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Hybrid Fuzzy Pattern Classifier and ARAS for Evaluating Type 2 Diabetes Medications: A Computer-Aided Decision-Making Approach

Abstract: **-** Effectively managing blood glucose levels in Type 2 Diabetes requires selecting medications with care, given the variety of available drugs, each with its own pros and cons. To get around this complexity, a study suggests using a fuzzy Multi-Criteria Decision-Making (MCDM) model-based approach to assist healthcare decision-making. This technique combines the multiplicative Additive Ratio Assessment (ARAS) approach with Ratio Analysis and a modified version of Fuzzy Multi-Objective Optimization. By integrating these methods, the system aims to offer a systematic and effective way to choose the most suitable medications for Type 2 Diabetes, considering factors like effectiveness, safety, cost, and patient preferences. This method shows potential in improving healthcare decision-making for personalized diabetes management, leading to better patient outcomes and quality of life. Integrating these advanced decision-making techniques simplifies and enhances the process of selecting the most appropriate pharmaceutical therapy for Type 2 Diabetes. This helps healthcare professionals make more informed decisions by balancing efficacy, safety, and other important factors. The Fuzzy ARAS approach evaluates each pharmaceutical option based on relevant criteria and expert opinions, ensuring a comprehensive assessment. To enhance the decision-making process, the study explores an extended reference point technique within the MCDM framework. The objective of this approach is to enhance the precision and dependability of the pharmacological medication selection process for Type 2 Diabetes by merging clinical guidelines, professional opinions, and sophisticated analytical techniques. Based on the computational results, it appears that DPP-4 inhibitors are the main treatment, while metformin is the recommended add-on drug for second line. Sulfonylureas are ranked third, glucagon-like peptide-1 receptor agonists are ranked fourth, and insulin is ranked fifth. A sensitivity analysis confirms the model's effectiveness, showing agreement with alternative methods in ranking anti-diabetic drugs.

Keywords: sensitivity, computational, alternative, MCDM, DPP-4

INTRODUCTION

The ADA (American Diabetes Association) defines diabetes as a condition marked by high blood sugar levels, known as hyperglycemia. These elevated levels may exacerbate diabetes-associated risk factors and lead to hypertension, heart attacks, strokes, ocular problems, kidney disease, and foot complications—all of which require ongoing medical care. For those with Type 2 Diabetes (T2D), blood sugar control, or glucose regulation, is crucial to preventing complications and effectively managing the disease.Adequate glycemic control substantially lowers the risk of diabetes-related issues such as nerve damage and small blood vessel disease, as demonstrated by studies like the Kumamoto study and the UKPDS (UK Prospective Diabetes Study).

Given their long-term benefits, implementing lifestyle modifications like as eating a balanced diet and getting regular exercise is the key strategy for keeping blood sugar levels within the target range. However, in patients with Type 2 Diabetes (T2D), medication therapy becomes necessary when lifestyle modifications are insufficient to regulate blood glucose levels. T2D drug regimen optimization is essential for increasing patients' life expectancy, enhancing their quality of life, and lowering hospital stays and associated expenses due to problems.Picking the best prescription for Type 2 Diabetes (T2D) can be challenging because there are many different hyperglycemia-lowering medications on the market, each with unique characteristics and possible side effects. The goal is to identify drugs with the highest level of efficacy, lowest cost, and minimal adverse effects. The finest medications can be chosen with the use of observational studies and randomized controlled trials (RCTs).

The goal of medical artificial intelligence (AI) is to develop AI applications that support therapy recommendations and diagnosis. AI provides doctors and general practitioners with computer-aided decision

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assistance, assisting them in accurately diagnosing patients and choosing the best course of action. The choice of pharmacological treatment for Type 2 Diabetes (T2D) is a multi-objective, intricate decision-making challenge. Consequently, improving physician confidence in their conclusions and raising the level of transparency in the decision-making process depend heavily on medical decision support. Multi-criteria decision-making (MCDM), a subset of operations research, is helpful for assessing a limited number of options for decisions based on various performance criteria. The criteria selection, alternative selection, aggregation method selection, and ultimate alternative selection based on outranking and aggregation findings are the fundamental tenets of MCDM approaches.

In this study, a hybrid multicriteria decision-making (MCDM) model is developed to optimize the selection of pharmacological therapy for Type 2 Diabetes (T2D). This model integrates the full multiplicative form (FMULTIMOORA) method with a modified fuzzy multi-objective optimization based on ratio analysis, complemented by the step-wise weight assessment ratio analysis (SWARA) method. Expert endocrinologists are consulted using the SWARA approach to determine the relative importance of each criterion, ensuring that expert opinions shape the weight distribution accurately. The FMULTIMOORA method then evaluates each therapeutic option against all criteria, using a combination of the point of reference approach, the entire multiplicative form, and the ratio system, which constitute the core of the MULTIMOORA technique. The study identifies a limitation in the traditional reference point approach, which often neglects the distance from the negative ideal point and can fail to rank options distinctly when they share the maximum distance from the positive ideal point. To address this, an extended fuzzy reference point technique is proposed, enhancing the FMULTIMOORA ranking process. This technique ensures that the optimal choice is positioned as close as possible to the fuzzy positive ideal point and as far as possible from the fuzzy negative ideal point, thereby providing a more accurate and distinct ranking of therapeutic options for T2D.

MATIRALS AND METHOD

According to clinical guidelines, there are seven primary types of glucose-lowering drugs used in the treatment of Type 2 Diabetes (T2D): Biguanides (Metformin), Thiazolidinediones (TZD), Sulfonylureas, DPP-4 inhibitors (DPP-4-I), GLP-1 receptor agonists (GLP-1-RA), Sodium–glucose co-transporter 2 inhibitors (SGLT-2-I), and Insulin. Among these, Metformin, a Biguanide, is recommended by the American Diabetes Association's (ADA) treatment algorithm as the initial pharmacological agent due to its proven efficacy, safety profile, and affordability.One more anti-diabetic drug from the remaining six classes should be added if Metformin alone is unable to adequately control blood glucose levels after around three months, converting single therapy to dual therapy. Triple therapy is used if, after around three months of dual therapy, glycemic objectives are still not met. This involves adding a third drug. Injectable medications such as GLP-1-RA, basal, or mealtime insulin are used as a therapeutic option if, after three more months, triple therapy is unable to achieve the targeted blood glucose levels.

When selecting the most suitable pharmaceutical regimen for Type 2 Diabetes (T2D), a variety of quantitative and qualitative factors can be considered. Efficacy is a crucial component that evaluates how successfully anti-diabetic medications lower blood glucose levels. Clinical guidelines place a strong emphasis on the value of a patient-centered strategy that takes their preferences into account. Because oral drugs are more convenient to take and have higher adherence rates than injectable ones, many patients prefer them. Furthermore, anti-diabetic drugs and diabetes supplies are expensive; they account for around 12% of all medical costs associated with diabetes. Treatment adherence may suffer as a result of these exorbitant expenses.

Diabetes-related side effects, both small and significant, can vary depending on the type of medication received. A higher risk of fracture, weight gain, and gastrointestinal (GI) issues are examples of minor hazards. Diabetes by itself increases the risk of fractures and has a detrimental effect on bone mineral density (BMD). Gaining weight as a result of improved glucose regulation raises the risk of hypertension and other illnesses that exacerbate hyperglycemia and heart disease. Furthermore, people with diabetes are more likely to experience gastrointestinal problems such upset stomach, indigestion, nausea, vomiting, gas, or changes in bowel habits.

Some serious side effects of anti-diabetic drugs include severe hypoglycemia, acute pancreatitis, bladder cancer, and an increased risk of congestive heart failure (CHF). Severe hypoglycemia is characterized by dangerously low blood glucose levels, which can result in symptoms like clumsiness, difficulty speaking, seizures, confusion, loss of consciousness, and even death. Diabetes is linked as a risk factor for CHF, a type of heart disease in which the heart is unable to pump enough blood to meet the body's needs. Pancreatitis, or inflammation of the pancreas, is another serious concern; using some diabetic medications can raise the chance of bladder cancer as well as pancreatitis.

For the treatment of Type 2 Diabetes (T2D), there is not enough empirical evidence to justify the prioritizing of pharmacological medications above metformin. Nonetheless, this problem has been the subject of numerous studies. For instance, Zhang et al. developed a population-based glycemic control Markov chain model to identify the optimal second-line medication following Metformin using data from privately insured T2D patients in the United States. Their findings indicated that the best options were insulin, GLP-1 receptor agonists (GLP-1-RA), DPP-4 inhibitors (DPP-4-I), and sulfonylurea in terms of both cost-effectiveness and length of insulin independence. Maruthur et al. employed the analytic hierarchy process (AHP) approach to evaluate T2D medication choices and gathered expert opinions through structured interviews. They conducted a study and found that sitagliptin (DPP-4-I class), sulfonylureas, and pioglitazone (DPP-4-I class) were the most effective adjunctive therapies for metformin. Using the AHP approach, Balubaid and Basheikh prioritized the drugs for patients with diabetes. The results showed that metformin, pioglitazone (DPP-4-I class), sitagliptin (DPP-4-I class), and glimepiride (sulfonylureas class) were the top-ranked oral medications for Type 2 Diabetes (T2D). Four clinicians filled out a questionnaire that was used to collect the data. This study is the first attempt to use an adapted version of the FMULTIMOORA method in conjunction with the SWARA methodology to rank and prioritize pharmaceutical treatments for diabetes. This approach was based on the writers' personal experiences as well as a careful reading of the literature.

Fuzzy ARAS: An advanced multi-criterion decision-making (MCDM) technique that incorporates fuzzy logic to address uncertainty and imprecision in decision-making processes is called the Fuzzy ARAS (Additive Ratio Assessment) method. The conventional ARAS approach evaluates alternatives according to a set of criteria, giving each criterion a certain weight. A thorough ranking is produced by adding up the weighted normalized values of all the criteria to determine how well each alternative performs. The fuzzy extension of the ARAS method enhances this process by incorporating fuzzy numbers to represent the criteria values and weights, allowing for a more flexible and realistic evaluation. This is particularly useful in complex decision-making scenarios where precise data is difficult to obtain or where subjective judgments play a significant role. The Fuzzy ARAS technique provides a strong foundation for choosing the optimal option in uncertain circumstances by applying fuzzy logic to reflect the inherent vagueness and uncertainty in human preferences and perceptions. This approach is especially valuable in fields such as healthcare, environmental management, and strategic planning, where decisions often involve a high degree of uncertainty and complexity.

Table 1 Evaluation Parameter

Criteria	Description
C1	Efficiency
C2	Hypoglycemia risk
C3	Effects on body weigh
C4	Injectable
C5	Cost

Table 1 presents the evaluation parameters for assessing different pharmacological treatments for Type 2 Diabetes. The criteria include Efficiency (C1), which measures the effectiveness of the treatment in controlling blood glucose levels; Hypoglycemia risk (C2), which evaluates the likelihood of experiencing low blood sugar levels as a side effect; Effects on body weight (C3), which considers whether the treatment causes weight gain or loss; Injectable (C4), indicating whether the treatment is administered via injection; and Cost (C5), which assesses the financial burden of the treatment. These criteria are crucial in determining the overall suitability and effectiveness of anti-diabetic medications, helping healthcare providers and patients make informed decisions about their treatment plans.

Table 2 Alternative

Alternative	Description
A1	Metformin
A2	Sulfonylurea
A3	DPP-4-I
A4	GLP-1-RA
A5	Insulin(L)
A6	Insulin(H)

Table 2 outlines the alternative pharmacological treatments for Type 2 Diabetes, including Metformin (A1), which is often the first-line treatment due to its efficacy and safety profile; Sulfonylureas (A2), which stimulate insulin secretion from the pancreas; DPP-4 inhibitors (DPP-4-I) (A3), which enhance insulin secretion and decrease glucagon production; GLP-1 receptor agonists (GLP-1-RA) (A4), which stimulate insulin secretion and reduce appetite; Insulin with a low dose (Insulin(L)) (A5), used when oral medications are not effective; and Insulin with a high dose (Insulin(H)) (A6), which is reserved for more severe cases of insulin resistance. These alternatives offer a range of options for managing Type 2 Diabetes, each with its own benefits and considerations for patients and healthcare providers.

Table 3. T2D glucose-lowering agent's data

	Efficiency	Hypoglycemia risk	Effects on body weight	Injectable	Cost ($)
Metformin	70%	5%	-2 kg	No	20
Sulfonylurea	50%	10%	+1 kg	No	15
DPP-4-I	40%	2%	Minimal	No	50
GLP-1-RA	60%	3%	-4 kg	Yes	200
Insulin(L)	80%	15%	+3 kg	Yes	150
Insulin(H)	90%	16%	+4 kg	Yes	200

Data on the effectiveness, risk of hypoglycemia, impact on body weight, injectability, and cost of different glucose-lowering medications for Type 2 Diabetes (T2D) are shown in Table 3. With a 5% chance of hypoglycemia, metformin reduces blood glucose levels 70% of the time and causes an average weight reduction of 2 kg. Oral administration is employed, and the cost is comparatively low at $20. Another oral drug that costs $15 and has a 50% efficiency rate but a 10% increased risk of hypoglycemia and a 1 kg weight gain is sulfonylureas. DPP-4 inhibitors (DPP-4-I) are more expensive at $50, but they offer 40% efficiency with a 2% hypoglycemia risk and no impact on body weight. Injectable GLP-1 receptor agonists (GLP-1-RA) have a 60% efficacy rate, a 3% risk of hypoglycemia, and a notable 4 kg weight loss; however, at $200, they are the priciest alternative. Insulin has the highest efficiency (80% and 90%, respectively) at both low and high doses (insulin(L) and insulin(H)). However, it also has the largest risk of hypoglycemia (15–16%, respectively) and promotes weight gain (150–200, respectively).

Table 4.criteriaFuzzy number

Linguistic variable	Denotation	Fuzzy number
Very low	VL	(1,2,3)
Low	L	(3,4,5)
Moderate (M)	M	(5,6,7)
High	H	(8,9,10)
Very High	VH	(9, 10,10)

Table 4 defines fuzzy values for the criteria used in evaluating Type 2 Diabetes (T2D) glucose-lowering agents. The linguistic variables include Very Low (VL), Low (L), Moderate (M), High (H), and Very High (VH), with corresponding fuzzy numbers representing the degree of membership in each category. For example, the fuzzy number (1,2,3) represents the Very Low category, indicating a very low degree of membership in the criterion being evaluated. These fuzzy values enable a more detailed evaluation of the criteria, taking into account the uncertainty and vagueness that are commonly encountered in real-world decision-making processes.

Table 5. Formula to calculate the Performance rating for criteria

	C1	C2	C3	C4	C5
A1	H	VL	L	VL	VL
A2	H	M	VH	VL	VL
A3	M	VL	L	VL	VH
A4	H	VL	VL	VH	VH
A5	VH	VH	VH	VH	VL
A6	VH	VH	VH	VH	VH

Table 5 presents the fuzzy values for the evaluation criteria of glucose-lowering agents for Type 2 Diabetes (T2D). Each row corresponds to a specific alternative (A1 to A6), and each column represents a criterion (C1 to C5). The fuzzy values indicate the degree of membership of each alternative in the linguistic variables defined for the criteria. For example, for alternative A1, the degree of membership in the "Efficiency" criterion (C1) is High (H), while for the "Hypoglycemia risk" criterion (C2), it is Very Low (VL). Similarly, for alternative A2, the degree of membership in the "Efficiency" criterion (C1) is High (H), in the "Hypoglycemia risk" criterion (C2) it is Moderate (M), in the "Effects on body weight" criterion (C3) it is Very High (VH), and so on. These fuzzy values provide a qualitative assessment of each alternative's performance across the different criteria, considering the uncertainty and imprecision inherent in decision-making processes.

Table 6.solved value of l’, l, m, u’, ufor criteria

	l	l'	m	u'	u
C1	5	11.57031	13.43308	14.75773	10
C2	1	3.322699	5.44814	7.166257	10
C3	1	5.799546	7.962143	9.440875	10
C4	1	3.737193	6.034176	7.696136	10
C5	1	3.737193	6.034176	7.696136	10

Table 6 presents the solved values for the lower bound (l), upper bound (u), midpoint (m), and their respective adjusted values (l', u') for each criterion (C1 to C5). These values are commonly used in decision-making processes that involve uncertainty or imprecision, where intervals are considered instead of precise values. For example, for criterion C1, the lower bound (l) is 5, the upper bound (u) is 10, the midpoint (m) is 13.43308, and the adjusted lower and upper bounds (l' and u') are 11.57031 and 14.75773, respectively. These values help in understanding the range within which each criterion falls, providing a more comprehensive perspective for decision-making.

Table 7. Performance Rating for Alternative

VP	(0, 0, 0.1)
P	(0, 0.1, 0.3)
MP	(0.1, 0.3, 0.5)
F	(0.3, 0.5, 0.7)
MG	(0.5, 0.7, 0.9)
G	(0.7, 0.9 , 1)
VG	(0.9, 1, 1)

Table 7 provides a set of performance rating categories along with their corresponding fuzzy numbers. Each category is defined by a linguistic variable (e.g., VP for Very Poor, P for Poor, MP for Moderate Poor, F for Fair, MG for Moderate Good, G for Good, and VG for Very Good) and a fuzzy number representing the range of values associated with that category. For example, the category VP (Very Poor) is defined by the fuzzy number (0, 0, 0.1), indicating that values between 0 and 0.1 are considered Very Poor. These performance rating categories and fuzzy numbers can be used in decision-making processes to assess and compare the performance of alternatives across different criteria.

Table 8. Number for place which represent the column and row of the above tabulationfor Alternative

	w1	w2	w3	w4	w5
	C1	**C2**	**C3**	**C4**	C5
Optimal					
A1	1,1	1,2	1,3	1,4	5,1
A2	2,1	2,2	2,3	2,4	5,2
A3	3,1	3,2	3,3	3,4	5,3
A4	4,1	4,2	3,4	4,4	5,4
A5	5,1	5,2	3,5	5,4	5,5
A6	6,1	6,2	6,3	6,4	6,5

Table 8 shows a tabulation where each cell represents the column and row of the corresponding criterion for each alternative. The criteria are represented by w1, w2, w3, w4, and w5, while the alternatives are denoted by A1 to A6. For example, the cell for A1 and w1 contains the values 1,1, indicating that alternative A1 corresponds to criterion C1. Similarly, the cell for A1 and w5 contains the values 5,1, indicating that alternative A1 corresponds to criterion C5. This tabulation provides a clear mapping of which criteria are associated with each alternative, aiding in the decision-making process to determine the optimal choice.

Table 9. Formula to calculate the Performance rating for Alternative

	C1	**C2**	**C3**	**C4**	C5
A1	VP,G,VG	P,G,F	G,MG,F	VP,P,MP	MP,G,MG
A2	MP,MG,G	MG,G,F	F,G,MG	VP,P,MP	VG,MG,G
A3	MP,F,MG	MP,G,VG	VG,MG,G	VG,MG,G	VP,P,MP
A4	MP,MG,G	MP,G,VG	MP,G,MG	VP,P,MP	MP,P,G
A5	VG,MG,G	VP,P,MP	MP,P,G	VP,G,VG	G,MG,VG
A6	F,G,MG	MP,MG,G	MP,P,G	MP,G,MG	MP,F,MG

Table 9 provides a matrix showing the performance rating for each alternative (A1 to A6) across criteria (C1 to C5). Each cell contains a combination of performance ratings (e.g., VP for Very Poor, G for Good, VG for Very Good) separated by commas, representing the performance rating of that alternative for the corresponding criterion. For example, the cell for A1 and C1 contains the values VP, G, VG, indicating that alternative A1 has a Very Poor performance rating for criterion C1, a Good rating for C2, and a Very Good rating for C3. These performance ratings are used to assess the performance of each alternative across different criteria, helping in the decision-making process to determine the best alternative.

Table 10. (6,1)solved value of l', l, m, u', u for Performance ratingfor Alternative

0.1	0.3	0.5		
0.3	0.5	0.7		
0.5	0.7	0.9		
0.1	0.246621	0.471769	0.680409	0.9
l	l'	m	u'	u

Table 10 provides the solved values for the lower bound (l), upper bound (u), midpoint (m), and their respective adjusted values (l' and u') for the performance rating of alternative A6 for criterion C1. The values 0.1, 0.3, and 0.5 represent the fuzzy numbers for the performance ratings VP, P, and MP, respectively. The solved values for l, l', m, u', and u are provided in the table to quantify the fuzzy ratings and facilitate decision-making processes that involve uncertainty or imprecision.

Table 10. allsolved value of l', l, m, u', u for Performance ratingfor Alternative

	l	l'	m	u'	u
1,1	0	0	0	0.464159	1
1,2	0	0	0.355689	0.594392	1
1,3	0.3	0.471769	0.680409	0.857262	1
1,4	0	0	0	0.246621	0.5
1,5	0.1	0.327107	0.573879	0.766309	1
2,1	0.1	0.327107	0.573879	0.766309	1
2,2	0.3	0.471769	0.680409	0.857262	1
2,3	0.3	0.471769	0.680409	0.857262	1
2,4	0	0	0	0.246621	0.5
2,5	0.5	0.680409	0.857262	0.965489	1
3,1	0.1	0.246621	0.471769	0.680409	0.9

3,2	0.1	0.397906	0.64633	0.793701	1
3,3	0.5	0.680409	0.857262	0.965489	1
3,4	0.5	0.680409	0.857262	0.965489	1
3,5	0	0	0	0.246621	0.5
4,1	0.1	0.327107	0.573879	0.766309	1
4,2	0.1	0.397906	0.64633	0.793701	1
4,3	0.1	0.327107	0.573879	0.766309	1
4,4	0	0	0	0.246621	0.5
4,5	0	0	0.3	0.531329	1
5,1	0.7	0.761166	0.93217	1	1
5,2	0	0	0	0.246621	0.5
5,3	0	0	0.3	0.531329	1
5,4	0	0	0	0.464159	1
5,5	0.1	0.327107	0.573879	0.766309	1
6,1	0.3	0.573879	0.766309	0.887904	1
6,2	0.1	0.327107	0.573879	0.766309	1
6,3	0	0	0.3	0.531329	1
6,4	0.1	0.327107	0.573879	0.766309	1
6,5	0.1	0.246621	0.471769	0.680409	0.9

Table 10 presents the solved values for the lower bound (l), upper bound (u), midpoint (m), and their respective adjusted values (l' and u') for the performance ratings of all alternatives (A1 to A6) across criteria (C1 to C5). These values are derived based on the fuzzy numbers representing the performance ratings (e.g., VP, P, MP) for each alternative-criterion combination. The adjusted values help quantify the fuzzy ratings, providing a more precise understanding of the performance of each alternative with respect to each criterion. This information is valuable for decision-making processes involving multiple criteria and uncertainty.

Table 11.A0 sum of solved value of l’, l, m, u’, ufor Alternative

A01	0.7	0.761166	0.93217	1	1
A02	0.3	0.471769	0.680409	0.857262	1
A03	0.5	0.680409	0.857262	0.965489	1
A04	0.5	0.680409	0.857262	0.965489	1
AO5	0.5	0.680409	0.857262	0.965489	1

Table 11 summarizes the total values for the lower bound (l), upper bound (u), midpoint (m), and their respective adjusted values (l' and u') for Alternative A0 across all criteria (C1 to C5). These values are calculated based on the individual performance ratings and their corresponding fuzzy numbers for A0. They provide a comprehensive view of how Alternative A0 performs overall, taking into account its performance across all criteria. This information is crucial for evaluating and comparing A0 against other alternatives in a decision-making context.

Table 12. Decision Matrix

A0	0.5	0.680409	0.857262	0.965489	1
M1	0	0	0	0.464159	1

M2	0.1	0.327107	0.573879	0.766309	1
M3	0.1	0.246621	0.471769	0.680409	0.9
M4	0.1	0.327107	0.573879	0.766309	1
M5	0.7	0.761166	0.93217	1	1
M6	0.3	0.573879	0.766309	0.887904	1
					6.9

Table 12 presents the decision matrix for the alternatives, showing their performance ratings across the criteria (C1 to C5). Each row corresponds to an alternative, and each column represents a criterion. The values in the matrix are the normalized and weighted performance ratings for each alternative and criterion combination. The final column on the right provides the total score for each alternative, which is the sum of the normalized and weighted performance ratings across all criteria. This total score gives an overall evaluation of each alternative's performance relative to the others, aiding in the decision-making process.

Table 13. Normalized Matrix C1

A0	0.072464	0.09861	0.124241	0.139926	0.144928
M1	0	0	0	0.067269	0.144928
M2	0.014493	0.047407	0.083171	0.111059	0.144928
M3	0.014493	0.035742	0.068372	0.09861	0.130435
M4	0.014493	0.047407	0.083171	0.111059	0.144928
M5	0.101449	0.110314	0.135097	0.144928	0.144928
M6	0.043478	0.083171	0.111059	0.128682	0.144928

Table 13 displays the normalized matrix for criterion C1, representing the relative performance of each alternative (A0, M1, M2, M3, M4, M5, M6) across this criterion. The values in the matrix are the normalized scores, ranging between 0 and 1, indicating the performance level of each alternative for criterion C1. A higher value suggests better performance relative to the other alternatives, while a lower value indicates poorer performance. This normalization process helps to standardize the evaluation criteria, facilitating a fair comparison between alternatives across different criteria.

Table 14. Weighted Normalized Matrix C1

weight	5	11.57031	13.43308	14.75773	10
A0	0.362319	1.140949	1.668938	2.06499	1.449275
M1	0	0	0	0.992744	1.449275
M2	0.072464	0.548511	1.117242	1.638984	1.449275
M3	0.072464	0.413548	0.918452	1.45526	1.304348
M4	0.072464	0.548511	1.117242	1.638984	1.449275
M5	0.507246	1.276367	1.81477	2.138802	1.449275
M6	0.217391	0.962313	1.49187	1.899051	1.449275

Table 14 presents the weighted normalized matrix for criterion C1. The weight values are 5, 11.57031, 13.43308, 14.75773, and 10. Each cell in the matrix represents the product of the normalized performance score (from Table 13) and the corresponding weight. This calculation is done for each alternative (A0, M1, M2, M3, M4, M5, M6) and each level of performance within the criterion. The resulting values indicate the weighted performance of each alternative for criterion C1, taking into account the relative importance of the criterion as determined by its weight.

Table 15. Weighted Normalized Matrix C2

A0	0.046154	0.241161	0.570302	0.945132	1.538462
M1	0	0	0.29813	0.655318	1.538462
M2	0.046154	0.241161	0.570302	0.945132	1.538462
M3	0.015385	0.203403	0.541738	0.875056	1.538462
M4	0.015385	0.203403	0.541738	0.875056	1.538462
M5	0	0	0	0.2719	0.769231
M6	0.015385	0.167212	0.481012	0.844857	1.538462

Table 15 presents the Weighted Normalized Matrix for criterion C2 across alternatives M1 to M6 and criterion A0. Each cell in the table represents the normalized and weighted value of the corresponding alternative and criterion combination. For instance, the value 0.046154 in the cell for M1 and A0 indicates the normalized and weighted value of alternative M1 for criterion C2 and criterion A0. These values are calculated based on the weights assigned to each criterion and the normalized scores of the alternatives for each criterion. The table provides a structured view of how each alternative performs relative to criterion C2 when compared to criterion A0, aiding in the decision-making process.

Table 16. Weighted Normalized Matrix C3

A0	0.071429	0.563724	0.975092	1.302152	1.428571
M1	0.042857	0.390864	0.773931	1.156186	1.428571
M2	0.042857	0.390864	0.773931	1.156186	1.428571
M3	0.071429	0.563724	0.975092	1.302152	1.428571
M4	0.014286	0.27101	0.652759	1.033519	1.428571
M5	0	0	0.341235	0.716602	1.428571
M6	0	0	0.341235	0.716602	1.428571

Table 16 displays the Weighted Normalized Matrix for criterion C3 across alternatives M1 to M6 and criterion A0. The matching alternative and criterion combination's normalized and weighted value is represented by each cell in the table. For example, the value 0.071429 in the cell for M1 and A0 indicates the normalized and weighted value of alternative M1 for criterion C3 and criterion A0. These values are calculated based on the weights assigned to each criterion and the normalized scores of the alternatives for each criterion. The table provides a structured view of how each alternative performs relative to criterion C3 when compared to criterion A0, aiding in the decision-making process.

Table 17. Weighted Normalized Matrix C4

A0	0.090909	0.462331	0.940522	1.351007	1.818182
M1	0	0	0	0.345096	0.909091

M2	0	0	0	0.345096	0.909091
M3	0.090909	0.462331	0.940522	1.351007	1.818182
M4	0	0	0	0.345096	0.909091
M5	0	0	0	0.649496	1.818182
M6	0.018182	0.222266	0.629616	1.072295	1.818182

Table 17 presents the Weighted Normalized Matrix for criterion C4 across alternatives M1 to M6 and criterion A0. For every choice and criterion combination, the relevant weighted value is represented by a cell in the table. For instance, the value 0.090909 in the cell for M1 and A0 indicates the normalized and weighted value of alternative M1 for criterion C4 and criterion A0. These values are calculated based on the weights assigned to each criterion and the normalized scores of the alternatives for each criterion. The table provides a structured view of how each alternative performs relative to criterion C4 when compared to criterion A0, aiding in the decision-making process.

Table 18. Weighted Normalized Matrix C5

A0	0.078125	0.397316	0.808261	1.161022	1.5625
M1	0.015625	0.191009	0.541076	0.921503	1.5625
M2	0.078125	0.397316	0.808261	1.161022	1.5625
M3	0	0	0	0.296567	0.78125
M4	0	0	0.282852	0.638935	1.5625
M5	0.015625	0.191009	0.541076	0.921503	1.5625
M6	0.015625	0.144011	0.444803	0.818207	1.40625

Table 18 shows the Weighted Normalized Matrix for criterion C5 across alternatives M1 to M6 and the criterion A0. The matching alternative and criterion combination's normalized and weighted value is represented by each cell in the table. For example, the value 0.078125 in the cell for M1 and A0 indicates the normalized and weighted value of alternative M1 for criterion C5 and criterion A0. These values are calculated based on the weights assigned to each criterion and the normalized scores of the alternatives for each criterion. The table provides a structured view of how each alternative performs relative to criterion C5 when compared to criterion A0, aiding in the decision-making process.

Table 19. Si values

A0	0.793863	2.543582	4.300686	5.737093	6.23449
M1	0.058482	0.390864	1.072061	3.149344	5.325399
M2	0.2396	1.180536	2.461475	4.085399	5.325399
M3	0.250186	1.643006	3.375804	4.983475	6.089563
M4	0.102134	1.022924	2.311739	3.892655	5.325399
M5	0.522871	1.276367	2.156005	3.7768	5.465259
M6	0.266583	1.351791	2.943732	4.532804	6.23449

Table 19 presents the Si values for a set of alternatives (M1 to M6) across five different criteria (A0 to A4). The performance or score of each option on each criterion is represented by the Si values. For criteria A0 to A4, for instance, option M1's Si values are 0.058482, 0.390864, 1.072061, 3.149344, and 5.325399, in that order. These values can aid in decision-making by allowing comparisons of the alternatives' performances based on several factors.

Table 20. Si, Qi values

Si	Qi
3.921943	1
1.99923	0.509755
2.658482	0.677848
3.268407	0.833364
2.53097	0.645336
2.639461	0.672998
3.06588	0.781725

Table 20 displays the Si and Qi values for a set of data points. Si represents the Si value, while Qi represents the corresponding Qi value. These values are used in various mathematical calculations and analyses to understand the relationship between the data points and their attributes. The Si values are continuous numerical values, while the Qi values are typically numerical values between 0 and 1. These values provide insights into the characteristics and properties of the data, helping to inform decision-making processes and analytical procedures.

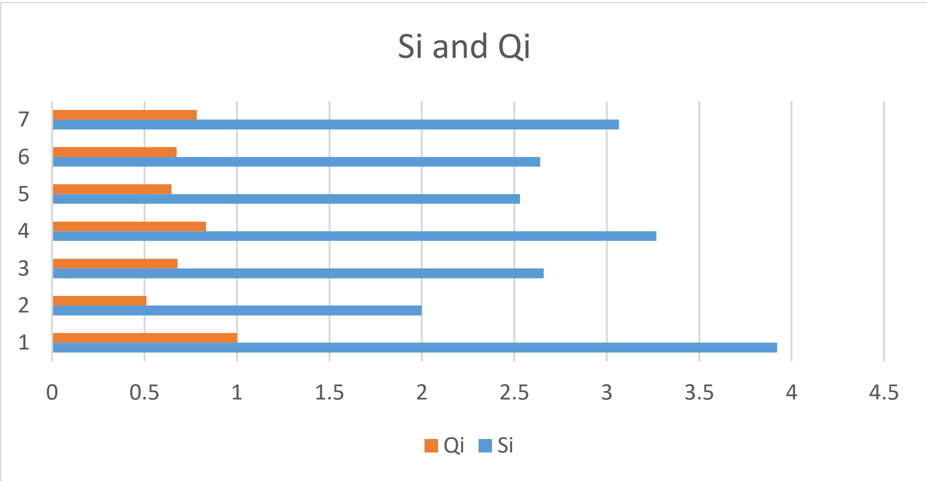

FIGURE 1. Si, Qi values

Figure 1 presents the Si and Qi values for various criteria. The Si values range from 1.99923 to 3.921943, indicating the relative importance of each criterion. A higher Si value suggests greater importance. The corresponding Qi values range from 0.509755 to 0.833364, representing the normalized importance of each criterion. These values are crucial for the decision-making process, as they help prioritize criteria based on their significance in the evaluation process.

Table 21. Rank

	Rank
Metformin	6
Sulfonylurea	3
DPP-4-I	1

GLP-1-RA	5
Insulin(L)	4
Insulin(H)	2

Table 21 shows the ranking of the alternatives (M1 to M6) based on their performance or preference order. The ranking indicates the position of each alternative relative to the others, with lower numbers indicating higher ranks. For example, alternative M3 has been ranked first, indicating that it is the most preferred or best-performing option among the six alternatives. Conversely, alternative M1 has been ranked last, indicating that it is the least preferred or least favorable option. Based on the criteria and evaluation parameters taken into consideration, these rankings offer a clear and straightforward method of comparing the options and determining which ones are the best.

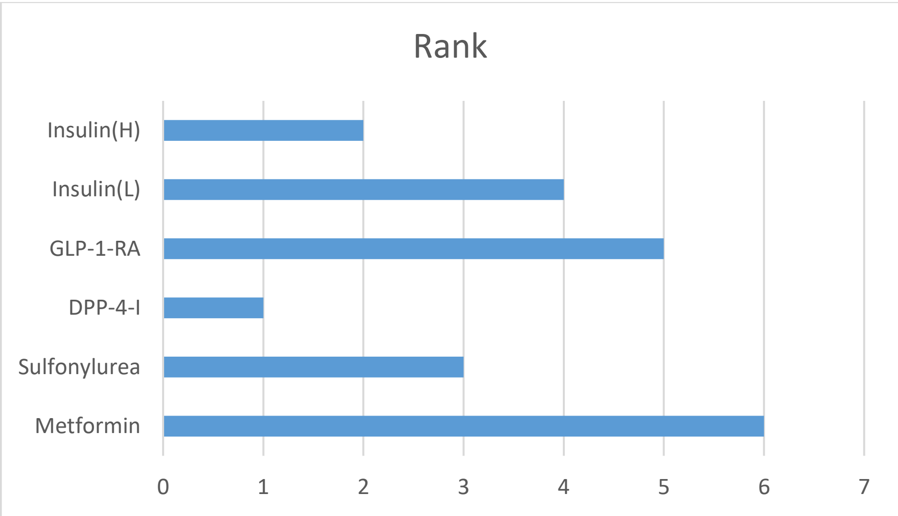

FIGURE 2. Rank

Table 21 shows the ranking of different diabetes pharmacological therapies. According to the analysis, DPP-4 inhibitors (DPP-4-I) are ranked first, indicating that they are the most preferred option after Metformin. Insulin (H), which likely refers to high-dose Insulin, is ranked second, followed by Sulfonylureas in third place. Metformin is placed sixth, and GLP-1 receptor agonists (GLP-1-RA) are ranked fifth. Low-dose insulin (insulin (L)) is ranked fourth. These rankings offer healthcare providers useful information to help them choose the best course of therapy for people with Type 2 Diabetes.

CONCLUSION

This study's hybrid model makes ranking anti-diabetic drugs possible, which is especially helpful when applying the three-step American Diabetes Association (ADA) treatment regimen (monotherapy, dual therapy, and triple therapy). Using the ranking, doctors can choose the best medication for the patient's condition during the monotherapy phase. For instance, sulfonylurea might be a good substitute for metformin if a patient is unable to take it because of gastrointestinal adverse effects. After around three months, if the first drug selected is unable to effectively manage blood glucose levels, an additional agent will be added, resulting in the selection of a single therapy from the remaining candidate pool. To sum up, this study's hybrid model provides a methodical way to rank anti-diabetic drugs, which can help doctors treat Type 2 Diabetes (T2D) by helping them make well-informed judgments. The model offers a thorough framework for assessing the effectiveness, safety, and cost-efficiency of various pharmacological interventions by incorporating the FUZZY ARAS. In the context of the ADA treatment algorithm, the model's rankings can be especially helpful in guiding decisions on single therapy, dual therapy, and triple therapy for T2D patients. Additionally, this study proposes possible directions for future investigation, including extending the model to take drug combinations into account and creating new standards for assessing multi-drug regimens. Future study could build on this approach by examining alternatives as medication combinations (double and triple combinations), concentrating on the selection of multi-drug regimens, and establishing new standards for assessing these combinations. In the end, this approach can improve decision-making processes' transparency by highlighting the advantages and disadvantages of different medical choices outside diabetes therapy.

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