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Multi-Agent System Applications in the Diagnosis of Diabetes: A Systematic Review

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Abstract- Diabetes prevalence is rising globally, demanding better management and treatment strategies. The use of artificial intelligence (AI), particularly Multi-Agent Systems (MAS), in healthcare is increasingly utilized. Multiple agents are used by MAS to gather information assist physicians and assist patients in managing their diabetes. This review article aims to explore the use of MAS in the treatment of diabetes. We looked for research on MAS and diabetes using the PRISMA guidelines, searching popular databases such as PubMed, IEEE Xplore, and ScienceDirect. We examined and evaluated studies that used MAS for diagnosis, treatment support, monitoring, and patient self-care after implementing inclusion and exclusion criteria. Our findings suggest that MAS can improve personalized treatment plans help patients stay engaged in their own care and improve the precision of diabetes diagnosis. However, there are still issues like data privacy system complexity and the need for real-world testing. This review shows how MAS can improve diabetes management and patient engagement.
Keywords Multi-Agent System, Diabetes, Artificial Intelligence, Diagnosis, Management

I. INTRODUCTION

Millions of individuals worldwide suffer from diabetes mellitus, a chronic illness (IDF, 2021). In 2021 the age-standardized prevalence of diabetes was 6 percent worldwide with higher rates seen in the Middle East and North Africa (International Diabetes Federation [IDF], 2021). When the body is unable to regulate blood sugar levels diabetes develops which can result in serious complications like kidney failure heart disease nerve damage and vision loss (World Health Organization [WHO], 2021). The aging population poor dietary habits modern lifestyles and decreased physical activity are some of the factors contributing to the rising prevalence of diabetes (IDF, 2021). This emphasizes how important it is to improve disease diagnosis monitoring and management techniques.

The medical field now has more opportunities thanks to recent technological advancements especially in the application of artificial intelligence (AI) to improve patient care. Computers can now process large amounts of health data and use AI to make well-informed decisions (Jiang et al., 2017). Among the different areas of artificial intelligence Multi-Agent Systems (MAS) have become a popular method for managing challenging tasks in dynamic settings. MAS are composed of multiple intelligent agents that exchange information communicate and collaborate to resolve problems (Shakshuki & Reid, 2015).

MAS can support diabetes care through lifestyle management real-time patient monitoring personalized treatment plans and early diagnosis. Agents in a MAS for example can gather information from wearable technology identify irregular glucose patterns suggest treatments and remind patients about following their dietary or medication regimens (Diabetes Technology Society, 2020). These systems are particularly useful in remote healthcare environments where continuous monitoring and automated decision-making can help both patients and healthcare professionals.

Multi-Agent Systems (MAS) driven by artificial intelligence (AI) have shown promising potential in enhancing patient outcomes when used in diabetes treatment. For instance 32 adults with type 2 diabetes participated in a randomized controlled trial conducted by Nayak et al. (2023). The time to optimal insulin dose was found to be significantly shorter for participants who used a voice-based conversational AI application (median 15 days vs. 56 days) as well as insulin compliance (83 percent vs. 50%) compared to those in this randomized clinical trial who were given standard care.

While considering the application of MAS, the challenges associated with data security and privacy must be addressed before MAS AI systems are implemented in the healthcare industry. Patients must give their express consent before any data processing can start in jurisdictions like the European Union where adherence to the General Data Protection Regulation (GDPR) is mandatory. Likewise adherence to the Health Insurance Portability and Accountability Act

(HIPAA) is necessary for the protection of patient data in the United States. By employing HIPAA-compliant technologies and gaining participants informed consent certain MAS platforms like the voice-based AI system utilized in the Managing Insulin with Voice AI (MIVA) have integrated these regulations.

Although the use of Multi-Agent Systems (MAS) in diabetes care have been proposed in several studies, there is currently no systematic review that compiles the various ways in which these systems are applied and their challenges. By reviewing existing studies on MAS in diabetes management this paper seeks to close that knowledge gap. It looks at the various MAS architectures commonly employed in diabetes care and focuses on how MAS can support patient monitoring diagnosis treatment and self-care.

2020 PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines by Page et al., 2021 are adhered to in this review in order to guarantee a transparent and high-quality research process. It aims to give researchers, healthcare providers and technology developers useful information about the state of MAS in diabetes care today. In addition, it responds to the research question: How can type 2 diabetes be diagnosed and managed more efficiently using Multi-Agent Systems (MAS) to enhance patient outcomes and healthcare efficiency?

II. METHODOLOGY

To guarantee thorough and transparent reporting this review was carried out in accordance with the PRISMA 2020 guidelines (Page et al., 2021). Compiling and summarizing research on the application of Multi-Agent Systems (MAS) in diabetes care was the aim.

Finding studies on the use of MAS in diabetes treatment was the aim of the review. The process followed PRISMA guidelines to ensure that the selection extraction and analysis of studies were transparent and systematic.

IEEE Xplore, PubMed, and ScienceDirect were the three databases that were thoroughly searched. Included in the search were articles published from 2010 to 2025. Among the search terms used are artificial intelligence, multi-agent systems, MAS healthcare system, and diabetes. Boolean operators (AND, OR) were used to combine these terms.

Peer-reviewed studies published between 2010 and 2025 were eligible for inclusion. Studies were only included if they were in English involved human subjects and concentrated on the application of MAS in diabetes management. Articles published before

2010 were excluded. Also, articles not related to diabetes or MAS AI were also excluded.
The results of the search were imported into reference management software and duplicate articles were removed. To determine if they met the inclusion requirements the abstracts and titles were independently screened. After that, full-text publications were obtained and further investigated.
A standardized form was used to extract important data from each study such as the study title, authors, year of publication, study design, AI/ML model, the use of MAS AI in diabetes management, and the main findings. With an emphasis on the various applications of MAS in diabetes care as well as the MAS AI/ML tools used was condensed into a narrative format as represented in table 2.0
The study selection process is depicted in the PRISMA 2020 flow diagram which provides an overview of how studies were located evaluated and included in the review.

III. RESULTS

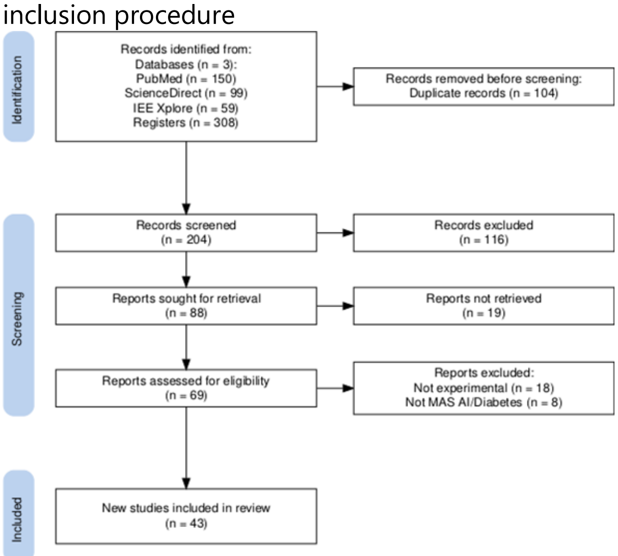
A total of 308 records were retrieved from the original database search. There were still 204 unique studies after duplicates were removed. Based on the set inclusion and exclusion criteria, 116 studies were removed during title screening and 19 more during abstract review. Out of the remaining 88 papers evaluated, 43 studies satisfied all eligibility criteria that were included in this review.
Fig. 1 depicts the complete selection procedure.

Eight key domains for Multi-Agent Systems (MAS) to be used in diabetes diagnosis and treatment were determined after a qualitative analysis of the studies. These areas show how MAS technology can help provide diabetes patients with more precise effective and personalized care.
The use of MAS to support personalized treatment plans is crucial in the management and treatment of diabetes. To forecast blood sugar levels and modify insulin dosages these systems analyze patient data in real time. The use of MAS in this field was the subject of 19 out of the 43 included studies.
In the diagnostic and imaging domain MAS aids in improving the accuracy of medical imaging instruments used to identify diabetes-related disorders. According to Avanzo et al. (2021), this involves analyzing data from scans such as MRIs and retinal images which can aid in the early identification of problems. There were eight studies done in this area.
Another important domain is health monitoring systems. Here MAS uses wearable technology such as continuous glucose monitors to continuously measure blood sugar levels. When blood glucose levels become unstable these systems can notify patients and caregivers allowing for quicker interventions (Vettoretti et al., 2020). Three studies addressed this topic.
Through predictive modeling MAS forecasts the onset of diabetes or its complications based on patient histories and datasets. These models can help with better treatment planning and early prevention strategies (Nomura et al., 2021). Thirty-three studies investigated this area.

Applications in public health are another area where MAS are utilized to create risk prediction tools for large populations. Strategies to prevent stroke or other diabetes-related conditions can be guided by these tools (Guan et al., 2023). In this context MAS was covered in eight studies.
Systems that help patients choose healthier foods and lifestyles are included in the Lifestyle and Diet Management domain. Based on patient habits and medical information MAS can personalize dietary recommendations (Li et al., 2020). Fifteen studies addressed the use of MAS in this area.
Another important area in which MAS helps medical professionals is in clinical decision support where it sorts and analyzes patient data to recommend the best treatment choices. Clinical decisions can become more accurate and data-driven with the help of these systems (Alowais, 2023). There were 22 studies that addressed this domain.
Lastly systems that assist patients in continuing to participate in their own care are referred to as Patient Engagement and Self-Management. Reminders patient progress tracking and advice on how to improve treatment plan adherence can all be provided by MAS-based apps and platforms (Karan, 2023). This domain was covered by twenty studies.
Overall, medical professionals can also benefit from MASs assistance in clinical decision support where it

sorts and evaluates patient data to suggest the best course of action. Figure 2 and the Appendix Table display the eight domains that were identified. The eight identified domains are shown in Figure 2 and the Appendix Table. While Table 1 displays the distribution of studies across these domains. Figure 3 details the specific contributions of MAS in the treatment of diabetes.

Fig. 1. PRISMA flowchart of study selection and inclusion procedure



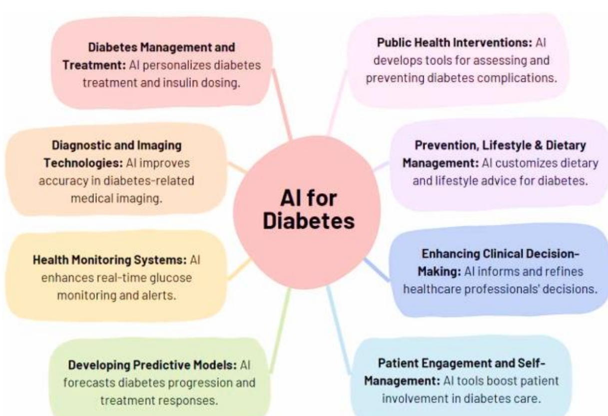


Fig. 2. Eight Domains in which MAS AI Enhances Diabetes Management (Khalifa and Albadawy, 2024).

Table 1: This table lists the eight areas where MAS AI improves diabetes care along with the number of studies covered by each of the 43 papers that were chosen.

Domain	**Number of studies discussing each**
Developing Predictive Models	33
Enhancing Clinical Decision Making	22
Patient Engagement and Self-management	20
Diabetes Management and Treatment	19
Lifestyle and Dietary Management	15
Public Health Interventions	8
Diagnostics and Imaging Technologies	8
Health Monitoring Systems	3

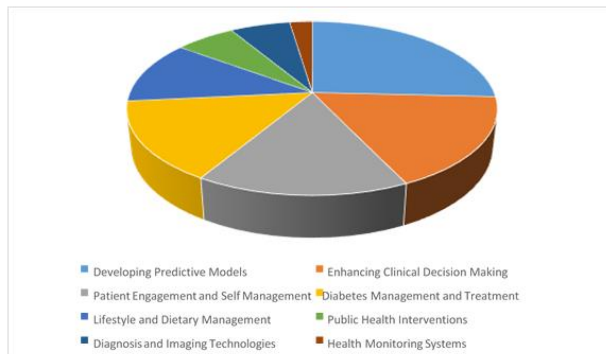


Fig.3. MAS AI Contribution to Diabetes Management based on the selected studies.

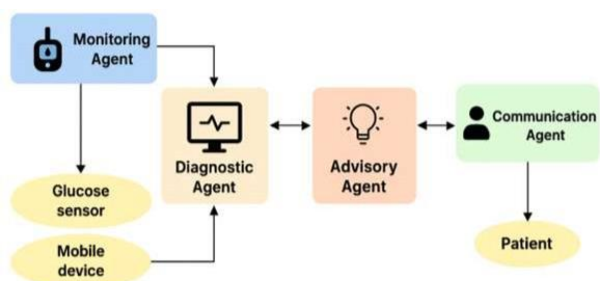


Fig. 4. Depicts interaction between core agents in MAS applications for management of diabetes.

Table 2: Author and Year of Publication, Outcome Measures, Population/Participants, Sample Size, Intervention/Exposure, and Findings.

SN	Author and Year	Aim	Population/ Participants	Sample Size	Intervention/ Exposure	Outcome Measures	AI./ML Model	Findings
1	Roberts et al., 2021	To check the volumetric changes intra-retinal and sub-retinal fluid in the DME in the course of anti-VEGF treatment using deep learning.	DME patients	570	Anti-VEGF treatment	Changes in fluid volume, acuity	Deep Learning Algorithms	The presence of sub-retinal fluid was linked to a lower baseline visual acuity but a good response to treatment according to automated fluid segmentation in diabetic macular edema.
2	Hong et al., 2021	To create a predictive model for urosepsis risk in patients with upper urinary tract calculi	Patients with upper urinary tract calculi	1716	Urinalysis and ultrasonography	Prediction of urosepsis	Artificial Neural Network (ANN)	A model based on artificial intelligence learning was able to accurately predict the risk of urosepsis in patients with upper urinary tract calculi.
3	Abraham et al., 2021	To identify biomarkers predicting response to	Patients having diabetic	24	Anti-VEGF therapy	OCT imaging biomarkers expression of cytokines	Optical coherence tomography machine learning	Identified biomarkers that connect cytokine expression and OCT phenotype

		anti-VEGF in DME	muscular edema				augmented segmentation platform	to predict how diabetic macular edema patients will respond to antivascular endothelial growth factor treatment.
4	Sun et al.,	To investigate how insulin resistance in T2D is influenced by exercise and vitamin D	Type 2 diabetic middle-aged adults	61	Endurance exercise and supplementation of vitamin D	Insulin resistance, plasma lipidome	Dietary-based AI management solution	Used a continuous glucose monitoring system and an AI-based dietary management solution to examine the effectiveness of a digitally integrated healthcare platform in patients with type 2 diabetes.
5	Nimri et al., 2020	To compare how physicians and AI-DSS youths with type 1 diabetes adjust insulin dosages	Youths with Type 1 Diabetes	108	AI-DSS for insulin adjustment	Time within target glucose range	Artificial Intelligence-based DSS	An automated artificial intelligence (AI) decision support system for optimizing insulin dosage was safe and successful in

		within the target glucose range (AI-DSS)						treating type 1 diabetes in young people.
6	Sampedro et al., 2020	To utilize ML to predict stent restenosis	Patients with stent implantation	263	Not specified	Stent restenosis prediction	Different ML classifiers	Stent restenosis in patients following percutaneous coronary intervention was predicted by a machine learning model that performed better than current scores.
7	Unsworth et al., 2023	To assess the ABC4D system for insulin bolus doses in T1D	Type 1 Diabetic adults	37	Insulin dosing ABC4D system	Glycemic control	Case-based reasoning techniques	Insulin bolus doses can be safely adjusted with the Advanced Bolus Calculator for Type 1 Diabetes (ABC4D) which also offers the same degree of glycemic control as the nonadaptive bolus calculator.

8	Moyen et al., 2022	To evaluate the app Keenoas dietary assessment validity in comparison to ASA24.	Adults with or without diabetes	136	Keenoa app for dietary tracking	Reported intake of nutrients and energy	AI enhanced app	When comparing the energy macronutrient and micronutrient intakes of diabetics and healthy adults to ASA24 showed moderate to strong validity according to the Keenoa app
9	Benhamou et al., 2019	To evaluate the effectiveness of digital health care platforms with AI-based dietary management for T2D	Type 1 diabetic adults	68	DBLG1 hybrid closed-loop system	Glucose target range hypoglycemic episodes	Machine Learning-based algorithms	The DBLG1 system is superior to sensor-assisted insulin pumps in terms of glucose control and closed-loop insulin use.
10	Zhao et., 2022	Utilizing ultrasound imaging examine how a comprehensive nursing plan affects patients with	Patients with diabetic kidney disease	44	Comprehensive nursing plan	Quality of life, renal function and complication.	K non-local-means filtering algorithm for ultrasound i	Patients with diabetic kidney disease can benefit greatly from nursing interventions that help them improve and control their

		diabetic kidney disease.						renal function and ultrasound images that employ a clever algorithm are able to recognize this dynamically.
11	Du et al., 2022	To evaluate the impact of Fmri UNDER AI on diabetic nephropathy home nursing	Patients with diabetic nephropathy	64	PDCA home nursing	Home nursing efficacy and nursing satisfaction	Fuzzy C-means clustering algorithm	FCM algorithm detected activation regions in fMRI images more effectively reducing error and aiding in diagnosis. for food identification..
12	Alfonsi et al. 2020	To test the app's usability and effect on carbohydrate counting accuracy	Type 1 diabetic youth	22	iSpy carbohydrate counting app	Accuracy of carbohydrate counting, HbA1c levels	Machine learning for food identification	The high acceptability of iSpy a new app for counting carbohydrates supports its use in the treatment of young individuals with type 1 diabetes.
13	Han et al., 2022	To evaluate the effectiveness of a deep	DME patients	96	Deep learning 3D convolutional neural network	Quality of MRI image,	3D-CNN	The diagnostic accuracy of diabetic macular edema was

		learning algorithm in diagnosing Diabetic Macular Edema (DME)			(3D-CNN) algorithm for MRI images	and diagnostic accuracy.		greatly increased by deep learning algorithm-based MRI.
14	Reddy et al., 2019	To develop algorithms to predict exercise-related hypoglycemia in T1D	Type 1 diabetic adults	43	Not specified	Hypoglycemia prediction during exercise	Decision tree and random forest models	Two algorithms for predicting hypoglycemia in adults with Type 1 Diabetes during physical activity were developed and evaluated.
15	Liu et al., 2020	To test exercise-induced alterations in gut microbiota and their impact on glucose homeostasis	Pre-diabetic men	39	Exercise	Glucose homeostasis, insulin sensitivity	Machine-learning algorithm	Changes in the gut microbiota brought on by exercise were linked to insulin sensitivity and glucose homeostasis in prediabetes.
16	Oikonomou et al., 2022	To develop an ML-based tool for personalized ASCVD	Type 2 diabetic patients	4327	Canagliflozin	Major adverse cardiovascular events	Extreme gradient boosting algorithm	The ability to biosynthesize short-chain fatty acids was improved in responders. A decision support

		effects of canagliflozin						tool based on machine learning to customize the benefits of canagliflozin for type 2 diabetes patients with atherosclerotic cardiovascular disease (ASCVD) was created.
17	Zou et al., 2024	To check the effects of stratifying prediabetes patients by diabetes progression risks on their response to interventions	Pre-diabetic patients	2,558	Lifestyle and/or pioglitazone intervention	Reversal of prediabetes and progression of diabetes	Machine learning model (XGBoost)	Patients' response to different interventions were affected when they were stratified by diabetes progression risks using a machine learning-based model for prediabetes.
18	Nayak et al., 2023	Examine the efficacy of a voice-based AI application in insulin titration	Type 2 diabetic patients	32	Voice-based AI application for insulin management	Optimal insulin dose, adherence, glycemic control	Conversational AI application	Comparing voice-based conversational AI to standard care the results showed significant

								improvements in time to optimal insulin dose insulin adherence glycemic control and emotional distress related to diabetes.
19	Varga et al., 2021	To compare the discriminative utility of various biomarkers for diabetes prediction	Prediabetic individuals	2590	Not applicable	Incident diabetes	Machine learning algorithms	NMR-derived biomarkers did not improve diabetes risk discrimination over conventional risk factors.
20	Faruqui et al., 2020	To predict daily glucose levels in T2DM based on lifestyle data	Type 2 diabetic patients	10	Mobile health lifestyle data	Prediction of blood glucose level	Long short-term memory-based RNNs	Future glucose levels in patients with type 2 diabetes were accurately predicted by a deep learning model based on mobile health data.
21	Wet et al., 2022	To evaluate the use of environmental chemical exposure in predicting	General population	8,501	Environmental chemical exposure	Prediction of diabetes	Random forest, LASSO regression	Diabetes mellitus was accurately predicted by environmental chemical

		diabetes mellitus						exposure dynamics and machine learning highlighting the predictive power of common environmental chemicals for complex diseases.
22	Popp et al., 2022	To compare the effectiveness of a personalized diet vs a low-fat diet for weight loss in adults with abnormal glucose	Adults with abnormal glucose metabolism and obesity	204	Personalized diet vs low-fat diet	Weight loss, body composition	Machine learning algorithm	At six months a customized diet aimed at lowering the postprandial glycemic response did not lead to more weight loss than a low-fat diet.
23	Wang et al., 2023	To develop and validate an ML-based prediction model for heart failure risk in patients with prediabetes or diabetes	Middle-aged and older individuals with prediabetes or diabetes	54	Not applicable	Heart failure risk prediction	Various ML algorithms, including random forest	The risk of heart failure in US people with diabetes or prediabetes was accurately predicted by a machine learning model.

24	Chauhan et al., 2021	To investigate a functional ingredient for glucose regulation in prediabetes	Individuals with elevated HbA1c	Not specified	NRT_N0G5IJ supplementation	Glycated hemoglobin levels reduction	AI for ingredient discovery	AI was used to find a useful pea ingredient that was demonstrated to lower HbA1c in pre-diabetic individuals.
25	Avari et al., 2021	To assess the safety and efficacy of the PEPPER system for personalized bolus advice in type 1 diabetes	Type 1 diabetic individuals	54	PEPPER system for bolus advice	Glycemic outcomes, and safety	Case-based reasoning AI	While the PEPPER Adaptive Bolus Advisor and Safety System was safe it had no effect on type 1 diabetes glycemic outcomes when compared to control.
26	Ashrafi et al., 2021	To assess postprandial glucose concentrations in patients post-bariatric surgery	Morbidly obese patients undergoing surgery	17	RYGB or OAGB surgery	Glucose concentrations, carbohydrate intake	Machine learning model	Explored the use of machine learning to model postprandial glucose levels in obese patients undergoing gastric bypass surgery.
27	Sarici et al., 2023	To investigate quantitative	Patients with diabetic	44	Aflibercept injection or	Changes in UWFA	Machine learning-enabled	Quantitative ultra-wide field angiographic

		UWFA parameters in DME treatment	macular edema		combined IAI/ nesvacumab	parameters, OCT metrics	feature extraction	parameters for diabetic macular edema eyes treated with IAI with or without nesvacumab significantly improved.
28	Khorraminezhad et al., 2021	To investigate the effect of high dairy intake on gut microbiota and insulin resistance	Adults with hyperglycemia	10	High dairy intake	Gut microbiota composition, insulin resistance	Machine learning analyses	In hyper-insulinemic individuals, dairy consumption negatively correlates with insulin resistance and changes the gut microbiotas composition.
29	Joshi et al., 2023	To evaluate the effect of DT-enabled personalized nutrition on T2D and MAFLD	Patients with T2D	319	Personalized meal plans by AI	Change in HbA1c, liver fat scores	Digital Twin technology	Patients with type 2 diabetes who received individualized nutrition enabled by digital twins saw a significant improvement in fatty liver disease linked to metabolic dysfunction.

30	Saux et al., 2023	To develop a model for predicting individual 5-year weight loss trajectories after bariatric surgery	Post-bariatric surgery patients	10,231	Bariatric surgery (different types)	5-year weight loss trajectories	LASSO, CART algorithms	A machine learning-based calculator successfully forecasted the weight trajectories of a multinational cohort five years following bariatric surgery.
31	Popp et al., 2019	To evaluate two dietary interventions for weight loss in T2D	Individuals with prediabetes and T2D	Not specified	Low-fat diet and personalized diet using ML algorithm	Changes in energy expenditure, body weight, and composition	Machine learning for dietary response	Two dietary interventions were used: a customized diet based on a machine-learning algorithm and a low-fat diet.to help people with prediabetes and type 2 diabetes lose weight.
32	Seethaler et al., 2022	To determine if the Mediterranean diet, via SCFAs, improves intestinal barrier integrity	Women with intestinal barrier impairment	260	Mediterranean diet	SCFA concentrations, intestinal permeability	Machine-learning algorithm	By producing short-chain fatty acids the Mediterranean diet improved the intestinal barriers integrity.

33	Oikonomou et al., 2022	To define personalized cardiovascular benefits of intensive systolic blood pressure controll	Patients with hypertension	Not specified	Intensive systolic blood pressure control	Prediction of cardiovascular events	XGBoost algorithm	By applying machine learning to clinical trial data it was possible to successfully customize the cardiovascular benefits of rigorous systolic blood pressure control in patients with or without type 2 diabetes.
34	Zhang et al., 2022	To create an algorithm for machine learning that will forecast the likelihood that young adults with Type 1 Diabetes will neglect their self-management.	Adolescents with Type 1 Diabetes	Not specified	Momentary assessment data, blood glucose data	Self-management behaviors	Machine learning-based filtering architecture	Machine learning showed promise in forecasting type 1 diabetes self-management when combined with short-term assessment data.
35	Habes et al., 2023	To assess brain age and AD-like atrophy in adults with	Type 1 diabetic adults	416	Not applicable	Cognitive performance, brain age, and atrophy	Machine learning indices for brain age	The study indicates that people with Type 1 Diabetes who do not

		type 1 diabetes.						exhibit early symptoms of Alzheimer's-related neurodegeneration may have an accelerated rate of brain aging...
36	Khanji et al., 2019	To look into therapeutic target prediction models for patients with cardiovascular disease who have dyslipidemia and hypertension.	Patients with hypertension, dyslipidemia, diabetes	870	Not specified	Achieving therapeutic targets	Lasso regression, machine learning	Found five process indicators that have good predictive validity for intermediate outcomes pertaining to the prevention of cardiovascular disease.
37	Gastaldelli et al., 2021	To understand the effect of PPAR-γ agonists on steatohepatitis in NASH	NASH patients	55	PPAR-γ agonists (pioglitazone)	Hepatic/visceral fat, adiponectin levels	Machine learning techniques	In NASH patients the histological benefits of PPAR-γ action are mediated by improved fat distribution reduced visceral fat and elevated adiponectin.

38	Park et al., 2020	To evaluate digital healthcare platform with AI-based dietary management for adults with type 2 diabetes	Type 2 diabetic adults	284	Digital healthcare platform with AI-based dietary management	Change in HbA1c, weight loss	AI-based dietary management solution	Evaluated how well a digitally integrated healthcare platform treated patients with type 2 diabetes using an AI-based dietary management tool and a continuous glucose monitoring system.
39	Lopez et al., 2019	To forecast and understand the response to intensive insulin therapy in early type 2 diabetes	Adults with early type 2 diabetes	24	Short-term intensive insulin therapy	Beta-cell function, postprandial glucose responses	Random survival forest and Cox models	Identified potential the pathophysiologic elements affecting the reversibility of beta-cell dysfunction and identified possible responders to intensive insulin therapy in early type 2 diabetes.
40	Lee et al., 2023	To evaluate an integrated digital health care platform	Type 2 diabetic adults	294	health care platform with AI-based	Glycemic control, and weight loss	AI-driven dietary management	Adults with type 2 diabetes who used an AI-driven dietary

		with AI-based dietary management for type 2 diabetes			dietary management			management system in conjunction with an integrated digital health care platform observed improved glycemia and increased weight loss.
41	Ben-Yacov et al., 2023	To assess a digital health care platform that combines AI-powered type 2 diabetes dietary management.	Prediabetic adults	200	Personalised postprandial targeting diet vs. Mediterranean diet	Microbiome composition, cardiometabolic markers	Machine learning for diet response prediction	Supported the idea that the gut microbiota plays a role in controlling how dietary modifications affect cardio-metabolic outcomes which in turn helps to reduce comorbidities in pre-diabetes.
42	Wang et al., 2022	To evaluate the role of MRI data characteristics in evaluating compound skin graft	Patients with diabetic foot	78	Compound skin graft treatment	Healing time, recurrence rate, scar score	KNL-Means filtering algorithm for MRI	With the use of deep learning algorithms and additional reference information from MRI image data

		treatment for diabetic foot						characteristics the effectiveness of compound skin transplantation for diabetic foot can be assessed.
43	Rein et al., 2022	To investigate the effects of a personalized postprandial-targeting diet on glycemic control in T2DM	Newly diagnosed Type 2 diabetic adults	23	Personalized postprandial-targeting diet	Glycemic measures, metabolic health parameters	Machine learning algorithm	Glycemic control was better with personalized diets based on glycemic response prediction in individuals with newly diagnosed type 2 diabetes than with a Mediterranean-style diet.

IV. DISCUSSION

The purpose of this systematic review was to investigate the use of Multi-Agent Systems (MAS) in the diagnosis and treatment of diabetes particularly type 2. The ability of MAS to handle massive volumes of data support early diagnosis and customize care for each patient has drawn interest in the healthcare industry. According to the reviewed studies MAS can significantly enhance the effectiveness and quality of diabetes care when paired with techniques like data analysis.

One of MAS main advantages is its ability to gather and assess data from multiple sources such as patient reports electronic health records and blood glucose monitors to support better diagnosis and treatment decision-making (Huang et al., 2023; Contreras and Vehi, 2018; Vettoretti et al., 2020). For example Li et al. (2020), demonstrated how MAS could provide patients with real-time guidance and instruction for managing chronic conditions like diabetes. In addition Nomura et al. and Guan et al. (2021), discovered that through large-scale health data analysis MAS can assist in the detection of complications such as diabetic retinopathy and kidney disease enhancing patient outcomes and early intervention.

Support for individualized care is another important advantage of MAS. Unlike conventional fixed treatment plans these systems are adaptable enough to modify to each patient's condition lifestyle and response to treatment (Rein et al., 2022; & Popp et al., 2022). This flexibility is essential for type 2 diabetes management as each patient's unique disease progression and health status require a personalized course of treatment. Joshi et al. for instance, in 2023, demonstrated that blood sugar levels in individuals with both diabetes and fatty liver disease were improved by a MAS intended to aid with nutrition. According to other research food-related MAS improved long-term control and lessened blood sugar swings (Ben-Yacov et al., 2023 & Lee et al., 2023).

Additionally MAS are essential in enabling patients to take charge of their own health care. These systems use real-time data to give patients recommendations on diet exercise and insulin use (Karan, 2023; Alowais et al., 2023; & Park et al., 2020). Zhang et al. (2022), and Avari et al. (2021), discovered that MAS assisted patients in controlling their blood sugar levels and preventing crises. Additionally research indicates that younger individuals with type 1 diabetes who utilized these systems expressed greater satisfaction and improved treatment plan adherence (Alfonsi et al., 2020).

However, a number of challenges must be addressed before MAS can be applied extensively in clinical settings. According to research, many MAS are still in the research stage and have not yet been put to the test in actual hospital settings (Contreras and Vehi, 2018; Tahir & Farhan, 2023). This limits the findings applicability and raises doubts about their reliability and usefulness. Concerns have also been raised regarding these systems usability data privacy and compatibility with current medical equipment (Bajwa et al., 2021). It is also difficult to approve and widely adopt these systems since there are no clear standards for assessing their performance and safety (Salinari et al., 2023).

It is also a problem how much patients and medical professionals can trust these systems particularly when it comes to making important medical decisions. Although MAS can provide useful recommendations some experts are concerned that a reliance on these systems may compromise clinical judgment by healthcare providers or patient-physician trust (Davenport & Kalakota, 2019). Maintaining human expertise at the forefront of healthcare while using MAS for decision support will require striking a balance.

This reviews studies demonstrated that the majority of Multi-Agent Systems (MAS) used to manage diabetes had a well-defined structure with distinct roles for each agent. Figure 4 shows the relationship between the primary agent types frequently found in MAS applications for diabetes management. First, the Monitoring Agent gathers information from a variety of sources including glucose sensors and mobile devices. This data is analyzed by the Diagnostic Agent to look for patterns or early warning signs of issues. Using this analysis the Advisory Agent creates personalized recommendations that are sent to the patient through the Communication Agent. This coordinated architecture supports patient engagement and ongoing adaptive care.

Despite challenges MAS has shown promise in helping healthcare providers by automating repetitive tasks identifying health risks and suggesting treatments (Nomura et al., 2021; Hong et al., 2023 & Wang et al., 2023). This can reduce the workload for clinicians enhance the quality of care and enable more effective use of medical resources.

This review concludes by pointing out that MAS may enhance diabetes diagnosis and treatment. Better results in the treatment of diabetes may result from MASs integration of various data sources individualized treatment and patient empowerment. More research in practical settings is necessary to address present issues and ensure that these systems can be safely and effectively used in clinical practice.

V. CONCLUSION

The review highlights how Multi-Agent Systems (MAS) can improve the diagnosis and treatment of diabetes especially type 2. There is great potential for enhancing diagnostic accuracy enabling individualized treatment plans and equipping patients with self-management resources through the integration of MAS into diabetes care. By analyzing complex data from various sources MAS enables more accurate decision-making and offers patients individualized treatments that meet their particular requirements. There are still significant challenges to be addressed in spite of these advantages. To validate the results of recent studies and guarantee the dependability of the systems in clinical practice further research is essential especially in real-world contexts. In order to address concerns regarding patient privacy and system compatibility strong data security and privacy protocols are essential as is seamless integration with existing healthcare systems. In order to guarantee the safety and efficacy of MAS applications over time it is also essential to establish unambiguous regulatory frameworks and conduct ongoing monitoring.

Cross-disciplinary cooperation will be essential to the development of MAS technology. To create tools that are not only technically sound but also useful and in line with the realities of clinical care healthcare professionals researchers and legislators must collaborate. Ensuring healthcare personnel have the required training to effectively use MAS and communicate its benefits and drawbacks to patients is also essential to the successful deployment of these systems

Despite continuing obstacles MAS integration into diabetes care holds great promise for improving patient outcomes and streamlining healthcare delivery. Increased interdisciplinary collaboration in research and a focus on patient-centered design could make these systems a significant component of modern healthcare offering diabetics more effective care.

Author Contributions

Desmond Afoakwa: Conceptualization, Methodology, Data curation, Writing- Original draft preparation, Visualization, Investigation. Konstantin Koshechkin: Supervision, Writing- Reviewing and Editing. Daniel Kofi Boakye: Validation.

REFERENCES

1. Abraham, J. R., Wykoff, C. C., Arepalli, S., Lunasco, L., Yu, H. J., Hu, M., Reese, J., Srivastava, S., Brown, D. M., & Ehlers, J. P. (2020). Aqueous cytokine expression and higher Order OCT biomarkers: Assessment of the Anatomic-Biologic Bridge in the IMAGINE DME study. *American Journal of Ophthalmology*, *222*, 328–339. https://doi.org/10.1016/j.ajo.2020.08.047
2. Alfonsi, J. E., Choi, E. E. Y., Arshad, T., Sammott, S. S., Pais, V., Nguyen, C., Maguire, B. R., Stinson, J. N., & Palmert, M. R. (2020). Carbohydrate counting app using image recognition for youth with Type 1 Diabetes: pilot randomized control trial. *JMIR Mhealth and Uhealth*, *8*(10), e22074. https://doi.org/10.2196/22074
3. Alowais, S.A. (2023). Revolutionizing healthcare: the role of artificial intelligence in clinical practice, *BMC Med. Educ*. 23 (1), 689. https://doi.org/10.1186/s12909-023-04698-z
4. Ashrafi, R. A., Ahola, A. J., Rosengård-Bärlund, M., Saarinen, T., Heinonen, S., Juuti, A., Marttinen, P., & Pietiläinen, K. H. (2021). Computational modelling of self-reported dietary carbohydrate intake on glucose concentrations in patients undergoing Roux-en-Y gastric bypass versus one-anastomosis gastric bypass. *Annals of Medicine*, *53*(1), 1885–1895. https://doi.org/10.1080/07853890.2021.1964035
5. Avanzo, M., Trianni, A., Botta, F., Talamonti, C., Stasi, M., & Iori, M. (2021). Artificial intelligence and the medical physicist: welcome to the machine. *Applied Sciences*, *11*(4), 1691. https://doi.org/10.3390/app11041691
6. Avari, P., Leal, Y., Herrero, P., Wos, M., Jugnee, N., Arnoriaga-Rodríguez, M., Thomas, M., Liu, C., Massana, Q., Lopez, B., Nita, L., Martin, C., Fernández-Real, J. M., Oliver, N., Fernández-Balsells, M., & Reddy, M. (2020). Safety and feasibility of the PEPPER Adaptive BOLUS Advisor and Safety System: a randomized control study. *Diabetes Technology & Therapeutics*, *23*(3), 175–186. https://doi.org/10.1089/dia.2020.0301

7. Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. *Future Healthcare Journal*, *8*(2), e188–e194. https://doi.org/10.7861/fhj.2021-0095
8. Benhamou, P., Franc, S., Reznik, Y., Thivolet, C., Schaepelynck, P., Renard, E., Guerci, B., Chaillous, L., Lukas-Croisier, C., Jeandidier, N., Hanaire, H., Borot, S., Doron, M., Jallon, P., Xhaard, I., Melki, V., Meyer, L., Delemer, B., Guillouche, M., . . . Charpentier, G. (2019). Closed-loop insulin delivery in adults with type 1 diabetes in real-life conditions: a 12-week multicentre, open-label randomised controlled crossover trial. *The Lancet Digital Health*, *1*(1), e17–e25. https://doi.org/10.1016/s2589-7500(19)30003-2
9. Ben-Yacov, O., Godneva, A., Rein, M., Shilo, S., Lotan-Pompan, M., Weinberger, A., & Segal, E. (2023). Gut microbiome modulates the effects of a personalised postprandial-targeting (PPT) diet on cardiometabolic markers: a diet intervention in pre-diabetes. *Gut*, *72*(8), 1486–1496. https://doi.org/10.1136/gutjnl-2022-329201
10. Chauhan, S., Kerr, A., Keogh, B., Nolan, S., Casey, R., Adelfio, A., Murphy, N., Doherty, A., Davis, H., Wall, A. M., & Khaldi, N. (2021). An Artificial-Intelligence-Discovered Functional Ingredient, NRT_N0G5IJ, Derived from Pisum sativum, Decreases HbA1c in a Prediabetic Population. *Nutrients*, *13*(5), 1635. https://doi.org/10.3390/nu13051635
11. Contreras, I., & Vehi, J. (2018). Artificial intelligence for diabetes management and decision support: literature review, *J. Med*. Internet Res. 20 (5), e10775
12. Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94
13. Diabetes Technology society. (2020). *Diabetes Technology: The role of artificial intelligence in Diabetes Care*. Retrieved from https://www.diabetestechnology.org
14. Du, Q., Liang, D., Zhang, L., Chen, G., & Li, X. (2022). Evaluation of Functional Magnetic Resonance Imaging under Artificial Intelligence Algorithm on Plan-Do-Check-Action Home Nursing for Patients with Diabetic Nephropathy. *Contrast Media & Molecular Imaging*, *2022*(1). https://doi.org/10.1155/2022/9882532
15. Faruqui, S. H. A., Du, Y., Meka, R., Alaeddini, A., Li, C., Shirinkam, S., & Wang, J. (2019). Development of a deep learning model for dynamic forecasting of blood glucose level for Type 2 diabetes mellitus: secondary analysis of a randomized controlled trial. *JMIR Mhealth and Uhealth*, *7*(11), e14452. https://doi.org/10.2196/14452
16. Gastaldelli, A., Sabatini, S., Carli, F., Gaggini, M., Bril, F., Belfort-DeAguiar, R., Positano, V., Barb, D., Kadiyala, S., Harrison, S., & Cusi, K. (2021). PPAR-γ-induced changes in visceral fat and adiponectin levels are associated with improvement of steatohepatitis in patients with NASH. *Liver International*, *41*(11), 2659–2670. https://doi.org/10.1111/liv.15005
17. Guan, Z., Li, H., Liu, R., Cai, C., Liu, Y., Li, J., & Sheng, B. (2023). Artificial intelligence in diabetes management: advancements, opportunities, and challenges. *Cell Reports Medicine*, *4*(10): 101213. doi: 10.1016/j.xcrm.2023.101213.
18. Habes, M., Jacobson, A. M., Braffett, B. H., Rashid, T., Ryan, C. M., Shou, H., Cui, Y., Davatzikos, C., Luchsinger, J. A., Biessels, G. J., Bebu, I., Gubitosi-Klug, R. A., Bryan, R. N., & Nasrallah, I. M. (2023). Patterns of regional brain atrophy and brain aging in Middle- and Older-Aged adults with Type 1 diabetes. *JAMA Network Open*, *6*(6), e2316182. https://doi.org/10.1001/jamanetworkopen.2023.16182
19. Han, X., Tan, J., & He, Y. (2022). Deep Learning Algorithm-Based MRI image in the diagnosis of diabetic macular edema. *Contrast Media & Molecular*

Imaging, *2022*, 1–9. https://doi.org/10.1155/2022/1035619

20. Hong, X., Liu, G., Chi, Z., Yang, T., & Zhang, Y. (2023). Predictive model for urosepsis in patients with Upper Urinary Tract Calculi based on ultrasonography and urinalysis using artificial intelligence learning. *International Braz J Urol*, *49*(2), 221–232. https://doi.org/10.1590/s1677-5538.ibju.2022.0450
21. Huang, J., Yeung, A. M., Armstrong, D. G., Battarbee, A. N., Cuadros, J., Espinoza, J. C., Kleinberg, S., Mathioudakis, N., Swerdlow, M. A., & Klonoff, D. C. (2022). Artificial intelligence for predicting and diagnosing complications of diabetes. *Journal of Diabetes Science and Technology*, *17*(1), 224–238. https://doi.org/10.1177/19322968221124583
22. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Seminars in Cancer Biology*, 47, 107-118. https://doi.org/10.1016/j.semcancer.2017.04.002
23. Joshi, S., Shamanna, P., Dharmalingam, M., Vadavi, A., Keshavamurthy, A., Shah, L., Mechanick, J.I. (2023). Digital Twin-Enabled Personalized Nutrition Improves Metabolic Dysfunction-Associated Fatty Liver Disease in Type 2 Diabetes: Results of a 1-Year Randomized Controlled Study. *Endocr Pract*. *29*(12):960-970. doi: 10.1016/j.eprac.2023.08.016
24. Karan, D. (2023). AI-Powered Patient Education: Transforming Type 2 Diabetes Management. *Indus Journal of Medical and Health Sciences*, *1*(01), 86–108. Retrieved from https://induspublishers.com/IJMHS/article/view/57
25. Khalifa, M., & Albadawy, M. (2024). Artificial intelligence for diabetes: Enhancing prevention, diagnosis, and effective management. *Computer Methods and Programs in Biomedicine Update*, *5*, 100141. https://doi.org/10.1016/j.cmpbup.2024.100141
26. Khanji, C., Lalonde, L., Bareil, C., Lussier, M., Perreault, S., & Schnitzer, M. E. (2018). LASSO regression for the prediction of intermediate outcomes related to cardiovascular disease prevention using the TRANSIT quality indicators. *Medical Care*, *57*(1), 63–72. https://doi.org/10.1097/mlr.0000000000001014
27. Khorraminezhad, L., Leclercq, M., O'Connor, S., Julien, P., Weisnagel, S. J., Gagnon, C., Droit, A., & Rudkowska, I. (2020). Dairy product intake modifies gut microbiota composition among hyperinsulinemic individuals. *European Journal of Nutrition*, *60*(1), 159–167. https://doi.org/10.1007/s00394-020-02226-z
28. Lee, Y., Kim, G., Jun, J. E., Park, H., Lee, W. J., Hwang, Y., & Kim, J. H. (2023). An integrated digital health care platform for diabetes management with AI-Based dietary management: 48-Week results from a randomized controlled trial. *Diabetes Care*, *46*(5), 959–966. https://doi.org/10.2337/dc22-1929
29. Li, J., Huang, J., Zheng, L., Li, X. (2020). Application of Artificial Intelligence in Diabetes Education and Management: Present Status and Promising Prospect. *Front Public Health*. *29*(8):173. doi: 10.3389/fpubh.2020.00173
30. Liu, Y., Wang, Y., Ni, Y., Cheung, C. K., Lam, K. S., Wang, Y., Xia, Z., Ye, D., Guo, J., Tse, M. A., Panagiotou, G., & Xu, A. (2019). Gut microbiome fermentation determines the efficacy of exercise for diabetes prevention. *Cell Metabolism*, *31*(1), 77-91.e5. https://doi.org/10.1016/j.cmet.2019.11.001
31. Lopez, Y. O. N., Retnakaran, R., Zinman, B., Pratley, R. E., & Seyhan, A. A. (2018b). Predicting and understanding the response to short-term intensive insulin therapy in people with early type 2 diabetes. *Molecular Metabolism*, *20*, 63–

78. https://doi.org/10.1016/j.molmet.2018.11.003

32. Magliano, D.J., Boyko, E.J. (2021). *IDF Diabetes Atlas 10th edition scientific committee*. IDF DIABETES ATLAS [Internet]. 10th edition. Brussels: International Diabetes Federation; Available from: https://www.ncbi.nlm.nih.gov/books/NBK581934/
33. Moyen, A., Rappaport, A. I., Fleurent-Grégoire, C., Tessier, A., Brazeau, A., & Chevalier, S. (2022). Relative validation of an Artificial Intelligence–Enhanced, Image-Assisted mobile app for dietary assessment in adults: randomized crossover study. *Journal of Medical Internet Research*, *24*(11), e40449. https://doi.org/10.2196/40449
34. Nayak, A., Vakili, S., Nayak, K., Nikolov, M., Chiu, M., Sosseinheimer, P., Talamantes, S., Testa, S., Palanisamy, S., Giri, V., & Schulman, K. (2023). Use of Voice-Based Conversational Artificial Intelligence for Basal Insulin Prescription Management Among Patients With Type 2 Diabetes: A Randomized Clinical Trial. *JAMA Netw Open*. 1;6(12):e2340232. doi: 10.1001/jamanetworkopen
35. Nimri, R., Battelino, T., Laffel, L. M., Slover, R. H., Schatz, D., Weinzimer, S. A., Dovc, K., Danne, T., Phillip, M., Phillip, M., Nimri, R., Shalitin, S., Bello, R., Nevo-Shenker, M., Fisch-Shvalb, N., Shiovitch-Mantzuri, G., Choresh, O., Drutz, I., Nava, Y., & Remus, K. (2020). Insulin dose optimization using an automated artificial intelligence-based decision support system in youths with type 1 diabetes. *Nature Medicine*, *26*(9), 1380–1384. https://doi.org/10.1038/s41591-020-1045-7
36. Nomura A, Noguchi M, Kometani M, Furukawa K, Yoneda T. (2021). Artificial Intelligence in Current Diabetes Management and Prediction. *Curr Diab Rep*. *21*(12):61. doi: 10.1007/s11892-021-01423-2
37. Oikonomou, E. K., Suchard, M. A., McGuire, D. K., & Khera, R. (2022). Phenomapping-Derived tool to individualize the effect of canagliflozin on cardiovascular risk in type 2 diabetes. *Diabetes Care*, *45*(4), 965–974. https://doi.org/10.2337/dc21-1765
38. Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *PLOS Med,* *18*(3), e1003583. https://doi.org/10.1371/journal.pmed.1003583
39. Park, S. W., Kim, G., Hwang, Y., Lee, W. J., Park, H., & Kim, J. H. (2020). Validation of the effectiveness of a digital integrated healthcare platform utilizing an AI-based dietary management solution and a real-time continuous glucose monitoring system for diabetes management: a randomized controlled trial. *BMC Medical Informatics and Decision Making*, *20*(1). https://doi.org/10.1186/s12911-020-01179-x
40. Popp, C. J., Hu, L., Kharmats, A. Y., Curran, M., Berube, L., Wang, C., Pompeii, M. L., Illiano, P., St-Jules, D. E., Mottern, M., Li, H., Williams, N., Schoenthaler, A., Segal, E., Godneva, A., Thomas, D., Bergman, M., Schmidt, A. M., & Sevick, M. A. (2022). Effect of a Personalized Diet to Reduce Postprandial Glycemic Response vs a Low-fat Diet on Weight Loss in Adults With Abnormal Glucose Metabolism and Obesity. *JAMA Network Open*, *5*(9), e2233760. https://doi.org/10.1001/jamanetworkopen.2022.33760
41. Popp, C. J., St-Jules, D. E., Hu, L., Ganguzza, L., Illiano, P., Curran, M., Li, H., Schoenthaler, A., Bergman, M., Schmidt, A. M., Segal, E., Godneva, A., & Sevick, M. A. (2019). The rationale and design of the personal diet study, a randomized clinical trial evaluating a personalized approach to weight loss in individuals with pre-diabetes and early-stage type 2 diabetes. *Contemporary Clinical*

Trials, *79*, 80–88. https://doi.org/10.1016/j.cct.2019.03.001

42. Reddy, R., Resalat, N., Wilson, L. M., Castle, J. R., Youssef, J. E., & Jacobs, P. G. (2019). Prediction of hypoglycemia during aerobic exercise in adults with type 1 diabetes. *Journal of Diabetes Science and Technology*, *13*(5), 919–927. https://doi.org/10.1177/1932296818823792
43. Rein, M., Ben-Yacov, O., Godneva, A., Shilo, S., Zmora, N., Kolobkov, D., Cohen-Dolev, N., Wolf, B., Kosower, N., Lotan-Pompan, M., Weinberger, A., Halpern, Z., Zelber-Sagi, S., Elinav, E., & Segal, E. (2022). Effects of personalized diets by prediction of glycemic responses on glycemic control and metabolic health in newly diagnosed T2DM: a randomized dietary intervention pilot trial. *BMC Medicine*, *20*(1). https://doi.org/10.1186/s12916-022-02254-y
44. Roberts, P. K., Vogl, W., Gerendas, B. S., Glassman, A. R., Bogunovic, H., Jampol, L. M., & Schmidt-Erfurth, U. M. (2020). Quantification of fluid resolution and visual acuity gain in patients with diabetic macular edema using deep learning. *JAMA Ophthalmology*, *138*(9), 945. https://doi.org/10.1001/jamaophthalmol.2020.2457
45. Salinari, A., Machì, M., Diaz, Y. A., Cianciosi, D., Qi, Z., Yang, B., Cotorruelo, M. S. F., Villar, S. G., Lopez, L. a. D., Battino, M., & Giampieri, F. (2023c). The Application of digital technologies and Artificial intelligence in Healthcare: An Overview on nutrition assessment. *Diseases*, *11*(3), 97. https://doi.org/10.3390/diseases11030097
46. Sampedro-Gómez, J., Dorado-Díaz, P. I., Vicente-Palacios, V., Sánchez-Puente, A., Jiménez-Navarro, M., Roman, J. a. S., Galindo-Villardón, P., Sanchez, P. L., & Fernández-Avilés, F. (2020). Machine learning to predict stent restenosis based on daily demographic, clinical, and angiographic characteristics. *Canadian Journal of Cardiology*, *36*(10), 1624–1632. https://doi.org/10.1016/j.cjca.2020.01.027
47. Sarici, K., Yordi, S., Martin, A., Lunasco, L., Mugnaini, C., Chu, K., Moini, H., Vitti, R., Srivastava, S. K., & Ehlers, J. P. (2023). Longitudinal Quantitative Ultrawide-field fluorescein angiography Dynamics in the RUBY Diabetic Macular Edema Study. *Ophthalmology Retina*, *7*(6), 543–552. https://doi.org/10.1016/j.oret.2023.01.018
48. Saux, P., Bauvin, P., Raverdy, V., Teigny, J., Verkindt, H., Soumphonphakdy, T., Debert, M., Jacobs, A., Jacobs, D., Monpellier, V., Lee, P. C., Lim, C. H., Andersson-Assarsson, J. C., Carlsson, L., Svensson, P., Galtier, F., Dezfoulian, G., Moldovanu, M., Andrieux, S., & Pattou, F. (2023). Development and validation of an interpretable machine learning-based calculator for predicting 5-year weight trajectories after bariatric surgery: a multinational retrospective cohort SOPHIA study. *The Lancet Digital Health*, *5*(10), e692–e702. https://doi.org/10.1016/s2589-7500(23)00135-8
49. Seethaler, B., Nguyen, N. K., Basrai, M., Kiechle, M., Walter, J., Delzenne, N. M., & Bischoff, S. C. (2022). Short-chain fatty acids are key mediators of the favorable effects of the Mediterranean diet on intestinal barrier integrity: data from the randomized controlled LIBRE trial. *American Journal of Clinical Nutrition*, *116*(4), 928–942. https://doi.org/10.1093/ajcn/nqac175
50. Shakshuki, E., & Reid, M. (2015). Multi-Agent System Applications in Healthcare: Current technology and future roadmap. *Procedia Computer Science*, *52*, 252–261. https://doi.org/10.1016/j.procs.2015.05.071
51. Sun, X., Yan, T., Li, Z., Zhou, S., Peng, W., Cui, W., Xu, J., Cao, Z., Shi, L., & Wang, Y. (2023). Effects of Endurance Exercise and Vitamin D Supplementation on Insulin Resistance and Plasma Lipidome in Middle-Aged Adults

with Type 2 Diabetes. *Nutrients*, *15*(13), 3027. https://doi.org/10.3390/nu15133027

52. Wang, Y., Hou, R., Ni, B., Jiang, Y., & Zhang, Y. (2023). Development and validation of a prediction model based on machine learning algorithms for predicting the risk of heart failure in middle-aged and older US people with prediabetes or diabetes. *Clinical Cardiology*, *46*(10), 1234–1243. https://doi.org/10.1002/clc.24104
53. Wang, C., Yu, X., Sui, Y., Zhu, J., Zhang, B., & Su, Y. (2022). Magnetic resonance imaging data features to evaluate the efficacy of compound skin graft for diabetic foot. *Contrast Media & Molecular Imaging*, *2022*(1). https://doi.org/10.1155/2022/5707231
54. Wei, H., Sun, J., Shan, W., Xiao, W., Wang, B., Ma, X., Hu, W., Wang, X., & Xia, Y. (2021). Environmental chemical exposure dynamics and machine learning-based prediction of diabetes mellitus. *The Science of the Total Environment*, *806*, 150674. https://doi.org/10.1016/j.scitotenv.2021.150674
55. World Health Organization (WHO). (2024, November 14). *Diabetes*. World Health Organization. Retrieved from https://www.who.int/news-room/fact-sheets/detail/diabetes
56. Unsworth, R., Armiger, R., Jugnee, N., Thomas, M., Herrero, P., Georgiou, P., Oliver, N., Reddy, M. (2022). Safety and Efficacy of an Adaptive Bolus Calculator for Type 1 Diabetes: A Randomized Controlled Crossover Study. *Diabetes Technol Ther*. 25(6):414-425. doi: 10.1089/dia.2022.0504
57. Varga, T. V., Liu, J., Goldberg, R. B., Chen, G., Dagogo-Jack, S., Lorenzo, C., Mather, K. J., Pi-Sunyer, X., Brunak, S., & Temprosa, M. (2021). Predictive utilities of lipid traits, lipoprotein subfractions and other risk factors for incident diabetes: a machine learning approach in the Diabetes Prevention Program. *BMJ Open Diabetes Research & Care*, *9*(1), e001953. https://doi.org/10.1136/bmjdrc-2020-001953
58. Vettoretti, M., Cappon, G., & Facchinetti, A. (2020). Advanced diabetes management using artificial intelligence and continuous glucose monitoring sensors, Sensors *20* (14) (2020), 3870. https://doi.org/10.3390/s20143870
59. Zhang, P., Fonnesbeck, C., Schmidt, D. C., White, J., Kleinberg, S., & Mulvaney, S. A. (2021). Using momentary assessment and machine learning to identify barriers to self-management in Type 1 diabetes: observational study. *JMIR Mhealth and Uhealth*, *10*(3), e21959. https://doi.org/10.2196/21959
60. Zhao, C., Shi, Q., Ma, F., Yu, J., & Zhao, A. (2022). Intelligent Algorithm-Based Ultrasound Image for Evaluating the Effect of Comprehensive Nursing Scheme on Patients with Diabetic Kidney Disease. *Computational and Mathematical Methods in Medicine*, *2022*, 1–9. https://doi.org/10.1155/2022/6440138
61. Zou, X., Luo, Y., Huang, Q., Zhu, Z., Li, Y., Zhang, X., Zhou, X., & Ji, L. (2023). Differential effect of interventions in patients with prediabetes stratified by a machine learning-based diabetes progression prediction model. *Diabetes Obesity and Metabolism*, *26*(1), 97–107. https://doi.org/10.1111/dom.15291