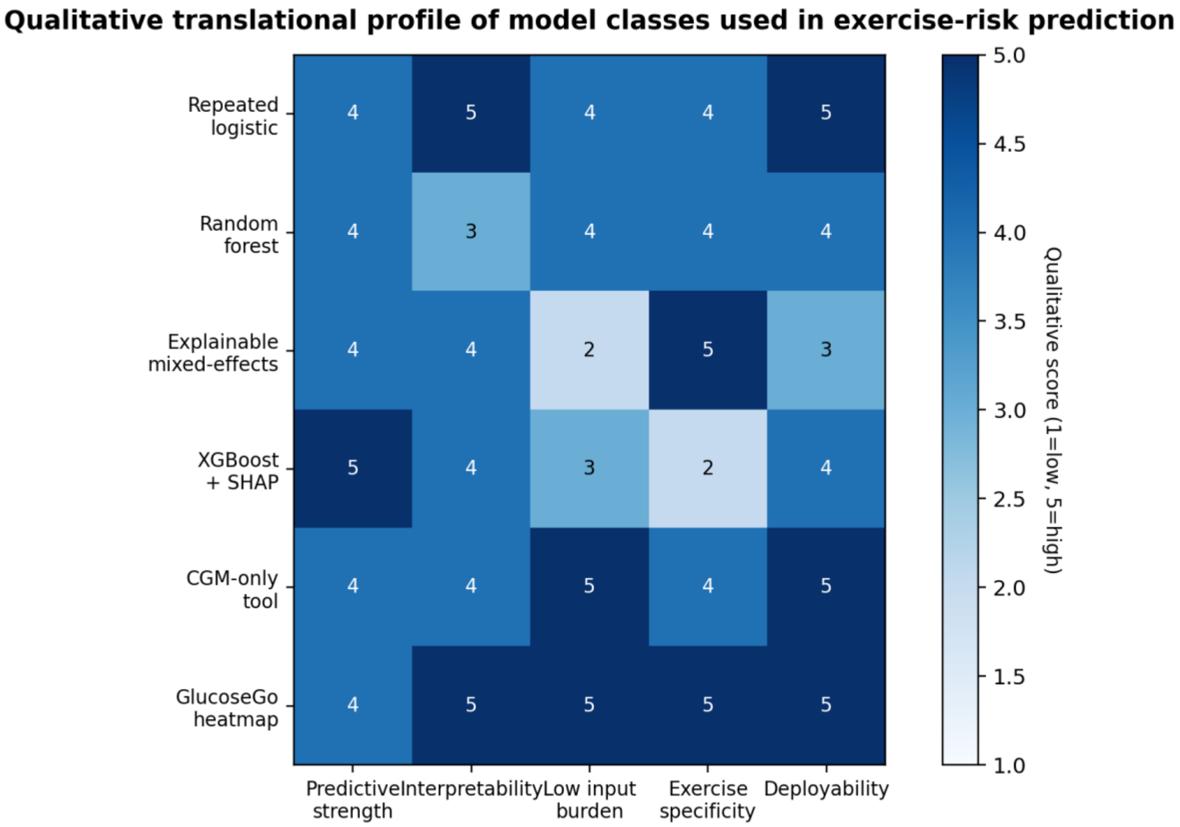

Fig. 2. Qualitative translational profile of model classes used in exercise-risk prediction.

4. Discussion

4.1. Exercise-specific predictors and multimodal data inputs

A common theme in current research into EAH (exercise-associated hypoglycemia) is that a limited number of factors are responsible for its occurrence. While the models may be different in each study most studies have found the same basic variables as being predictive of hypoglycemic risk during physical activity. The similarity in results from these studies is encouraging since this indicates that there are identifiable clinical signs associated with hypoglycemia that can be applied generally (Bergford et al., 2023; Bergford et al., 2024; Ma et al., 2025; Mosquera-Lopez et al., 2023; Russon et al., 2026; Tyler et al., 2022).

Beginning glucose is the only variable which was identified as the best indicator of whether an adolescent will have an episode of exercise-induced hypoglycemia. The area under the receiver operator curve (ROC AUC) for beginning glucose in this study of 13 adolescents was 0.78 even when using only this measure (Russon et al., 2026). Bergford et al. (2024) found that if you begin exercising at interstitial blood glucose levels of 130-160 mg/dl and your glucose trends are either stable or downward trending then your risk of experiencing dysglycemia will be reduced.

The second major predictive factor for the risk of hypoglycemia in adults with type 1 diabetes is the glucose trajectory. A negative pre-exercise glucose rate of change increased probability of hypoglycemia during exercise in adults with type 1 diabetes (Bergford et al., 2023). In addition to starting glucose and duration of exercise added to the simplified XGBoost model adding glucose trend arrows materially improved discrimination. The final heatmap was explicitly divided into panels showing stable/rising vs falling glucose (Russon et al., 2026).

Duration is consistently identified as an important predictor. In addition to duration, the GlucoseGo study found that among all features examined starting glucose was the best predictor. The results from this study further indicate that model accuracy decreased with increasing session durations and that the models were less accurate when predicting exercise sessions greater than 60 minutes in length (Helleputte et al., 2023; McClure et al., 2023; Mosquera-Lopez et al., 2023; Murillo et al., 2022; Riddell et al., 2024; Riddell et al., 2023; Russon et al., 2026; Tyler et al., 2022).

There is an important debate about what number of input modality types is necessary. The models developed by Ma et al. (2025) included demographics/clinical factors, CGM summaries, carbohydrate consumption, insulin administration history and activity characteristics. However, the authors stated that while they found CGM models to perform equally as well for most peri-exercise measures their deployment was much simpler. Thus, there exists a positive and beneficial dynamic within this field - multimodal models represent a better representation of physiological processes. However, fewer input modalities (parsimony) allow greater scalability (Ma et al., 2025; Russon et al., 2026).

Physiologic signals from wearable devices offer another area for exploration. The use of wearables to predict ML based on physical activity levels in type 1 diabetes has been demonstrated as feasible using CGM in combination with heart rate data. Heart rate features improved performance when used in conjunction with CGM compared with CGM alone (Denes-Fazakas et al., 2022). Thus, while this study has not proven the ability to improve hypoglycemic prediction in general practice settings the results support the idea that multi-modal wearable derived physiologic signal will add to the development of future exercise aware predictive systems through the inclusion of additional physiologic information which can be captured by CGM alone.

What stands out to me in this regard is that the least complicated variables have been consistently demonstrated as being most reproducible. Starting glucose, Trend Direction, Insulin Exposure, Recent Low-Glucose Burden and Exercise Duration have all been shown to be consistent across translational, explainable-ML, adolescent and adult exercise risk research. Although the inclusion of more complicated input variables can help increase model accuracy the literature clearly supports the notion that these simple variables serve as a foundational backbone for clinically useful exercise-risk predictions (Bergford et al., 2023; Bergford et al., 2024; Ma et al., 2025; Mosquera-Lopez et al., 2023; Russon et al., 2026).

From an operational point of view, these findings suggest that future approaches to providing evidence-based counseling regarding physical activity need to be more structured than past ones. The pre-exercise screening of patients with diabetes should involve assessing all three domains of their glycemic state: their current glycemic state (the glucose level as measured at the moment), their glycemic momentum (the rate of decline or rise in blood glucose levels over time) and the physiological context (the timing of the meal and the type and duration of the planned physical activity). To put it simply, instead of asking "what are your numbers?" we can ask "are you coming down?", "how much insulin do you have working", "have you had a low recently?" and "when are you planning to exercise?" (Adolfsson et al., 2022; Bergford et al., 2023; Bergford et al., 2024; Ma et al., 2025; Riddell & Peters, 2023; Russon et al., 2026).

Real-life data also show that many individuals with T1D take preventive amounts of carbs prior to or during an activity in order to avoid hypoglycemia. Such actions will be ignored in studies that do not account for them. However, if they are included in a model, they may make it more difficult to apply that model to other situations due to differences among individuals with respect to their knowledge level about managing their diabetes, fear of hypoglycemic episodes and their environment (Cavallo et al., 2024; Ma et al., 2025; Parent et al., 2023). One reason for this is that the cumulative impact of rescue carbs could already be embedded in a patient's CGM readings, potentially making some CGM-only models competitive with more complex multimodal systems because accurate meal reporting would be required to obtain complete information about how these additional carb sources affect glucose levels. Table 4 shows exercise-specific predictors of impending hypoglycemia.

Table 4. Exercise-specific predictors of impending hypoglycemia

Predictor	Strength of signal in recent literature	Clinical interpretation
Starting glucose	Very strong	The single most reproducible pre-exercise risk variable.
Glucose trend / rate of change	Very strong	A stable 150 mg/dL is not equivalent to a rapidly falling 150 mg/dL.
Insulin-on-board	Strong	Higher active insulin before exercise increases the probability of glucose decline.
Prior time below range / recent low-glucose burden	Strong	Recent lows may reflect unstable control or impaired counterregulation.
Exercise duration	Strong	Longer sessions increase cumulative risk and predictive uncertainty.
Exercise type / intensity	Moderate to strong	Aerobic exercise usually lowers glucose more than resistance or interval work.
Time of day	Moderate	May modify post-exercise and nocturnal risk.
Person-level phenotype	Moderate	Fitness, HbA1c, BMI, and disease duration help explain between-person variability.
Wearable physiology	Emerging	Heart-rate and related signals may strengthen future multimodal models.

4.2. Clinical applicability and barriers to implementation

The clinical utility of an AI-based predictive model of exercise-induced hypoglycemia will depend upon factors beyond those based upon discrimination metrics. A model used in "real world" settings must be able to provide adequate lead time for the taking of corrective measures, be understood by both the patient and clinician and have a data burden that is acceptable during the normal course of exercise. Therefore, the most clinically important question when considering the utility of such models is not merely how well a model can predict low blood glucose levels as compared to a baseline comparator, but whether it will help individuals make safer choices relative to their pre-exercise and peri-exercise dietary and insulin adjustments, timing of their workouts and post-workout self-monitoring (American Diabetes Association Professional Practice Committee, 2025; Ma et al., 2025; Moser et al., 2025; Perkins et al., 2024; Russon et al., 2026).

Beginning to show evidence of clinical relevance as well are the findings that predictions can lead to actual improved health care benefits. The PACE randomized controlled study found use of a CGM system with alerts for impending hypoglycemia resulted in significantly less time spent at values lower than 2.8 mmol/l both overall and over the 24 hour post-exercise when compared to the standard threshold alerts used by a traditional CGM system (Rilstone et al., 2024). While this was not a fully realized machine learning decision support tool; it does represent a significant step forward in a key area of development, transitioning from reactive-threshold based warnings to proactive-risk notifications will likely have positive effects on patient outcomes during physical activity.

A key goal in implementing these systems will likely be to use as few input parameters as possible using data that is already being collected through regular use of existing technologies used to manage diabetes. As reported by Ma et al. (2025) the CGM-only models they tested performed well in predicting the occurrence of glycemic events associated with physical activity while requiring minimal effort from users due to automatic collection of all required inputs. In addition to testing the ability to predict glycemic excursions when a person chooses to engage in physical activity the GlucoseGo study by Russon et al. (2026) examined how best to translate this research into practice by developing simple graphics that could help guide people before engaging in an activity. The researchers found that even the simplest version of their model which included just three variables (starting glucose level, amount of time spent engaged in physical activity and direction of glucose trend arrow) would retain almost all of the accuracy of their more detailed version and was therefore suitable for use immediately prior to engaging in physical activity.

Clinical adoption also depends on interpretability. Some researchers have demonstrated how the same risk forecasting capabilities could be developed as a form of explainable ML so when clinicians need to make an exercise decision they will know which factors contributed to their patient's high-risk assessment (Duckworth et al., 2024; Mosquera-Lopez et al., 2023). The point is that exercising is very much about behavior and about the context of the individual. A model that identifies a high level of risk but does not specify what are the key risk drivers would likely provide significantly less utility in real-world settings than a model that provides clear rationale. Thus, this ability to explain may further support increased clinician/patient dialogue and clinician/patient confidence in recommendations.

Firstly, the reliability of predictive performance will be based upon how accurate the original data stream is. The accuracy of CGMs themselves can also potentially decrease with exercise-induced hypoglycemia. A 2024 experimental study demonstrated that exercise has a significant impact on the accuracy and ability to detect hypoglycemia for 2 well-established CGM systems (Maytham et al., 2024). Although this is not intended to minimize the utility of AI-based prediction in general. It means that model outputs should be viewed from both the physiological limitations of the interstitial glucose sensor and the technological limitations of interstitial glucose sensors during exercise.

Secondly, the user's experience is still a significant practical problem. If there are an excessive amount of (more advanced) predictions that can potentially undermine some of the benefits by providing an inordinate amount of alerts which are either too often, at poor times or not sufficiently contextualized with respect to the user's environment (American Diabetes Association Professional Practice Committee, 2025; Duckworth et al., 2024; Rilstone et al., 2024).

Thirdly, integration of ai with existing diabetes technology ecosystems is still incomplete. In its 2025 EASD/ISPAD position statement on artificial intelligence in diabetes around physical activity. It was stated that while aids have many of the potential to offer large-scale health benefits for people living with diabetes through the use of physical activity. This is important since the most effective way to implement new ai tools would be by embedding them as an analytical tool within CGM and AID workflows rather than developing the tools independently as stand alone prototypes. While development of a good algorithm is necessary for implementation of ai, compatibility of the algorithm with the technological environment where physical activity monitoring takes place may be even more important. (Moser et al., 2025; Perkins et al., 2024).

The studies indicate that there is a potential for use of AI in clinical applications for diabetes management. However, it will be dependent on several factors. The AI models that have the greatest potential to be applied in clinical settings would include those that can provide clinically relevant lead times to recognize hyperglycemia, minimize the need for user intervention, explain the risk associated with identified patterns of glucose levels, and integrate seamlessly into an individual's daily routine using their existing CGM or AID. There are many barriers to applying AI based systems for diabetes monitoring and treatment including, technical issues such as sensor inaccuracies during physical activity, excessive alarms from continuous glucose monitors, difficulty integrating devices with existing technology and lack of sufficient study validating the effectiveness of AI-based systems (American Diabetes Association Professional Practice Committee, 2025; Katsarou et al., 2025; Ma et al., 2025; Maytham et al., 2024; Moser et al., 2025; Perkins et al., 2024; Russon et al., 2026).

In addition to the technical aspects of implementing a model for sports medicine practitioners one would also assess its impact on workflow. While an informal recreational athlete may find value in using a colorcoded or probabilistic risk assessment prior to each session, endurance athletes and competitive teams will require an updated system that identifies delayed post-exercise risk (for example, indicating elevated risk in the evening or overnight). The needs of clinicians, diabetes educators, coaches and their respective patients may vary in terms of what they want to see from a platform even though all parties may use the same algorithmic predictive engine. This indicates that future applications may provide multiple layers of output including a patient facing alerting tool, a clinician facing educational display, and/or a data export feature for either research or coaching purposes (Cavallo et al., 2024; Ma et al., 2025; Perkins et al., 2024; Russon et al., 2026).

4.3. Evidence gaps and future directions

Although there has been a great deal of advancement in the field since 2022 the evidence base is fragmented in ways that prevent strong comparative assessments to be made among studies. The studies vary greatly from each other with respect to their study populations, exercise methodologies, how they define outcomes, when predictions will be generated, which features were used for model development and what type(s) of evaluation metrics were used. For example some predictive models use low blood sugar levels (less than 70 mg/dL) others have used a threshold value representing more serious blood sugar levels (54 mg/dl) while yet another group of models simultaneously predict both hyperglycemic episodes and/or combined pre- and post-exercise dysglycemia. Thus, it may be difficult to interpret differences between predictive models as being indicative of one model's superior performance to that of another due to the fact the prediction task of interest differs considerably across models (Katsarou et al., 2025; Ma et al., 2025; Tsichlaki et al., 2022; Zhang et al., 2023).

There are also many unaddressed issues related to "validation" outside of the clinical trial (i.e., how well does the system perform outside of the population it was trained on). The majority of the literature has been based upon development and assessment of models using specific data sets from small groups of patients, with very little testing done prospectively in other patient populations. It's easy to overlook this limitation. A model can be excellent at making predictions for one group of patients but have poor performance in another group due to differences in training regimens, age distributions, delivery of insulin and/or the manner in which sensors behave during physical activity (Katsarou et al., 2025; Ma et al., 2025; Russon et al., 2026; Tsichlaki et al., 2022; Zhang et al., 2023).

One additional weakness in most research on predictive tools for people with diabetes is that very few have tested to see if predictive tools lead to better health care outcomes instead of simply better statistics. AUROC, sensitivity, specificity and calibration are all important measures of how well a predictive model performs. However, none of these will tell us if a predictive tool helps reduce a person's fear of exercising, increase a person's level of physical activity, help build confidence in their ability to manage their own condition or decrease the amount of time an individual spends in hypoglycemia each day when they engage in regular daily physical activities. The PACE trial was significant because it went further than evaluating the performance of the predictive model and demonstrated a positive effect from receiving alerts based upon a predictive model both during and after exercise (Rilstone et al., 2024).

There is a significant evidence gap that includes the issue of population specificity. Most existing research has focused on the physically active individual with type 1 diabetes which may be useful for clinical purposes. However, it does not provide an adequate assessment of the subgroup needs including elite athlete status, high level endurance athlete status, and those with very variable exercise patterns. The evidence base thus supports general exercise-related risk prediction to a greater degree than sport specific, competition specific and/or elite performance decision-making (Cavallo et al., 2024; Ma et al., 2025; Parent et al., 2023; Russon et al., 2026).

Future developments in predicting hypoglycemia will focus on developing systems that can be scaled to a clinical setting. Hypoglycemic risk associated with physical activity is affected by many factors beyond just glucose levels. Studies have shown that integrating additional parameters such as type of physical activity, insulin dosing information and the most recent glycemic trends into the model improves stratifying the risk. On the other hand, there also exists the possibility of using simpler CGM-only based risk prediction models when balancing model performance with feasibility of deployment (Bergford et al., 2023; Ma et al., 2025; Mosquera-Lopez et al., 2023; Tyler et al., 2022).

It seems that there needs to be higher standard of methodology in this area as well. In the future reports of the calibration, performance of subgroups, missing data, an approach to update models and external validation need to be consistent across studies instead of only measuring performance by a few discrimination measures (Katsarou et al., 2025; Tsichlaki et al., 2022; Zhang et al., 2023). Better reporting of methodologies in predicting diabetes through physical activity will be particularly valuable due to the nature of the available data and possible imbalance in outcome variables and/or limited availability of features. Figure 3 shows why AI should augment rather than replace conventional CGM during exercise.

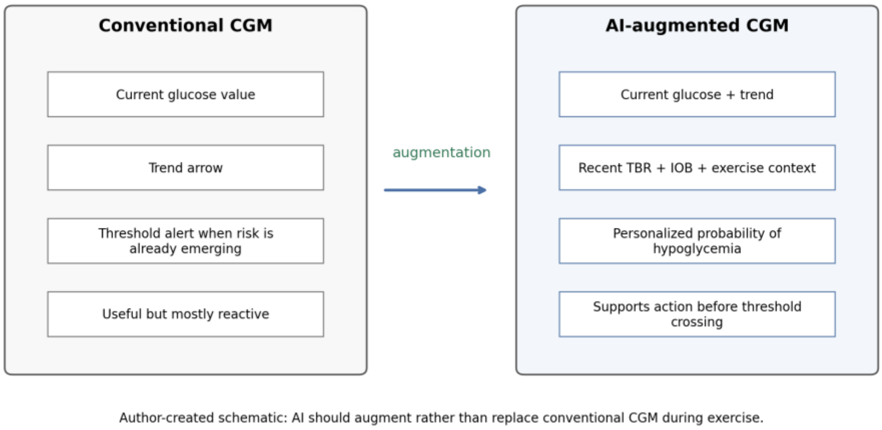

Fig. 3. *Why AI should augment rather than replace conventional CGM during exercise.*

5. Conclusions

Across many research studies have shown that AI/ML methods for predicting EAH in PWD-T1D during physical activity can be both effective and meaningful. Across numerous research studies (using data from various sources) researchers have been able to predict the occurrence of EAH by using one or more CGM-based feature(s). Those predictor characteristics that were found most frequently across all studies were as follows, starting glucose value, current rate of glucose change, remaining insulin dose in body, last recent episode of low blood sugar level prior to physical activity or during physical activity and how long a person is exercising (Bergford et al., 2023; Bergford et al., 2024; Ma et al., 2025; Mosquera-Lopez et al., 2023; Russon et al., 2026).

At this point, there are the greatest potential benefits for clinicians by using predictive alert systems, explaining how machine learning works, and simplifying pre-exercise decision-making as ways to enhance current continuous glucose monitoring (CGM) systems rather than replace them. The use of these approaches may allow for the transition of current clinical practice from reactive responses to the detection of hypoglycemia toward proactive anticipation of an increased risk of hypoglycemia (Duckworth et al., 2024; Ma et al., 2025; Rilstone et al., 2024; Russon et al., 2026).

However, the current evidence does not yet support unqualified claims that AI-based systems are ready to supplant traditional methods of managing exercise. The implementation of these systems has been constrained in part by the heterogeneity of study designs, insufficient external validation, limitations associated with using sensors during physical activity, high levels of alarm generation and poor integration into existing glucose monitoring (CGM) and artificial pancreas (AID) systems (Katsarou et al., 2025; Ma et al., 2025; Maytham et al., 2024; Moser et al., 2025; Tsichlaki et al., 2022; Zhang et al., 2023).

AI-supported exercise-risk prediction may also become an important component of personalized diabetes care if future work can combine accurate predictions with both practical useability and trustworthy validation to help people with type 1 diabetes to exercise more consistently, safely and confidently (Ma et al., 2025; Russon et al., 2026).

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