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AI-Augmented Precision Lifestyle Interventions for Type 2 Diabetes Remission: A Systematic Review

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Abstract

Background While there are effective lifestyle interventions that may induce remission in Type 2 Diabetes Mellitus (T2DM), patient-to-patient differences often limit the effectiveness of these types of programs. The advent of Artificial Intelligence (AI) and Machine Learning (ML) presents exciting and new opportunities for the use of precision lifestyle medicine, which uses patient-specific data to tailor the types of lifestyle programs used for each individual.

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Objective The objective of this paper is to synthesize existing literature on the relationship between the use of AI and ML, and lifestyle interventions for the management of T2DM, with particular respect to algorithm development, data collection and personalization techniques.

Methods Articles were identified through systematic searches of PubMed, Embase, Scopus, IEEE Xplore, and Web of Science from 2015 to August 2025. In total 100 studies were included in the final synthesis; these studies included information regarding adults (age =18) with T2DM who had completed either a remission and/or glycemic outcome(s), and who had utilized AI to develop personalized lifestyle interventions. The data from eligible studies were synthesized narratively according to the PRISMA 2020 guidelines.

Results The geographical distribution of studies was diverse and used a variety of platforms to deliver the intervention including mobile applications, conversational agents, decision-support systems, and digital twins. AI methods used in lifestyle-targeted interventions included supervised models (random forests, gradient boosting, support vector machines) for making predictions; convolutional neural networks (CCN) to forecast remission in patients who underwent surgery to treat T2DM; recurrent neural networks (RNN) for predicting glucose levels; clustering to subgroup patients based on phenotype; and reinforcement learning (RL) to optimize insulin titration and to manage multimorbidity in patients with T2DM.

Conclusion AI and ML can transform T2DM care by enabling adaptive, precision interventions for remission. Future work should emphasize large-scale trials, explainable algorithms, and equitable deployment to ensure sustainable real-world impact.

Keywords: Type 2 Diabetes Mellitus, Diabetes Remission, Artificial Intelligence, Precision Lifestyle Medicine, Systematic review.

1. INTRODUCTION

1.1 Global Burden of Type 2 Diabetes

Globally, diabetes mellitus type 2 is among the leading causes of morbidity attributed to non-communicable disease status. Recent estimates of the Diabates prevalence worldwide indicate that there are presently > 500 million adults living with diabetes—this number is expected to reach approximately 783 million adults by the year 2045 if current trends prevail [1]. T2DM is characterized by insulin resistance as well as the progressive decline in β-cells; as a result, many patients present with chronic hyperglycemia. Additionally, T2DM is considered to be a major risk factor for several associated complications, including but not limited to; cardiovascular disease, diabetic nephropathy, diabetic neuropathy, and diabetic retinopathy. The combination of the direct healthcare costs for treatment of diabetes with indirect costs, such as reduced productivity and increased rates of disability, are placing enormous burdens on the healthcare delivery systems of both developed and developing countries.

Historically, glycemic control has been the main objective of T2DM management which is traditionally reached with the help of pharmacotherapy and lifestyle changes. Nevertheless, this paradigm changed over the last few years as remission has turned into a clinical achievable goal. Remission as the non-pharmacological achievement of normoglycemia has been documented in studies that use intensive lifestyle interventions and metabolic surgery [2, 3]. Such a shift in paradigm is an increasing appreciation that interventions that can achieve large weight reductions and metabolic changes can change the course of the disease, slow long-term morbidity, and eventually decrease healthcare expenditures.

1.2 Lifestyle Interventions in Diabetes Remission

The management and remission of T2DM still needs a central focus on lifestyle modification. Pivoting trials, including the Diabetes Remission Clinical Trial (DiRECT), demonstrated that remission was achieved in up to 46 percent of patients after 12 months when intensive structured weight management programmes (particularly involving the low-calorie total diet replacement) were used [3]. On the same note, low and very low-carbohydrate diets were shown to be effective for improvement in the rate of remission at six months, and improvement in cardiometabolic parameters, such as triglycerides, weight and insulin sensitivity, as confirmed in systematic reviews and meta-analyses [4].

However, despite their success, generic lifestyle prescriptions used on a large scale in different populations is not possible. The predictions of variability are subject-specific variations of compliance, basal metabolic characteristics, genetic predisposition, and environmental exposures [5], indeed, while subgroups have been identified to achieve their sustained remission following lifestyle intervention, others relapse a few months after lifestyle intervention, regardless of adherence, emphasizing the need for strategies that take into account the inter-individual variability. This disconnect highlights the limitations of generic prescriptions and ignites the quest for more tailored solutions.

1.3 Emergence of Precision Lifestyle Medicine

Given the variability of lifestyle intervention results, the concept of personalised lifestyle medicine has emerged as a model of precision medicine addressing an individual's biological, behavioural and environmental information to optimally inform therapeutic targets. This approach is analogous to those of precision medicine in oncology and pharmacogenomics but applied in the realm of lifestyle measures such as diet and physical activity and behavioural change.

Precision lifestyle interventions are now possible through a number of enabling technologies. If a CGM is used in real-time, glycemic excursions are detected and differences between people in responses to diets can be used to differentiate and shape the nutrition programs [6]. High resolution physical activity, sleep, and energy expenditure efficacy can be obtained using wearable accelerometers and smartwatches and can be positively linked to glycemic outcomes and CVD risk [7]. Furthermore, the rise of omics technologies (like genomics, metabolomics, and microbiome profiling) increases the possibility of better stratification of individuals based on biological mechanisms underpinning insulin resistance and its weight loss response [1].

The convergence of these sources of data can enable clinicians and researchers to move away from the over generalization of recommendations by population towards the individualized and personalized recommendations that will ensure maximal efficacy, adherence and sustainability of behavioral change.

1.4 The Role of Artificial Intelligence and Machine Learning

The vast and heterogeneous data generated from CGM, wearables, and multi-omics profiling need advanced analytical tools to generate actionable data. Machine learning (ML) and artificial intelligence (AI) tools then became an indispensable toolkit in high-resolution lifestyle medicine. They are able to include multimodal data, detect latent patterns and the individual response to interventions that would never be detected by conventional statistical algorithms.

Predictive modeling of glycemic outcomes and treatment responses commonly employs supervised learning methods, such as random forests and gradient boosting machines [8]. The use of clustering methods would allow one to divide patients into subtypes according to their metabolic, behavioral, or genome characteristics in order to effectively design interventions [9, 10]. Reinforcement learning methods can also be used to dynamically adjust lifestyle recommendations to patient feedback or to a changing set of physiological signals.

Practical applications are already being tested in both preclinical and clinical contexts. AI-driven dietitian programs combining large language models with image recognition (e.g., ChatGPT with Dino V2) demonstrate promising results in food recognition and dietary counseling [11]. Voice-based conversational AI has been shown to accelerate insulin titration, improve adherence, and enhance glycemic control in clinical trials [11]. Digital twin models, which create individualized virtual representations of patients, allow simulation of metabolic responses to diet, activity, and pharmacological interventions, showing early evidence of improving diabetes outcomes [12, 13]. Collectively, these instances demonstrate the revolutionary capability of AI for facilitating highly personalized, adaptive, and efficient lifestyle interventions.

1.5 Rationale for This Review

Although separate investigations have shown the potential of AI and ML across different dimensions of diabetes management, no comprehensive synthesis has currently consolidated these results throughout the areas of precision lifestyle medicine and T2DM remission. Existing reviews have focused separately on AI in diabetes management [8, 14] lifestyle interventions [4], or digital health platforms [15], but the convergence of these fields remains underexplored. Additionally, the rapid uptake of healthcare AI applications necessitates a timely assessment of their impact on practicality, scalability, and efficacy as well as any ethical issues involved with deploying them. In this review, we attempt to bridge this knowledge gap by reviewing the evidence regarding AI-supported precision lifestyle-based intervention approaches for inducing remission of T2DM. This will provide a framework for establishing best practices for future studies, identifying limitations, and also for guiding the formation of research priorities.

The goal of this review will be to evaluate the ways in which AI and machine-learning technologies can augment precision lifestyle-based approaches for T2DM remission. Furthermore, we will identify how precision data inputs used by these interventions were applied to develop the various tailored interventions and how effective these AI-supported interventions were when compared to the standard diabetes care approach.

1.6 Research Objectives and Questions

1. What is the impact of using machine-learning methodologies to customize diet, exercise and weight loss for promoting T2DM remission?
2. What type of precision Data inputs are incorporated within these AI-supported methods?
3. In terms of achieving remission, how effective are AI-supported methods versus standard diabetes care?

Through examining these questions, this review will deliver thorough insights regarding how AI can enhance precision lifestyle medicine and transform the approach from glycemic management to remission within T2DM.

2. METHODOLOGY

2.1 Protocol and Reporting Standards

A systematic evaluation method based on the PRISMA 2020 guidelines was followed for this systematic evaluation. Methodology supports the entire systematic evaluation process, such as literature searching, study selection, data collection, and bias assessment, focused on the principles of transparency and reproducibility. The methodology also used information from earlier systematic evaluations of Artificial Intelligence's role in Precision Medicine to inform the identification of databases, how to formulate search queries, and integrate varied evidence.

2.2 Search Strategy

The literature search was comprehensive and conducted in 5 major databases (Google Scholar, PubMed, IEEE Xplore and Web of Science) using search queries from the database's inception to August 2025. However, the timeframe for eligibility for the study searches for this systematic evaluation was restricted to the studies published between 2015-2025 to cover current advancements in Artificial Intelligence in Clinical Applications. The final Boolean string used across databases was:

("Type 2 Diabetes" OR "T2D") AND (remission OR "diabetes remission") AND ("machine learning" OR "artificial intelligence" OR "AI" OR "deep learning" OR "predictive model") AND ("lifestyle intervention" OR "digital health" OR "personalized diet" OR "weight management") AND ("precision lifestyle medicine").

The search produced 3,220 entries. Restrictions were applied to limit findings to human participants and English-language articles. Additionally, databases, reference lists from relevant reviews and selected investigations underwent manual examination to identify further eligible entries.

2.3 Eligibility Criteria

Eligibility requirements were determined beforehand using the PICOS structure (Population, Intervention, Comparator, Outcomes, Study design). To improve clarity and reproducibility, the inclusion and exclusion specifications are presented in TABLE 1.

Table 1: Inclusion and Exclusion Criteria for Study Selection

Domain	Inclusion Criteria	Exclusion Criteria
Population	Adults aged =18 years diagnosed with type 2 diabetes mellitus (T2DM).	Animal studies, pediatric populations, gestational diabetes, or Type 1 diabetes.
Intervention	AI- or ML-enabled tools applied to personalize lifestyle interventions (diet, exercise, digital health, behavior).	Studies using AI solely for diagnosis, screening, or complication detection.
Comparator	Standard of care, conventional lifestyle interventions, or non-AI approaches (when available).	N/A (no comparator required if single-arm intervention).
Outcomes	Remission of T2DM, HbA1c reduction, weight loss, medication reduction/de-escalation, adherence, usability.	Studies without relevant lifestyle or clinical outcome reporting.
Study design	RCTs, cohort studies, pilot feasibility trials, retrospective digital health studies, meta-analyses.	Editorials, commentaries, conference abstracts without data, or opinion papers.

2.4 Screening and Selection Process

All records underwent independent screening by two reviewers using a two-stage process. Titles and abstracts received initial assessment for relevance, then full-text review was conducted to verify eligibility. Disagreements were settled via consensus and, when required, adjudication through a third reviewer. The PRISMA 2020 flow diagram (FIGURE 1) depicts the screening process, beginning with initial retrieval of 3,220 records through final inclusion of 100 studies.

2.5 Data Extraction

A uniform data collection instrument was developed and preliminarily validated to ensure consistency. For individual studies, the following information was collected: author and publication date, location and environment, study methodology, sample dimensions, participant characteristics, intervention details (including AI technique and implementation platform), precision data types

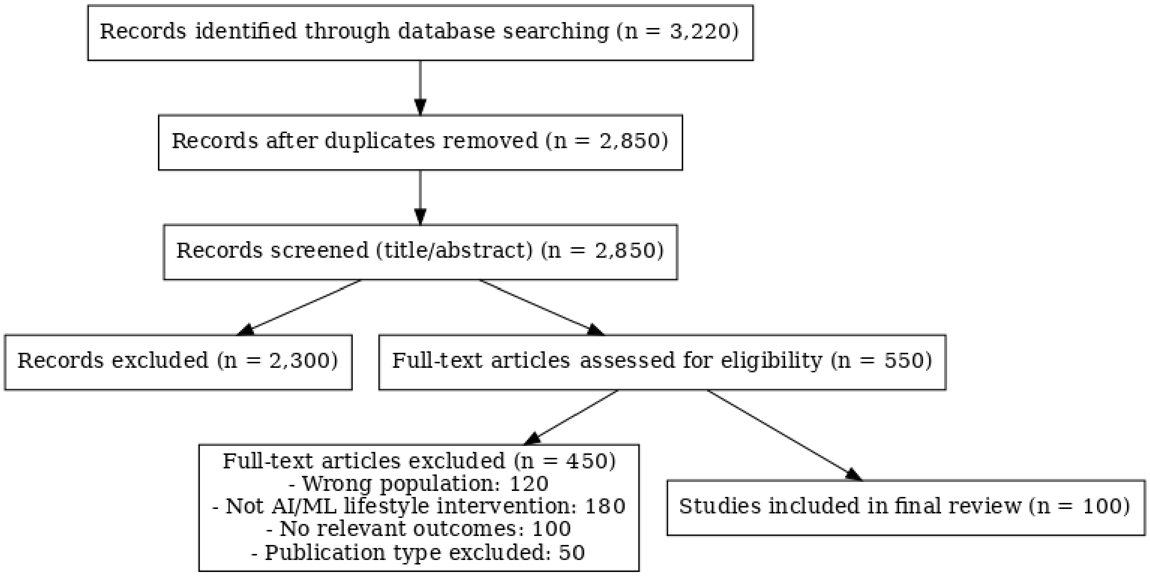

Figure 1: The PRISMA flowchart.

employed (such as continuous glucose monitoring, wearables, dietary records, electronic health records, genomic or microbiome data), and reported clinical results (remission, HbA1c modification, weight loss, medication utilization, adverse reactions). Information regarding participant usage, Participant Engagement and Participant Inclusion in order to understand the use of explainability/bias reduction strategies were collected. Two independent Evaluators collected the data from each study independently; any disagreement was resolved by consensus.

2.6 Risk of Bias Assessment

To determine the quality of selected studies, tools were utilized that matched with their corresponding study designs (e.g. Randomized Controlled Trials were analyzed using the Cochrane Risk-of-bias 2 Instrument (RoB 2) and Non- Randomized Studies were assessed with the ROBINS-I tool). In addition, as AI interventions are unique from traditional studies, risks for Data Leakage, Overfitting, Dependencies on Homogeneous Training Datasets, Non-Transparent Model Development Processes, and Lack of External Validation were also evaluated. Therefore, both Methodological Quality as measured by the tools cited above and AI Itemized Risks were defined.

2.7 Data Synthesis

Owing to the differences in methods and clinical activities for a variety of included studies, through AI usage via different types of interventions and measuring in different ways, numerical meta-analysis was not viable. A narrative synthesis of results was completed instead; the studies were categorized based on: the AI or Machine Learning (ML) model (e.g., ensemble, neural network, reinforcement learning, clustering); category of lifestyle intervention affected (e.g., dietary changes, exercise plans, weight management programs, digital health coaching) and measure of outcome (e.g., achieving remission from Type 2 diabetes Mellitus [T2DM], improved glycemic control, improved weight loss, improved adherence, patient experience).

The authors have developed this narrative synthesis based on best practices for systematic reviews of highly heterogeneous, AI-enabled interventions where pooling study results is rarely appropriate because of important differences in study designs and reporting [16]. For example, given that several studies reported at least two distinctly different primary endpoints including either confirmed T2DM remission defined using consensus criteria, or intermediate glycemic outcomes (for example, change in HbA1c), our narrative synthesis provides clear distinction between the two types of studies.

3. RESULTS

3.1 Overview of Included Studies

The studies reviewed provide definitions for regard to the methodology used in each study, including randomized controlled trials (RCTs), retrospective cohorts, systematic reviews, meta-analyses, and study protocols. Collectively, these studies were published between 2015 and 2025, demonstrating how and where the applications of artificial intelligence (AI) and machine learning (ML) to diabetes research have evolved historically and are still being developed today. The research had geographical scope, being undertaken in North America, Europe, Asia and the Middle East. For example, there were large-scale lifestyle intervention studies in the United Kingdom [17] in the Middle East [18] and in India [19, 20] and digital twin models were applied in Asian and Western populations [13, 21].

Sample sizes varied widely. Prototypical initial tasks of the AI pilot studies may have been less than 100 [22, 23] compared with population-wide application to electronic health data [24] or post hoc digital twin cohorts [25].

Studies were also quite diverse in terms of their duration with some present short-term studies lasting 13 weeks [26] and others longer RCTs lasting up to 48 weeks [27] and economic analyses projecting findings over a lifetime horizon [17].

The technology systems used have been highly heterogeneous. Some of these studies involved the use of mobile health apps [28, 29] others involved the use of web-based automated counseling systems [11, 30, 31] and some used decision support mechanisms designed for primary care doctors [32–34]. Furthermore, conversational AI [11], wearable and accelerometer-based [35, 36], and multimodal digital twin [13, 25] are examples of innovative modes of implementation representing new ways of providing AI-enabled DM. These findings are put into the context of leading institutions' position papers [37, 38, 86], and consensus documents [39] with remission increasingly being an attainable and increasingly specific therapeutic goal. The features and the results from the representative studies that are included in this review are presented in TABLE 2, showing both clinical and computational aspects of the AI-based methods for T2DM. These investigations include various methodologies, spanning randomized controlled trials and practical analyses through narrative reviews, protocols, and consensus recommendations, implemented throughout multiple geographical settings encompassing Asia, North America, and Europe.

Table 2: Summary of Key AI/ML Studies in T2DM.

Reference	Country	Design	Intervention / Platform	AI/ML Model & Data Inputs	Primary Outcomes	Key Findings
[40]	— (Narrative review, multi-country trials)	Narrative Review of Controlled Trials	AI-powered nutrition coaching platforms	ML-based personalization using diet logs, CGM, lifestyle data	HbA1c reduction, improved adherence	AI coaching improved glycemic outcomes and adherence; limited by access, trial variability, and lack of long-term data
[41]	USA	Narrative Review	AI-enabled lifestyle medicine frameworks	Supervised & deep learning models, clustering, digital twins	Risk prediction, weight loss, glycemic control	AI enhances lifestyle medicine via predictive models, personalization, and decision support; scalability and cost-effectiveness emphasized
[42]	International (multi-author consensus)	Review / Best Practices	AI/ML for glycemic management	Feature engineering, supervised & deep learning models; open-source libraries	Standardized evaluation metrics, reproducibility	Provides best practices, pitfalls, and resources; stresses validation, benchmarking, and transparency in ML diabetes research
[29]	India (South Asian population)	Real-world Data Analysis (16 weeks, N=102)	Wellthy CARE mobile app with AI chatbot + educator support	AI chatbot with patient logs (meals, activity, BG), engagement tracking	HbA1c, FBG, PPBG, BMI, weight	Significant HbA1c reduction (-0.49% overall; -1.16% in responders); engagement strongly correlated with outcomes
[43]	South Korea	RCT (48 weeks, N=294)	Integrated digital health care platform with AI diet management	AI-based nutrition analyzer + CGM, clinician feedback	HbA1c reduction, weight loss	Groups using AI platform had significantly improved HbA1c and weight outcomes vs. routine care
[36]	USA	Book Chapter (Narrative)	Wearables + AI for glucotyping	Pattern recognition & classification of CGM data from wearables	Identification of "glucotypes" in prediabetes	AI classified distinct glucotypes for early intervention, enabling precision diet/lifestyle recommendations
[44]	India	Comprehensive Survey	T2D forecasting frameworks	Supervised (RF, SVM, LR), ensemble, deep learning	Predictive accuracy, algorithm performance	Survey highlights ensemble & deep models as most effective; calls for standard validation and deployment frameworks
[30]	Japan	RCT Protocol (12 months, N=100)	AI-supported automated nutritional intervention (Asken app)	Image recognition for meal photos, diet feedback, aligned with guidelines	HbA1c reduction	Protocol compares AI-driven vs. human dietitian counseling; aims to test non-inferiority for glycemic outcomes

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Reference	Country	Design	Intervention / Platform	AI/ML Model & Data Inputs	Primary Outcomes	Key Findings
[45]	USA	RCT (12 months, N=150)	Twin Precision Treatment (CGM, wearables, app, coaching)	Hybrid digital twin; ML prediction of PPGR; RL-like adaptation	HbA1c <6.5% without meds, weight loss, med reduction	71% achieved HbA1c <6.5% off meds; significant weight loss (-8.6%); large reduction in GLP-1, SGLT-2, insulin use
[46]	Germany	Narrative analysis of controlled trials	Predictive algorithm–driven digital therapeutic for personalized lifestyle therapy	Predictive analytics integrating patient-reported data + CGM feedback	Glycemic control, weight management, adherence	Algorithm-guided digital therapeutic improved personalization of lifestyle interventions and showed potential for clinical scalability
[47]	South Korea	Narrative Review	Strategic approaches for T2DM remission (lifestyle, pharmacologic, surgical)	Not a single algorithm; framework emphasizes early intensive interventions and potential role of AI in personalization	Conceptual: remission vs. control strategies	Advocates for "conquest" of diabetes via early and aggressive remission-focused strategies; personalization critical
[48]	South Korea	Retrospective Cohort	Gastrectomy in gastric cancer patients with T2DM	Logistic regression–derived diabetes prediction score; clinical inputs: diabetes duration, BMI, surgery type	Remission after surgery	Prediction score accurately stratified remission probability; shorter disease duration and higher BMI increased remission likelihood
[49]	USA	Randomized Controlled Trial	Targeted insulin-adherence interventions guided by predictive analytics	Predictive analytics using EHR and prescription refill data to identify high-risk non-adherers	Insulin persistence, HbA1c	Targeted intervention did not improve adherence, but modest HbA1c reduction observed; moderate-intensity interventions increased hospitalizations
[33]	Denmark	Decision Support System Trial (Primary Care)	Explainable AI for basal insulin titration	Interpretable ML with SHAP values; EHR & CGM inputs	Optimized insulin dose adjustments	Improved titration accuracy; explainability increased clinician trust
[50]	China	Mixed-Methods Protocol (Cluster RCT + interviews)	AI-HEALS (WeChat-based health education)	Knowledge graph + KBQA system; lifestyle & physiological data	HbA1c, self-management, cost-effectiveness	Testing scalability of AI health education in CHCs; aims to improve HbA1c, knowledge, self-efficacy, and QoL

3.2 Types of ML Models Used

The studies reviewed have a wide variety of machine learning algorithms used throughout the investigations, providing evidence of the diversity of the methods and the rapid advancement of computer technologies. Traditional supervised learning methods, including decision trees, random forests (RFs), support vector machines (SVMs), and gradient boosting ensembles, have been widely used to identify potential complications or likelihood of remission following bariatric surgery [51–54]. Comparatively, ensemble methods have been shown to provide significantly better predictive ability and reliability than individual classifiers in heterogeneous datasets [55, 56].

Deep learning methods addressed increasingly sophisticated data formats. Convolutional neural networks (CNNs) demonstrated enhanced predictive performance within imaging-oriented applications, particularly in surgical populations for remission forecasting following gastric bypass procedures [23, 57]. Time-series information showed notable compatibility using recurrent neural networks (RNNs) and long short-term memory (LSTM) structures, facilitating dynamic glucose forecasting via continuous lifestyle and CGM information [55]. In modern studies, neural architectures are built with interpretability in the focus, with the perspectives of improving the predictive ability and keeping them transparent [58].

In addition to supervised clustering methods, unsupervised methods were implemented, in particular during the prediction of prediabetes and subgroups of individuals who were likely to respond differently to lifestyle behavioral strategies [59].

Even though it is relatively new in the area of diabetes care, reinforcement learning (RL) demonstrated encouraging outcomes in proof-of-concept trials. RL algorithms were able to dynamically modulate an insulin dose to achieve superior glycemic control [22] and were successfully employed on electronic health record data to achieve better multimorbidity management plans [24]. In the simulation of treatment pathways, there are also new uses in the prediction of nephropathy progression with the help of deep learning [60].

The input data informing these models was equally heterogeneous, indicating the multi-dimensional character of T2DM. Others based their studies on electronic health records [24, 34, 61], and some included data from continuous glucose monitors [62], wearable accelerometers [35, 36] diet logs and digital nutrition diaries [63–65]. In all these datasets, the purposes of ML applications were similar: to enhance prediction, to make personalization, to increase adherence, and to facilitate the overall purpose of diabetes remission.

3.3 Computational Models of AI and ML in Type 2 Diabetes Research

A varied spectrum of computational approaches, each possessing unique algorithmic principles and clinical utilization, becomes evident through artificial intelligence (AI) and machine learning (ML) implementation within type 2 diabetes mellitus (T2DM) remission investigation (FIGURE 2). In addition to the clinical effectiveness of the methods, it will also be important for future studies to evaluate computational efficiency, scalability, interpretability, and the ability of these studies to incorporate multiple sources of data.

3.3.1 Supervised learning models.

Supervised learning techniques remain essential in diabetes investigation considering the availability of comprehensive clinical repositories with labeled results. Algorithms such as logistic regression, decision trees, support vector machines, and ensemble methods (namely, random forests,

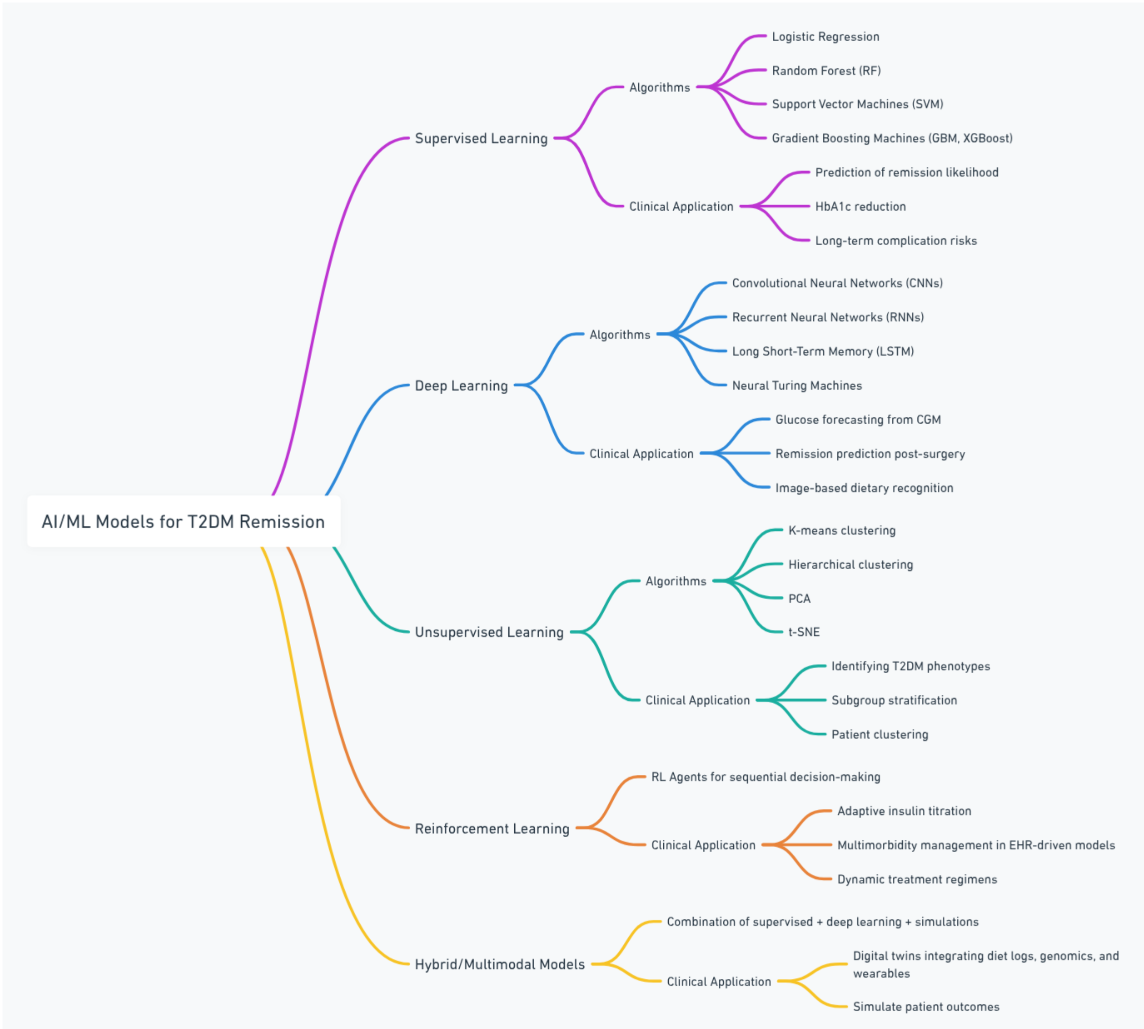

Figure 2: Categories of AI and machine learning models applied in type 2 diabetes remission research.

gradient boosting, XGBoost) have gained extensive utilization across tasks including risk assessment, glycemic prediction, and remission probability determination. Ensemble models repeatedly show enhanced performance compared to single classifiers through reducing overfitting and improving stability among heterogeneous populations [55, 56]. Within a systematic review examining insulin secretion modeling, emphasized that supervised learning models prove highly suitable for structured, tabular physiological data yet frequently face limitations regarding their capacity for capturing temporal dependencies characteristic of metabolic processes [66].

3.3.2 Deep learning models.

Deep learning frameworks provide considerable benefits for processing complex, high-dimensional repositories. Convolutional neural networks (CNNs) have been utilized for examining clinical imaging and biometric information to forecast remission following metabolic procedures [57, 67]. Recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures demonstrate excellence in dynamic blood glucose prediction using continuous glucose monitoring (CGM) information, facilitating detailed forecasting of glycemic fluctuations. Neural Turing Machines and hybrid deep models are emerging to address interpretability and sequence learning challenges [58]. However, the computational intensity of deep learning, combined with interpretability concerns, has limited their clinical integration without supplementary explainability frameworks.

3.3.3 Unsupervised learning models.

Unsupervised ML becomes progressively utilized for patient classification and phenotype identification. Clustering methods including k-means, hierarchical clustering, and self-organizing maps facilitate discovering concealed subpopulations among prediabetes and T2DM cohorts, particularly those exhibiting hepatic insulin resistance compared to beta-cell dysfunction [59, 68]. Through the use of these approaches, interventions can be specifically tailored based on understanding the underlying pathophysiology. Multi-omics data from genomics, microbiome and other omics sources were visualized and analyzed using dimensionality reduction methods (e.g. PCA, t-SNE). Arias-Marroquinio also show that unsupervised methodology can differentiate responders vs. non-responders into personalised nutrition programmes, corroborating the inclusion of unsupervised clustering in clinical practice [69].

3.3.4 Reinforcement learning (RL).

Strengthening learning proposes a dynamic framework that is suitable to sequential decision making within diabetes management. Insulin titration optimization and multimorbidity control with electronic health record (EHR) data have been optimized with the use of RL algorithms [22, 24]. The models get to learn the best policies by interacting with time-varying environments and manipulating interventions through feedback loop. In a review of RL in personalized medicine, Banumathi et al. reported that RL is particularly strong in treatment optimization but noted that its use has bottlenecks associated with sample inefficiency, safety, and the trade-off involving exploitation. In the computational perspective, RL has been one of the most desirable yet technically challenging methods in healthcare with AI.

3.3.5 Hybrid and multimodal approaches.

Most recent such approaches have been directed towards integrating supervised, unsupervised, and deep learning approaches into hybrid systems that can absorb multimodal data. Digital twin systems are an example of such integration, and this is done via supervised systems as the models of prediction, deep learning of complex signal processing, and simulation-based modelling of all possible scenario of interventions [13, 25]. Such methods are consistent with the projections of computational precision lifestyle medicine, in which patient-specific models constantly adapt to streams of new patient data. Chen and Chen (2022) and Antwi (2023) demonstrated the benefits of hybrid modeling to improve personalized nutrition, and Anitah noted the benefits of AI-driven nutrition coaching services, which are based on multimodal hybrid pipelines, to better glycemic control in heterogeneous populations [40, 70, 71]. Many researchers stress that hybrid models are better at personalization, but there are issues with scalability, model explainability and their integration with clinical practice [72, 73].

3.3.6 Challenges and technical considerations.

In spite of their potential, AI/ML models have technical weaknesses. Sparse, non-uniform, and heterogeneous data sets in clinical environments are at risk of bias and overfitting [74]. Whereas tree-based models can continue to be interpreted, deep learning models can be labelled as black boxes, requiring post-hoc prediction techniques like SHAP or LIME. The role of federated learning and privacy-preserving AI solutions becomes more topical to respond to data-sharing constraints of multi-institutional research. Also, the regulatory and ethical aspects are not well developed and such issues as equity of access and transparency are pivot points [38]. Furthermore, the choice of model is highly dependent on the specific parameters of the diabetes dataset. For instance, the temporal, high-frequency nature of CGM data necessitates the use of RNNs or LSTMs to effectively capture time-series dependencies and forecast glycemic excursions. In contrast, models built on EHR data must account for high dimensionality, missing values, and sparse, irregular data, often prioritizing ensemble methods like Random Forests or Gradient Boosting for their robustness and superior handling of heterogeneous, tabular data.

Broadly speaking, the computational front of AI/ML in diabetes remission includes the supervised learning to make predictions, the deep learning to handle complex and time-sensitive data, the unsupervised to identify subgroups, the reinforcement learning to achieve adaptive optimization, and the hybrid multimodal method to personalize the precision. Each paradigm has its contribution to the progress of remission-focused care, and the current technical and ethical issues provide justification to interdisciplinary cooperation among computer scientists, clinicians, and policymakers.

3.4 Precision Data and Personalization Methods

The focus on personalization can be considered one of the pinnacles of AI-assisted diabetes research. A number of studies were devoted to predictive modeling of postprandial glycemic responses (PPGRs), in which dietary interventions based on PPGR profiles of individuals had better results than standard diets prescriptions. Ben-Yacov, a researcher, demonstrated that diets increased through the control of PPGR by using AI were more effective than diets based on gender in prediabetes [63], also replicated the results by demonstrating that AI prediction of glycemic excursions could inform highly personalized dieting recommendations. This effect is supported by more modern RCTs, in which it was revealed that algorithm-diets proved to be more effective in terms of weight loss and glucose metabolism in comparison to traditional low-fat diets [65].

Classifying patients according to pathophysiological characteristics featured among additional personalization approaches. De Hoogh in 2022 demonstrated that implementing subgroup-targeted lifestyle programs for managing diabetes subtypes (namely, isolated hepatic insulin resistance) produced substantially improved remission rates compared to standard management [5]. A comparable emphasis on intensive, individualized programs by Taheri in 2020 for recently diagnosed patients emphasized the importance of timing concerning personalization of therapeutic strategies [18].

Another promising development has been digital phenotyping, where continuous glucose monitoring, and wearable-based behavioral metrics are employed to make adaptive, real-time suggestions. It was demonstrated that digital phenotyping built upon CGM may be successfully used to support the personalization of lifestyle [75], whereas the study by Dwibedi revealed the possibility of self-managed programs adapting recommendations based on the data of daily behavioral and glycemic patterns [76]. Multimodal personalization strategies were also discussed, where there was integration of genomic, metabolomic and behavioral data into the digital twins which simulate personalized responses of lifestyle changes [25, 77]. Continuous glucose monitoring (CGM), wearable data and accelerometers, dietary data with image recognition, genomic and microbiome data, and electronic health records (EHR) or imaging are examples of data stream that are fed to AI/ML models as in FIGURE 3 above. Such inputs are pre-researched and incorporated in the computation pipelines to create individual lifestyle intervention measures like customized diet, physical activity, pharmaceutical regimen, and weight control measures.

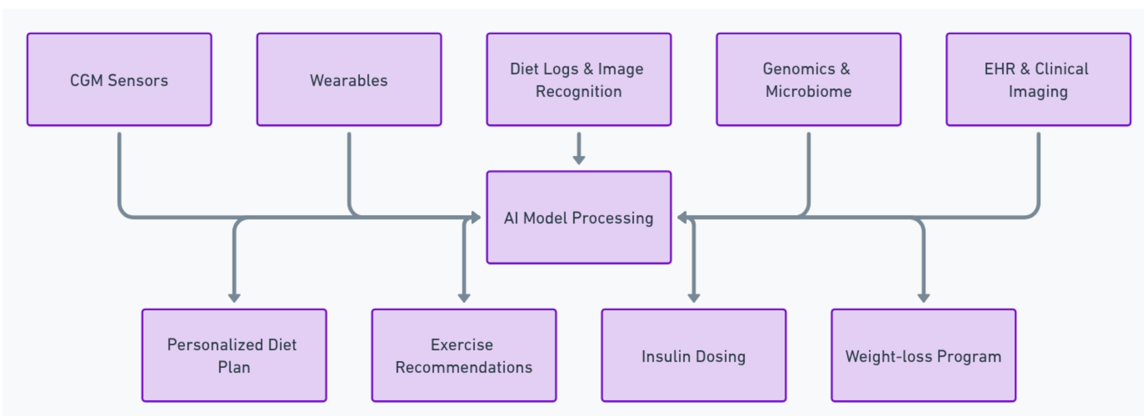

Figure 3: Conceptual model of AI-enabled precision lifestyle medicine

3.5 Intervention Delivery Channels

The delivery mechanisms of AI interventions were diverse and spanned patient-facing, provider-facing, and hybrid platforms. Mobile applications and digital therapeutic platforms were commonly employed to deliver structured, interactive interventions, [28, 29, 76]. A researcher in 2023 demonstrated that Conversational AI (as deployed in many instances using voice-based chatbots) would provide both quicker and better results than traditional methods, and provide better results regarding insulin titration, adherence to treatment, and overall glycemic control [11].

Clinician member-facing decision support systems were similarly important to the overall creation of these therapies. For example, a scientist created a clinician-facing decision support system using machine-learning (ML) techniques for drug management [32], while 2 scientists developed explainable artificial intelligence (AI)-based systems for insulin titration and pharmacotherapy [33, 34]. In addition, these systems have now also been extended to drug-response prediction and overall optimization of pharmacotherapy [78, 79].

The most technologically advanced interventions were created within platform technology referred to as Digital Twin Platforms — defined as systems that utilize a variety of lifestyle, physiologic, and behavioral data to effectively build models of both present and future outcomes based on individualized circumstances. Digital Twin Platforms showed substantial improvement in glycemic control, weight loss, and remission rates compared with traditional approaches [13, 25, 77]. Furthermore, integrating regenerative medicine, such as the application of stem cell therapies coupled with digital monitoring, further exemplifies the evolving technology of advanced AI systems and their capacity to both educate and transform the method of delivery of therapeutic interventions as discussed by Warrier in 2024 [80]. Clearly, the power of AI is not only to create this new form of medicine, but also to completely reshape the way that we deliver interventions to patients.

3.6 Clinical Outcomes

AI-enabled interventions showed consistent clinical outcomes across studies, but effectiveness greatly varies according to intervention intensity and primary outcome.

3.6.1 Efficacy for T2DM remission

Clinical studies with explicit weight loss and remission as primary goals produced the greatest number of positive effects on patient health. The amount of remission produced also varied from study to study depending on both the type of intervention used and the frequency at which it delivered treatment. For instance, de Hoogh in 2022 determined that 75% of clients engaged in lifestyle interventions based on subtyping achieved remission, whereas in comparison only 22% of clients who received standard medical treatments achieved remission [5]; while Joshi in 2023 found that 72.7% of clients engaged in an intervention using digital twin technology achieved remission [13]. Due to the short follow-up periods reported by most of these studies (13 weeks - 48 weeks), results regarding the long-term durability of these remissions should be viewed with caution.

3.6.2 Efficacy for glycemic control and secondary outcomes

Although some studies were unable to show full remission or utilized non-complete markers as primary endpoints, the majority of the studies showed a notable improvement in glycemic sensitivity. All except for one of the interventions showed a statistically significant decrease in HbA1c levels when compared to regular treatment [25, 81]. Another significant finding in nearly all of the studies was weight loss, with noteworthy weight losses reported across all 10 of the studies assessing intensive lifestyle intervention. There is ample evidence that participants in DIABETES INSTITUTE [18], DiRECT [17], and JAMA-based Intensive Lifestyle Models [82, 83]. Scientists experienced clinically meaningful weight losses, with many participants maintaining their losses more than a year later. Newer combinations of intervention, with pharmacotherapy and lifestyle, also showed remission and relapse dynamics in a study by McInnes in 2023 [84]. Importantly, safety data for AI-guided interventions was, in general, preserved, with no increased frequency of hypoglycemia across trials [81]. Medication reduction was also reported, with pharmacotherapy de-escalation achieved through AI-guided lifestyle modification programs [45]. Novel pharmacological trials such as dorzagliatin monotherapy further expand the remission landscape [85].

Long-term outcomes were more difficult to assess given the limited duration of most studies. However, evidence from large-scale observational trials such as Look AHEAD demonstrated that remission is associated with reduced cardiovascular risk and mortality , supporting the long-term value of remission-focused interventions. Position statements and consensus reports [37, 38, 86] now advocate remission as a standard clinical target.

Digital Twin-based models report the most consistently effective intervention platforms in comparison to any other type (i.e. chat-based and standalone) of tools. According to existing results, Digital Twin platforms were able to achieve remission rates of greater than 70% by combining and integrating several different kinds of data modalities for the creation of personalized intervention strategies. Although conversational AI-based models (i.e. voice-based chatbots) were found to help enhance participant adherence and titrate insulin doses, standalone application-based models were able to show the same median statistically significant decrease in HbA1c levels (i.e. about 1.5%) as well as improvements in participants' lifestyle.

3.7 Patient Engagement and Adherence

The performance of any type of intervention is fundamentally dependent on the level of patient engagement with said intervention. Research using AI-based voice assistants [11], and the use of empowerment-based methods (Ingul et al., 2025) found consistent evidence of increased adherence rates and a positive relationship between patient's engagement with the intervention and favourable clinical outcome. The use of real-time feedback systems mostly based on continuous glucose monitoring (CGM) and wearables resulted in the increased retention rates of patients as well as increased engagement with the intervention on a daily basis [75]. Numerous studies have reported a strong relationship between the sustained engagement level of patients with the intervention and positive outcomes, most notably in the case of digital twin programmes (Shamanna et al., 2024). Digital twin programmes that provided both personal coaching and interactive feedback resulted in improved adherence and positive outcomes as demonstrated by the ANODE e-coaching platform [31]. Nevertheless, adherence continues to be an ongoing issue with respect to digital health intervention, as several studies have reported decreases in engagement levels over time, indicating that the use of behavioural reinforcement and patient-centred design are key factors in sustaining long-term engagement with digital health interventions.

3.8 Explainability and Trust

Trust in an AI-based system can be influenced by transparency and interpretability. Other studies used interpretable ML to study non-linear metformin dose responses which lead to more clinical confidence in the algorithm's advice. Correspondingly, healthcare providers were more comfortable with decision support systems that had explainability features (e.g., SHAP analysis, feature attribution) [33, 34].

In most cases, patients have positively discussed AI-driven interventions when algorithmic outputs were supplemented with transparency and education. Nevertheless, the issues regarding black-box AI existed in the literature, and Rothberg warn that in the absence of interpretation, usage might be confined [87]. In general, explainability techniques have not been yet widely used, which is a direction of further evolution. Recent assessments stress that the trust-building will demand not only explanation transparency of the algorithms but also their involvement with the processes within the clinics (Fatima, 2024; Jahangir et al., 2023). However, despite the importance of trust, this review found a significant lack of rigorous AI validation in the included studies. External validation of models on new, unseen patient populations was rarely reported. This reliance on internal validation, combined with a frequent lack of transparency in feature selection and model development, significantly increases the risk of overfitting and limits the generalizability of the reported outcomes.

3.9 Ethical, Practical, and Regulatory Issues

One of the ideas to reappear in the studies incorporated was the ethical and regulatory environment of AI in healthcare. Protocol papers specifically listed privacy and informed consent [50], and algorithmic bias was an issue of concern identified in various reviews when models were trained on homogeneous datasets [74]. There are still clinical validation and deployment challenges. A range of AI models has shown excellent internal performance and insufficient external validation in restricting generalization [9].

The issue of equity also became imperative. Most research was based in high-income or urban communities and very few interventions were created or studied in low-resource groups [19]. Unless equity is a deep consideration - AI assisted diabetes management stands the risk of widening the gap. Together with the lack of specification of regulatory mechanisms for new artificial intelligence systems such as digital twins and reinforcement learning agents, this represents a significant barrier for future clinical translation. Sampling is in line with the suggestions from Casey et al. (2019) and expert position statements for standardisation including homogeneous definition, consistent outcome reporting and the incorporation of ethical approaches as a guide for clinical implementation [37, 38, 86]

4. DISCUSSION

4.1 Summary of Key Findings

This review illustrates that artificial intelligence (AI) and machine learning (ML) are fast changing the way of treating type 2 diabetes mellitus (T2DM), and remission is becoming an accepted therapeutic goal instead of maintenance with glycemic control. In the studies that were evaluated, AI-based programs demonstrated significant clinical improvements, and one study reported remission rates of over 70%. For example, the lifestyle sub-typing led to a remission in three-quarters of the subjects compared to one-fifth of controls, respectively [5], while a person-specific nutrition and lifestyle intervention based on a digital twin has resulted in a remission of three-quarters of the subjects and a reduction of fatty liver disease markers [13]. Similarly, the DiRECT and DIADEM-I studies revealed that comprehensive, early lifestyle programs correlate with remission among substantial patient proportions, particularly individuals with briefer disease duration [3, 17, 18].

New evidence also supports the wider remission therapeutic background. Scientists demonstrated sustained remission in intensive lifestyle interventions for one year, with the help of systematic reviews and meta-analyses supported the idea that structured lifestyle programs positively affected the increase of remission. On a guideline level, the American College of Lifestyle Medicine [38] and the international consensus report on remission definitions [39] now formally acknowledge remission as a practical clinical outcome, consistent with the paradigm shift that is happening in AI-based interventions. Furthermore, recent pharmacological research, including the study by Zeng in 2023 about the use of a glycemic-lowering agent in patients, demonstrates that novel drugs may induce remission but only medications in drug-naive patients; therefore, a combination of pharmacotherapy and the personalization of lifestyle programs with AI might be possible [85].

The benefit-deriving subpopulations were usually those who had recently diagnosed diabetes or shorter duration of the disease or certain metabolic phenotypes. Scientists report that in DiRECT, the duration of diabetes and HbA1c were the predictors of the successful remission, whereas the Asian studies have shown that patients who are not obese can also receive digital lifestyle programs [19]. Precision nutrition and digital twin methods demonstrated AI has the ability to individualize interventions to these inhomogeneous patient populations [21]. Notably, based on updates to practitioners, remission is not a dichotomous end state and should not remain a stable situation but is a process that should be monitored and subject to care measures [88, 89].

4.2 Interpretation and Implications

Compared to traditional lifestyle and pharmacotherapy (only), AI-based precision strategies achieve distinctive benefits because they customize treatment based on the biological and behavioral portraits of a particular patient. E.g., customized postprandial glucose response (PPGR) diets provided better glycemic results than a regular Mediterranean diet [63] and predictive AI algorithms could predict glycemic excursions based on a given food [90, 91].

Equally, standard insulin titration was surpassed by a reinforcement learning (RL) algorithm, which allowed more glycemic control and lower hypoglycemia [22]. These findings indicate the effectiveness of adaptive AI-based models versus non-adaptive clinical guidelines.

AI systems can develop an individual digital phenotype based on precision measurements of continuous glucose [6] wearable acceleration data [35, 36], and genomics/microbiome profiling [92, 93]. Global consolidation of such multimodal data into systems is an integral part of digital twins [13, 25] producing a paradigm shift between one-size-fits-all prescriptions and a highly granular, precision lifestyle medicine. Notably, AI does not substitute clinicians but increases their abilities to provide more personalized and efficient care [33, 34]

The latest clinical trials also demonstrate how individualized diets with the assistance of digital tracking and AI analytics can be used to produce clinically significant results. A researcher revealed that diets, tailored to reduce PPGR, had better weight loss than low-fat diets, which confirms the usefulness of algorithm-based source customization even in non-diabetic groups with abnormal glucose metabolism. Collectively, these studies indicate that personalization mediated by AI can not only increase remission rates but also overall significant cardiometabolic risks reduction [65].

To illustrate how multiple data streams and computational models interact within precision lifestyle medicine, we developed a conceptual framework that depicts the flow of patient data into AI-based processing, leading to adaptive, personalized interventions. The model emphasizes the feedback loop whereby clinical outcomes are continuously reintegrated into the system to refine recommendations through reinforcement learning and continuous training (FIGURE 4).

4.3 Clinical Translation and Scalability

Although several AI interventions are already being deployed in practice, including mobile diabetes apps [28], conversational AI for insulin titration [11], and digital therapeutics in South Asian patients [29], most studies remain proof-of-concept. Wider translation faces hurdles such as workflow integration, clinician acceptance, and regulatory oversight [8, 14]. Studies that incorporated explainability, such as Akimoto on metformin dose–response modeling [94] and Xiao on interpretable neural architectures, demonstrated that transparency enhances clinician trust [58]. Without explainability, however, AI adoption may be limited, as highlighted in cautionary perspectives [87].

Scalability also requires demonstration of cost-effectiveness. The DiRECT/Counterweight-Plus program was found to be cost-effective in the short term and cost-saving over a lifetime horizon [17]. The majority of digital twin methods and programs utilize computational infrastructure and have also performed well regarding the scalability of retrospective cohorts >1000 participants [25]. Reviews of bariatric surgery remission models corroborate that while predictive accuracy continues to improve, the development of better real-world validation and the establishment of standardized approaches is paramount if they are employed on a wider scale [57]. In addition to lifestyle and surgery, emerging regenerative approaches such as stem cell therapy are supported through AI monitoring. Warrier offers an avenue for future integration of advanced biological therapy and precision-based digital health systems [80].

4.4 Limitations of Included Studies

While the results are encouraging, there are many limitations of the evidence base. One significant limitation is that most of the interventional studies were short-term, with a follow-up of 13 to 48 weeks. Therefore, we cannot conclude whether remission achieved from these AI-driven interventions will be sustained long term [5, 81]. Although there were high rates of remission, we do not know how long the long-term durability of remission will be in AI-driven interventions. In contrast to AI driven interventions, long-term follow-up from traditional lifestyle interventions (e.g., Look AHEAD) confirmed that achieving sustained remission was associated with reduced cardiovascular morbidity and mortality [95]. When designing future clinical trials of AI-based interventions, researchers should utilize long-term (= 1-2 years) follow-up assessments.

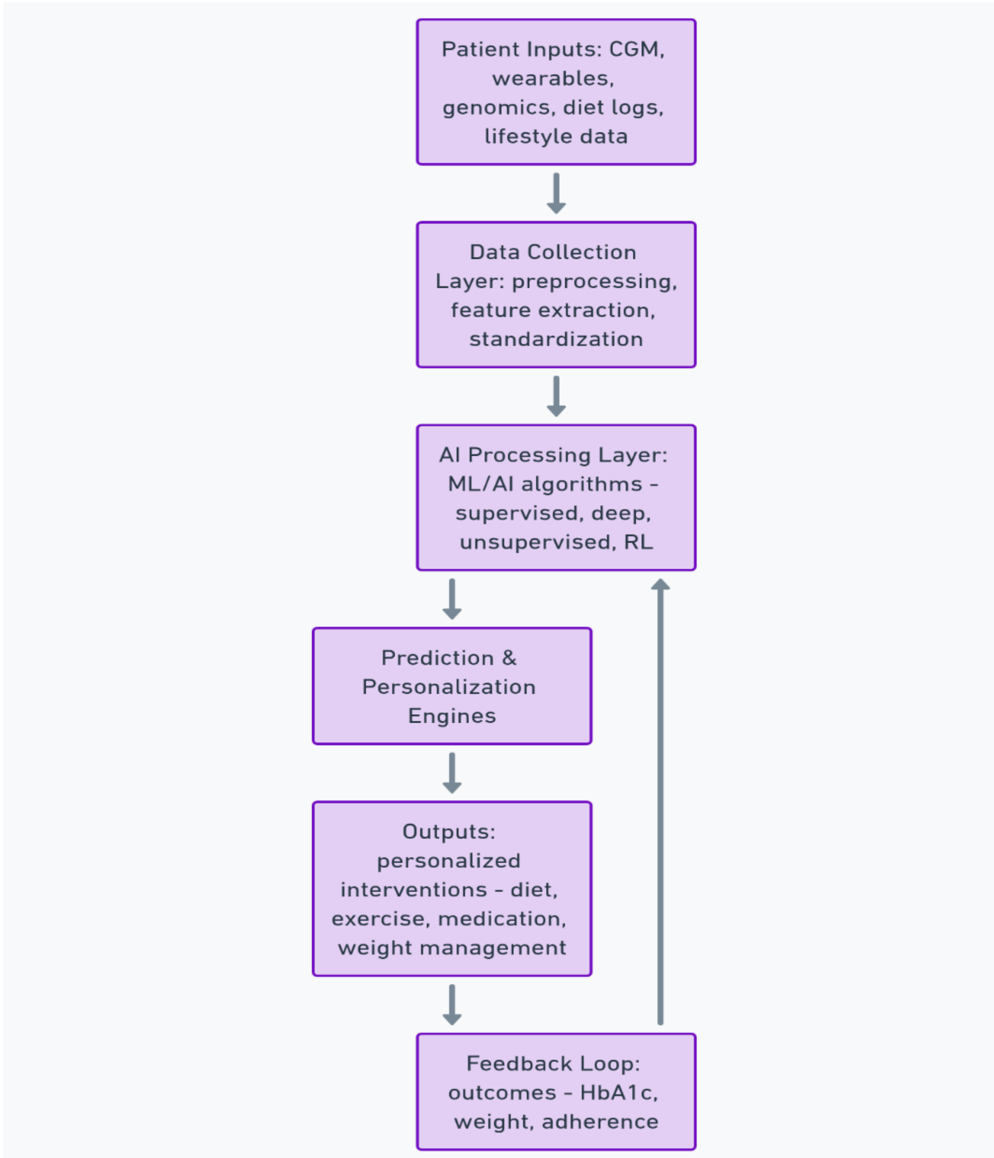

Figure 4: Conceptual model of AI-enabled precision lifestyle medicine

In addition, we found a lack of methodological rigor and transparency in both AI and ML studies. ML frameworks are challenged by bias, as demonstrated by the lack of homogeneity in the datasets used to train most algorithms, which increases the likelihood of overfitting and reduces the generalizability of results [74, 96]. Very few of the studies included external validation, and the majority of studies provided little information about how the algorithms were developed, including how features were selected, how they handled class imbalance, and how they calibrated their models. A lack of transparency and rigor in the development and validation of these algorithms presents a significant barrier to clinical translation and reproducibility.

Third, many studies on AI and ML were conducted with relatively few participants [22] in the early phases of reinforcement learning and only looked at ”n of 1” nutrigenomic investigations [64].

Bias present in ML frameworks presents a second challenge. Numerous systematic increaser views have pointed out [74, 96], that most algorithms are often trained on homogeneous datasets, which increases overfitting and reduces generalizability. In addition, external verification of models has been uncommon, and models are often developed using a limited demographic, primarily middle-aged individuals from high-income countries [9, 91]. In addition, design considerations regarding ethical issues such as informed consent, privacy and equity were highlighted in investigations of protocols, including AI-HEALS [50]. Other limitations include the inability of studies to agree on the use of standard criteria to assess remission in all studies [39].

4.5 Research Gaps and Future Directions

Multiple significant limitations in the literature exist at this time, including the lack of studies involving children and older adults, yet these populations have the highest burden of diabetes. Additionally, very few studies explore the developing world and low- to middle-income countries. An exception to this is the DIADEM-I study conducted in Qatar [18] and the digital programs on diabetes from India [19] underlining the need for equitable access to AI-enabled healthcare for all.

Methodologically, multimodal ML models integrating genomic, microbiome, behavioral, and clinical data remain rare. While digital twins [13, 25, 77] represent an important step in this direction, further work is needed to scale multimodal personalization. Reinforcement learning, which showed strong proof-of-concept results [22, 24], also requires larger randomized trials to confirm safety and efficacy. Ethical and regulatory frameworks must also evolve. Without agreed upon norms for transparency, liability and validation, there is risk that black-box AI will be deployed even before it is ready, because it facilitates precarious use, bringing out worse inequities [74, 87].

High-quality research projects to come will be larger-patient RCTs with clinical outcomes, cost-effectiveness, and sustainability of interventions powered by AI over more extended periods. Research combining digital phenotyping, nutrigenomics, reinforcement learning, and regenerative medicine is the most exciting frontier [22, 64, 70, 75] More broadly, dynamic conceptual models of remission (where remission should be viewed as a continuum requiring surveillance and adaptive strategies rather than an endpoint) should be part of the evidence base [88, 89].

5. CONCLUSION

This review highlights the revolutionary impact that artificial intelligence may have in changing the paradigm of type 2 diabetes management, in particular the shift in therapeutic focus away from achieving lifelong glycemic control toward the more ambitious but reachable goal of remission. As the evidence from varied interventions continues, it appears that AI-enabled systems are increasingly able to integrate complex, multimodal data streams and generate personalized strategies which can change dynamically to meet the needs of individual patients. The use of Continuous Glucose Monitoring (CGM), Wearables, Dietary Tracking Apps, Genomic Data, Behavioral Data along with Artificial Intelligence enables Lifestyle Interventions to be more tailored to each individual than has ever been achieved using a traditional One Size Fits All Approach. AI Platforms not only enable precise and accurate interventions but also facilitate improved Patient Engagement by enabling Patients to take an active role in their Health Management, increase their sense of Self-Efficacy, improve compliance to prescribed treatment and decrease the Emotional Burden of having Diabetes through Digital Support Mechanisms, Conversational Interfaces, and Adaptive Feedback mechanisms that provide means for Patients to more effectively manage their Diabetes, Tools to assist them with adherence to prescribed treatment, A way for them to enhance their Self-Efficacy regarding Diabetes Management, A reduced Emotional Burden due to having Access to Digital Support Mechanisms, Conversational Interfaces and Adaptive Feedback Mechanisms that empower Patients to manage their own Diabetes.

Furthermore, while the use of AI holds great promise, we must also acknowledge the limitations of the quality of the current body of Evidence supporting the effectiveness of these types of interventions. To date, the majority of studies have only been of very short duration with very small Sample Sizes; thus, it is not possible to make any firm conclusions regarding the Long-Term Sustainability of Remission. Addressing the gap in knowledge regarding this issue is one of the Primary Research Priorities.

The need for efficacy assessment of diabetes management strategies across different populations (children, elderly, and resource-poor) who have been traditionally underrepresented in clinical research presents a unique opportunity and challenge in diabetes management as AI is applied to diabetes care. In order for AI to successfully help close the existing health disparities gap without exacerbating it, efficacy assessment of these treatment modalities will be necessary.

As AI continues to be utilized in the management of diabetes, the three key pillars for progress in the development of effective AI-based diabetes management tools will be scientific integrity, transparency, and equitable access to the care being facilitated through the use of artificial intelligence. Further, the results of future randomized clinical trials focused on the sustainability over time of any successful treatment response and also the economic benefit of utilizing an AI-equipped treatment delivery system will need to be evaluated. Finally, to ensure that the medical and patient stakeholders have confidence in the reliability of the decisions being made based on the use of AI-assisted treatment tools, there will need to be clear justification as to the rationale for the clinical and patient decision-making processes, as well as to ensure the ethical basis of that decision-making. Lastly, in all future design, implementation and scale of innovation based on artificial intelligence, the goal should be equitable access to those innovations for all patient populations, regardless of where they live, what their socioeconomic status is, or their level of digital literacy.

In summary, through using artificial intelligence in the management of type 2 diabetes around the world, millions of people will have access to remission as a viable outcome for their condition through artificial intelligence and its different channels of development, research, testing, and future use of AI, AI based precision lifestyle medicine will be developed, validated and ethically translated to the clinical setting in order to create an individualized easier more efficient and revolutionary way of managing diabetes than has been available in the past.

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