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# Evaluation of Diabetic Medications Using Hybrid Fuzzy Pattern Classifier and TOPSIS

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**Abstract:** Given the plethora of pharmaceuticals available to regulate blood glucose levels, in medical decision-making, choose which ones to take for Type 2 Diabetes is a difficult task. Making decisions is made more difficult by the variety of hyperglycemia-lowering medications, each of which has distinct benefits and potential drawbacks. The study proposes a fuzzy Multi-Criteria Decision-Making model-based computer-aided healthcare decision-making system. This methodology combines the full multiplicative form of the TOPSIS method with Ratio Analysis and a modified version of Fuzzy Multi-Objective Optimization. The goal is to help with the decision-making process while choosing Type 2 Diabetes pharmaceutical therapy. The Fuzzy TOPSIS approach analyzes each option by taking into account all criteria in compliance with a published clinical guideline, On the other hand, while applying the TOPSIS technique to determine the relative relevance of particular criteria, expert opinions are taken into account. In order to address the drawbacks of conventional reference points and improve the ranking process in fuzzy multi-criteria decision-making, this study investigates an extended reference point technique inside the hybrid MCDM paradigm. The principal medicine, DPP-4-I, is confirmed by computational results, and Metformin is recognized as the second-line add-on therapy. The third, fourth, and fifth options are sulfonylurea, glucagon-like peptide1 receptor agonist, and insulin, in that order. To assess the effectiveness of the model, a sensitivity study is carried out by contrasting the outcomes with previous research, different fuzzy MCDM approaches, and an interval TOPSIS method based on observational data. Endocrinologists should be aware of the substantial agreement found between the final anti-diabetic drug rankings produced by the proposed hybrid model and alternative approaches.

***Keywords:*** *Diabetes, Metformin, Anti-diabetic drug, Fuzzy Method*

## 1. Introduction

In accordance with an International Diabetes Federation (IDF) report from 2017, 425 million people globally have diabetes. Of the 727 billion dollars spent on worldwide health care, around 12 percent goes toward solving the problems this complex chronic illness presents. Hyperglycemia, or high blood glucose levels, is a characteristic that the American Diabetes Association (ADA) uses to define diabetes. Elevated blood sugar levels are associated with the escalation of diabetes risk factors and the emergence of problems related to diabetes. Continuous medical treatment is required for these side effects, which include heart disease, stroke, hypertension, visual issues, kidney illness, and foot problems. Glucose management refers to the long-term maintenance of steady blood glucose levels in individuals with type 2 diabetes. For the purpose of successfully controlling the sickness and preventing the morbid problems indicated above, this proactive approach is essential. Securing and preserving glycemic control is essential for drastically reducing problems associated with diabetes, such as neuropathy and microvascular damage. Taking up lifestyle habits like eating a balanced diet and exercising frequently, further contributes to this positive impact, serves as the initial strategy for T2D patients to keep their blood sugar levels within recommended ranges due to the enduring impact of these practices. In cases where individuals with T2D find it challenging to achieve blood glucose control solely through lifestyle modifications, the incorporation of pharmacotherapy becomes necessary. Optimizing T2D medication treatment regimens is also essential to prolong patient life, enhance their quality of life, and lower hospitalization and other expenditure-related costs.

Choosing drugs for Type 2 Diabetes involves a variety of medicines used to regulate blood glucose levels, making it a difficult medical decision-making process. The vast array of hyperglycemia-lowering drugs, each with unique effects and possible adverse effects, makes choosing a prescription more difficult. Precision in choosing the appropriate agents is essential to maximize efficacy, minimize costs, and mitigate side effects. To identify the most suitable medication, reliance on resources such as randomized control trials (RCTs) and observational studies becomes imperative. These studies serve as the primary means of discerning the effectiveness, safety, and overall appropriateness of different medications for T2D. Zhang et al. introduced a groundbreaking glycemic control Markov chain model at the population level, which was both developed and validated. Finding the best second-line medication to use after taking metformin was the goal. The

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algorithm was calibrated to maximize medication selections using a dataset of US patients with Type 2 Diabetes who had private insurance. As supplementary treatments to metformin, they believe that sulfonylurea, DPP-4-I, GLP-1-RA, and insulin are the best choices. The longest period of insulin independence and the lowest predicted drug cost per quality-adjusted life year (QALY) are linked to this order. In a study by Maruthur et al., the AHP method was used to help choose medications for Type 2 Diabetes. By conducting organized interviews with diabetes specialists, the researchers assessed available therapy alternatives. Their findings indicated that Sitagliptin, Sulfonylureas, and Pioglitazone were the final rankings for add-on therapy to Metformin. Through pre-testing and a group evaluation of computational results, the authors validated the results of their model. This all-inclusive strategy was created to enhance the Analytic Hierarchy Process's dependability and suitability for directing T2D medication selections.

An AHP approach was presented by Balubaid and Basheikh as a mathematical decision-making model to help diabetic patients prioritize their available treatment options. Four doctors answered a questionnaire that was designed as part of their study in order to gather data. This work is notable since it is the first to integrate a modified version of the FUZZY TOPSIS approach with the TOPSIS method for ranking and prioritizing pharmaceutical treatments for diabetes. Decision-making has benefited from the application of MCDM approaches, a subset of operations research that is especially beneficial in the healthcare sector. When decision-makers individually or in groups must assess a small number of options in the context of a set of performance standards, these approaches serve as useful instruments. The choice of criteria, alternatives, and aggregation techniques are crucial to the MCDM methodology. The procedure of outranking and the aggregate findings are then used to determine the final choice amongst options. When there are several variables influencing the decision-making process, like when choosing pharmaceutical treatments for diabetes, this methodical approach makes it easier to make well-informed and thorough decisions.

## 2. Materials and Methods

Metformin: Metformin, a widely used biguanide for treating type 2 diabetes, has demonstrated anticancer activity in preclinical models. Research suggests that metformin may help those with diabetes who also have colorectal, prostate, or breast cancer live longer. On the other hand, little is known about how metformin may affect lung cancer patients' chances of survival. Known for its insulin-sensitizing properties and its ability to improve glycemic control, metformin has garnered attention for its potential anticancer effects. These effects are supported by preclinical evidence showcasing its inhibitory impact on the growth of breast cancer cells. As research delves deeper into the multifaceted roles of metformin, particularly in the context of various cancer types, its potential therapeutic benefits in lung cancer survival are a subject of ongoing exploration.

Sulfonylureas: Sulfonylureas have been used for a long time to treat diabetes because they were the first oral medications to lower blood sugar levels in clinical settings. In the UK, they are still often given and used as the backup option for oral glucose lowering following metformin. About 25% of persons who started taking oral diabetic medications still use sulfonylureas, either exclusively or in combination with other diabetes medications, as their primary diabetes treatment. The main way that sulfonylureas work is by blocking ATP-sensitive potassium channels in the pancreatic beta cells, which causes the release of insulin. Sulfonylureas can reduce HbA1c by 1.5%, or 16 mmol/mol, according to a consensus study published jointly by the American Diabetes Association and the European Association for the Study of Diabetes. It is crucial to keep in mind that the information used to reach this result came from a single clinical study. Furthermore, because these findings were based on a specific sulfonylurea in combination with metformin, they do not provide a comprehensive assessment of the effects of sulfonylurea monotherapy.

DPP-4-I: The ability of dipeptidyl peptidase inhibitors (DPP-4-I) to selectively block the DPP-4 enzyme sets them apart. They function by raising incretin hormone levels, which have strong impacts on satiety, stomach emptying, insulin and glucagon release, and insulin release. Our review's objective is to assess the safety factors related to DPP-4-I. DPP-4-I falls into the anti-hyperglycemic group and is an extra option with a noteworthy benefit: a low rate of hypoglycemia. Because of this feature, patients who are elderly or have heart problems may find these medicines especially intriguing. In comparison to sulfonylureas, DPP-4-I may carry a lower cardiac risk, according to a number of large trials. It is expected that the ongoing CAROLINA Trial, which contrasts glimepiride and linagliptin, will offer important insights into the safety profile of both inhibitors and offer a more definitive response to the topic of cardiac risk linked with DPP-4-I.

GLP-1RA: The study conducted a comprehensive search of MEDLINE using MeSH search terms, specifically focusing on publications that compared GLP-1RAs in patients with T2D. After titles and abstracts were reviewed, all phase III trials and post hoc studies that looked into the agents' licensed indications had to be chosen in order to meet the inclusion criteria. In their investigation, the researchers also included product prescribing information, published treatment regimens, and their own clinical experiences. Based on clinical evidence gathered from these searches, GLP-1RAs are superior to DPP-4 inhibitors in terms of

glycemic management and weight loss. This implies that, in situations where local rules allow for their usage, GLP-1RAs are a suitable and effective therapy choice. However, there are some situations when using DPP-4 inhibitors may be favored due to their oral delivery. It is stressed that each patient's unique demands should be taken into account when making treatment selections. Interestingly, GLP-1RAs are peptide-based medications that work similarly to insulin but need to be injected subcutaneously to avoid being broken down by digestive enzymes. As DPP-4-resistant GLP-1RA medicines, there are now two approved GLP-1RAs: lixisenatide, which was recently approved, and liraglutide, a human GLP-1 counterpart, in addition to exenatide, a GLP-1-like xenopeptide. Approximately half of the sequences of synthetic exendin-4, exenatide, and lixisenatide and native GLP-1 are similar.

Insulin: Exogenous insulin is mostly excreted via the kidneys, as opposed to endogenously released insulin, which is heavily broken down in the liver. Insulin is substantially reabsorbed in the proximal tubule after being released from restriction at the glomerulus. Filtered insulin is taken up by proximal tubular epithelial cells and passes through their apical membrane, where it is broken down by enzymes into different-sized peptide fragments that are then reabsorbed. Moreover, renal epithelial and peritubular endothelial cells absorb and degrade insulin, leading to a total renal clearance that is greater than the glomerular filtration rate (GFR). The degradation of filtered insulin decreases as renal failure worsens, but this is offset by an increase in peritubular insulin absorption, which continues until the GFR falls below around 20 ml/min. Following this, there is a reduction in the total amount of insulin required, an increase in the half-life of insulin, and a decrease in insulin clearance. The metabolic effects of both short- and longer-acting insulin formulations linger longer when renal impairment lowers insulin clearance and catabolism, raising the possibility of symptomatic hypoglycemia. The amount of insulin needed appears to drop similarly in patients with type 1 and type 2 diabetes when renal function declines, despite the fact that those with type 2 diabetes mellitus can still secrete insulin spontaneously.

FUZZY TOPSIS: Fuzzy MCDM is a significant and versatile topic within expert systems and operations research. It is essential for determining which alternative, or alternatives, among a range of options, best meets predetermined criteria. MCDM techniques are valuable tools that can address a diverse array of challenges in engineering, economics, management, and social sciences. Its effectiveness lies in providing a systematic and structured approach for decision-making in complex and multi-faceted scenarios, making it a valuable asset in problem-solving across different domains. In MCDM, problems are solved through a variety of methods. Two methodologies are used in MCDM: the AHP is part of the human approach. Preferences influence both the mathematical and human approaches. The most widely utilized mathematical approach method is TOPSIS. The TOPSIS's primary idea is to calculate the distance between every alternative and the positive (PIS) and negative (NIS) ideal solutions in order to identify the optimum choice. When optimizing cost criteria and restricting benefit criteria, decision makers (DMs) choose PIS over NIS, which stands for the least desired alternative. The option that is both the farthest from the NIS and the closest to the PIS is then chosen to establish the preference order. This produces a scalar criterion that combines the best option with the two distance measurements.

The FUZZY TOPSIS involves a systematic process outlined in several key steps. Firstly, a decision matrix is created to represent the alternatives and criteria. Then, depending on human preferences, criteria weights are calculated using techniques like the Analytic Hierarchy Process (AHP) and mathematical procedures like entropy. After that, the decision matrix is normalized to guarantee data consistency. The weighted normalized fuzzy decision matrix is then computed using the weights of the generated criteria. The fuzzy negative ideal solution (FNIS) and fuzzy positive ideal solution (FPIS) are discovered in the next phase. A closeness coefficient (CCi) is computed for each alternative, and the distance of each option from FPIS and FNIS is measured. Lastly, the proximity coefficients of the alternatives are used to rank them, with the option with the highest closeness coefficient being deemed the best option. TOPSIS has faced several challenges, including concerns related to the type of normalization technique used and its impact on both data and final selections. Another issue arises from the distance measurement within TOPSIS, where different techniques can yield diverse results. MCDM approaches often entail the integration of subjective evaluations and decision-maker preferences, which include grading criteria both qualitatively and quantitatively as well as weighting them. These difficulties emphasize how crucial it is to take into account the complexities of decision-making procedures and how reliable approaches are required for MCDM applications. However, when dealing with real-world issues, these inputs could be vague, ambiguous, and unpredictable, which would make decision-making more difficult. When dealing with such issues, it might not always be appropriate to use real data, particularly when subjective assessments play a significant role. In order to address this issue, Zadeh's fuzzy set theory provides an insightful framework for managing ambiguous and subjective aspects of decision-making processes.

## 3. Results and Discussion

**Table 1:** Criteria and Alternative

| Criteria | Description | Alternative | Description |
|---|---|---|---|
| C1 | Efficiency | A1 | Metformin |

| | | | |
|---|---|---|---|
| C2 | Hypoglycemia risk | A2 | Sulfonylurea |
| C3 | Effects on body weigh | A3 | DPP-4-I |
| C4 | Injectable | A4 | GLP-1-RA |
| C5 | Cost | A5 | Insulin |

The Table 1 first criterion, efficiency (C1), assesses the overall effectiveness of a treatment in managing blood glucose levels. Hypoglycemia risk (C2) becomes a pivotal concern, considering the potential adverse effects associated with low blood sugar. Effects on body weight (C3) are another crucial aspect, recognizing the impact that certain treatments may have on weight management. Injectable forms of treatment (C4) may be preferred in specific cases, addressing both practical and patient preference considerations. Additionally, the cost factor (C5) is a practical consideration that influences accessibility and long-term adherence to a chosen treatment regimen. The provided alternatives encompass a range of pharmaceutical options for the management of diabetes. Metformin (A1) stands out as a widely used and effective oral medication for glycemic control. Sulfonylurea (A2) represents an alternative that addresses blood sugar levels but is associated with considerations regarding hypoglycemia risk. DPP-4-I (A3) offers an alternative approach, focusing on effects on body weight. GLP-1-RA (A4) introduces an injectable option, catering to individuals who may prefer or require such forms of treatment. Insulin (A5), a hormone critical for glucose regulation, serves as a versatile alternative that can be administered through various means. Each alternative brings distinct characteristics, allowing healthcare professionals to tailor treatment plans based on the unique needs and preferences of patients, considering factors such as efficacy, side effects, and mode of administration.

Table 2 (APPENDIX) presents a comprehensive snapshot of glucose-lowering agents for T2D, offering valuable insights into their key attributes. Metformin, with an efficiency of 70%, minimal hypoglycemia risk (5%), and a weight reduction of 2 kg, emerges as an effective oral option at a moderate cost of $20. Sulfonylurea, while moderately efficient at 50%, poses a higher hypoglycemia risk (10%) and a modest weight gain of 1 kg, with a lower cost of $15. DPP-4-I demonstrates a balanced profile, with 40% efficiency, minimal hypoglycemia risk (2%), and no significant impact on body weight, though it comes at a higher cost of $50. GLP-1-RA, an injectable option, exhibits 60% efficiency, low hypoglycemia risk (3%), and notable weight reduction of 4 kg, albeit at a higher cost of $200. Insulin, with the highest efficiency at 80%, comes with an increased hypoglycemia risk (15%), a weight gain of 3 kg, and an injectable form at a cost of $150. This comprehensive data aids in tailoring diabetes management strategies based on individual patient needs, preferences, and cost considerations.

**Table 3:** Fuzzy values

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

Table 3 introduces a linguistic variable framework associating denotations with fuzzy numbers, providing a structured representation of qualitative measurements. For instance, "Very Low" is characterized by the fuzzy number (1,2,3), signifying a range that spans from 1 to 3. The "Low" category corresponds to (3,4,5), "Moderate" to (5,6,7), "High" to (8,9,10), and "Very High" to the range (9,10,10). This fuzzy value system allows for a more flexible and nuanced representation of imprecise or uncertain data, offering a linguistic framework that aids in capturing the gradations within each category. Such an approach is particularly useful in contexts where precise numerical values may be challenging to define, allowing for a more qualitative and nuanced understanding of variables in various applications, such as decision-making and fuzzy logic systems.

**Table 4:** Fuzzy values for Criteria

| **Criteria** | **DM1** | **DM2** | **DM3** |
|---|---|---|---|
| **C1** | VH | H | VH |
| **C2** | H | L | H |
| **C3** | L | H | VL |
| **C4** | M | H | H |
| **C5** | H | VH | M |

Table 4 outlines fuzzy values assigned to specific criteria (C1 to C5) for three distinct decision-makers (DM1, DM2, and DM3). These fuzzy values and linguistic variables offer a qualitative representation of decision-makers' assessments, capturing the inherent uncertainty and subjectivity in the evaluation process. Such an approach enables a more nuanced consideration of criteria in decision-making processes, particularly when dealing with imprecise or subjective information.

**Table 5:** Fuzzy decision matrix for Criteria

| DM1 | | | DM2 | | | DM3 | | |
|---|---|---|---|---|---|---|---|---|
| 9 | 9 | 10 | 8 | 9 | 10 | 9 | 10 | 10 |
| 8 | 9 | 10 | 3 | 4 | 5 | 8 | 9 | 10 |
| 3 | 4 | 5 | 8 | 9 | 10 | 1 | 2 | 3 |
| 5 | 6 | 7 | 8 | 9 | 10 | 8 | 9 | 10 |
| 8 | 9 | 10 | 9 | 10 | 10 | 5 | 6 | 7 |

Table 5 illustrates a fuzzy decision matrix that reflects the evaluations of various criteria by three decision-makers. Each cell in the matrix contains numerical values corresponding to the assessments made by the respective decision-makers for each criterion. For instance, in the first row, DM1 rates C1 as 9, C2 as 10, and C3 as 8. Similarly, DM2 assigns scores of 9, 9, and 9 to C1, C2, and C3, respectively, and DM3 gives scores of 10, 10, and 10 to the same criteria. Analyzing this matrix allows for a comprehensive understanding of how each decision-maker assesses the importance or performance of different criteria, contributing to a more informed decision-making process. Fuzzy logic techniques can be applied to interpret and analyze these values, providing a flexible framework for handling imprecise or subjective information in decision support systems.

**Table 6:** Aggregated fuzzy number

| Criteria | DM1 | DM2 | DM3 |
|---|---|---|---|
| **C1** | 8.666667 | 9.333333 | 10 |
| **C2** | 6.333333 | 7.333333 | 8.333333 |
| **C3** | 4 | 5 | 6 |
| **C4** | 7 | 8 | 9 |
| **C5** | 7.333333 | 8.333333 | 9 |

The provided table displays a numerical representation of the aggregated scores for each criterion (C1 to C5) as evaluated by three decision-makers. The scores are presented as decimal values, reflecting the average assessments made by each decision-maker for each criterion. For example, DM1 rates C1 with an average score of approximately 8.67, DM2 assigns an average score of around 9.33, and DM3 gives the highest possible score of 10 for C1. Similar calculations are carried out for all criteria and decision-makers, offering a quantitative overview of their assessments. These averaged scores can serve as a basis for further analysis and decision-making processes, providing a more concrete and interpretable representation of the decision-makers' preferences and evaluations. It's worth noting that these scores are continuous and provide a more precise basis for decision-making compared to fuzzy values, offering a clearer numerical foundation for comparisons and prioritization of criteria.

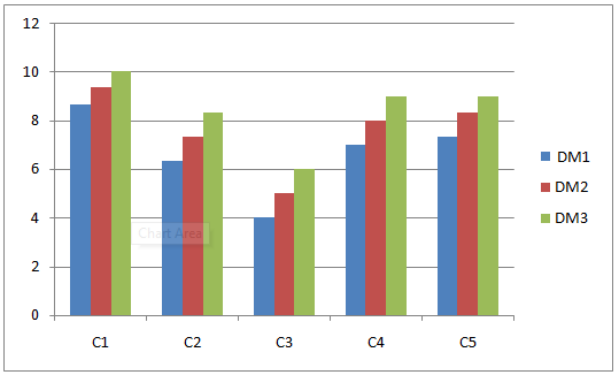


**Fig 1:** Aggregated fuzzy number

The provided Figure 1 displays a numerical representation of the aggregated scores for each criterion (C1 to C5) as evaluated by three decision-makers.

Table 7 presents a comprehensive set of fuzzy values assigned to alternatives (A1 to A5) across distinct criteria (C1 to C5). Each alternative is characterized by linguistic variables denoting its performance level in relation to specific criteria. For example, A1 is deemed "High" in efficiency (C1) but rated as "Very Low" in hypoglycemia risk (C2), "Low" in effects on body weight (C3), and "Very Low" in both injectability (C4) and cost (C5). These fuzzy values offer a qualitative and flexible representation of the performance of each alternative, acknowledging the inherent subjectivity and uncertainty in decision-making.

**Table 7:** Fuzzy values for Alternatives

| Alternatives | 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 |

This framework allows decision-makers to consider and weigh the trade-offs between different fuzzy values for each alternative, facilitating a more nuanced and comprehensive evaluation of the available options based on their preferences and the specific criteria at hand.

**Table 8:** Matrix of fuzzy decisions for alternatives

| | C1 | | | C2 | | | C3 | | | C4 | | | C5 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 8 | 9 | 10 | 1 | 2 | 3 | 3 | 4 | 5 | 1 | 2 | 3 | 1 | 2 | 3 |
| A2 | 8 | 9 | 10 | 5 | 6 | 7 | 9 | 10 | 10 | 1 | 2 | 3 | 1 | 2 | 3 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A3 | 5 | 6 | 7 | 1 | 2 | 3 | 3 | 4 | 5 | 1 | 2 | 3 | 9 | 10 | 10 |
| A4 | 8 | 9 | 10 | 1 | 2 | 3 | 1 | 2 | 3 | 9 | 10 | 10 | 9 | 10 | 10 |
| A5 | 9 | 10 | 10 | 9 | 10 | 10 | 9 | 10 | 10 | 9 | 10 | 10 | 1 | 2 | 3 |

Table 8 provides a fuzzy decision matrix, illustrating the evaluations of various alternatives (A1 to A5) across different criteria (C1 to C5). The matrix is populated with numerical values, each representing the degree to which an alternative satisfies a particular criterion. For instance, A1 receives scores of 8, 9, and 10 for criteria C1, C2, and C3, respectively, and lower scores of 1, 2, and 3 for C4 and C5. The matrix synthesizes the subjective assessments of each alternative's performance, incorporating a range of numerical values that correspond to the fuzzy values outlined in Table 7. This comprehensive representation allows decision-makers to analyze and compare the relative strengths and weaknesses of each alternative across the specified criteria. The fuzzy nature of the matrix acknowledges the inherent uncertainty and subjectivity in decision-making, offering a flexible framework for capturing imprecise information and supporting informed decision processes.

The normalization fuzzy decision matrix for the alternatives in relation to the given criteria is shown in Table 9. The numerical values in the matrix have been normalized to facilitate a more consistent and comparable assessment across criteria. The normalization process scales the original scores to a range of 0 to 1, where 1 represents the maximum possible score for a criterion within the given set of alternatives. For instance, in the first row, the scores for A1 in C1, C2, and C3 are 0.8, 0.9, and 1, respectively. Similarly, the scores for A2, A3, A4, and A5 are normalized accordingly for each criterion. This normalization aids in eliminating any potential bias arising from differing scales in the original fuzzy decision matrix. The resulting normalized values provide a basis for a more objective comparison of the alternatives' performance across criteria, facilitating a clearer understanding of their relative strengths and weaknesses in the decision-making process.

Table 10 (APPENDIX) depicts the weighted normalized fuzzy decision matrix for alternatives across different criteria. The normalized scores from Table 9 (APPENDIX) have been multiplied by corresponding weights to underscore the relative importance of each criterion in the decision-making process. The resulting weighted values provide a more nuanced representation of the alternatives' performance, accounting for the priorities assigned to each criterion. For example, in the first row, the weighted scores for A1 in C1, C2, and C3 are 6.93333, 8.4, and 10, respectively. The same process is applied to calculate the weighted scores for A2, A3, A4, and A5 across all criteria. These weighted and normalized values allow decision-makers to more precisely evaluate and compare the alternatives, considering both their relative importance and performance across the specified criteria. The table serves as a foundation for a comprehensive decision analysis, aiding in the identification of the most suitable alternative based on the specified criteria and their respective weights.

**Table 11:** D+, D- and c- values

| | D+ | D- | c- |
|---|---|---|---|
| Metformin | 15.86667 | 20.86667 | 0.568058 |
| Sulfonylurea | 19.38333 | 24.38333 | 0.557121 |
| DPP-4-I | 9.4 | 14.4 | 0.605042 |
| GLP-1-RA | 24.4 | 29.4 | 0.546468 |
| Insulin | 31.85 | 36.85 | 0.53639 |

Table 11 provides D+, D-, and c- values for a set of diabetes treatment alternatives, including Metformin, Sulfonylurea, DPP-4-I, GLP-1-RA, and Insulin. In the context of MCDM, these values are crucial for assessing the performance of each alternative.

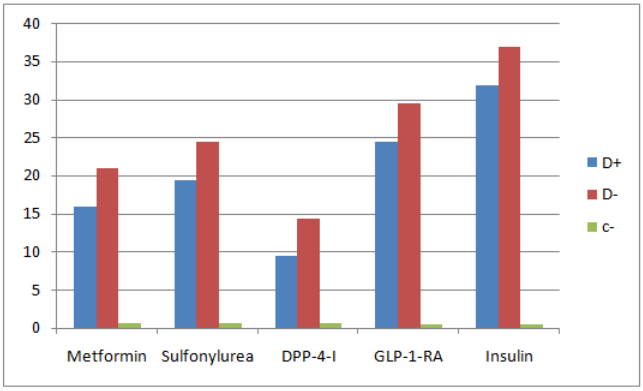


**Fig 2:** D+, D-, and c- values

The D+ values represent the positive ideal solutions, quantifying the distance of each alternative from the ideal positive solution. Lower D- values, the negative ideal solutions, indicate the proximity of each alternative to the ideal negative solution. These values contribute to the overall assessment of each alternative's performance in the decision-making process. Notably, DPP-4-I exhibits the lowest D- value of 9.4, suggesting its superior performance in the negative ideal context. The c- values, reflecting compromise solutions, provide information about how each option compares overall to the optimum answer. Insulin, with a c- value of 0.53639, emerges as a strong contender, indicating its competitive performance across the evaluated

criteria. Decision-makers can leverage these values to make informed choices, taking into account each option's benefits and drawbacks within the designated framework for making decisions.

**Table 12:** Rank

| | Rank |
|---|---|
| Metformin | 2 |
| Sulfonylurea | 3 |
| DPP-4-I | 1 |
| GLP-1-RA | 4 |
| Insulin | 5 |

DPP-4-I is ranked first, suggesting it is the most favorable alternative based on the calculated values. Metformin is ranked second, indicating its relative performance compared to the other alternatives. Sulfonylurea holds the third rank among the considered alternatives. GLP-1-RA is ranked fourth. Insulin is ranked fifth, suggesting it performed relatively less favorably compared to the other alternatives in the given decision-making context.

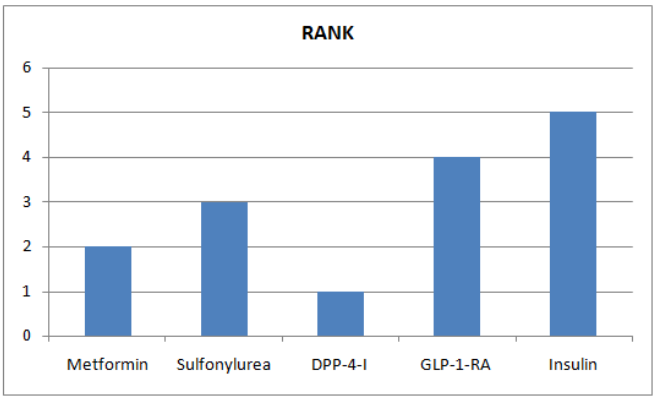


**Fig 3:** Ranking

The rankings presented in Figure 3 offer decision-makers a clear order of preference for diabetes treatment alternatives. This information aids in the selection of the most suitable option based on the specified criteria and the results of the decision analysis. Such visual representations enhance the interpretability of the decision-making process, facilitating informed and effective choices in diabetes treatment.

## 4. Conclusion

In conclusion, the decision-making process for diabetes treatment alternatives has been systematically evaluated and ranked using a comprehensive approach. The fuzzy decision matrices, normalized scores, and weighted values allowed for a nuanced consideration of each alternative's performance across multiple criteria. The subsequent application of the VIKOR method resulted in D+, D-, and c-values, offering a quantitative basis for ranking the alternatives. DPP-4-I emerged as the top-ranked alternative, showcasing superior performance in the decision-making framework. Metformin and Sulfonylurea secured the second and third positions, respectively, followed by GLP-1-RA and Insulin. These rankings provide valuable insights for healthcare professionals and decision-makers, facilitating the selection of diabetes treatments that align with specific criteria and priorities. The systematic and analytical approach employed in this decision-making process ensures a comprehensive evaluation, enhancing the likelihood of choosing the most effective and suitable treatment option for individuals managing Type 2 Diabetes.

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## APPENDIX

**Table 2:** T2D glucose-lowering agents' 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 | 80% | 15% | +3 kg | Yes | 150 |

**Table 9: Fuzzy decision matrix normalized for alternatives**

| C1 | | | C2 | | | C3 | | | C4 | | | C5 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.8 | 0.9 | 1 | 0.1 | 0.2 | 0.3 | 0.3 | 0.4 | 0.5 | 0.1 | 0.2 | 0.3 | 0.1 | 0.2 | 0.3 |
| 0.8 | 0.9 | 1 | 0.5 | 0.6 | 0.7 | 0.9 | 1 | 1 | 0.1 | 0.2 | 0.3 | 0.1 | 0.2 | 0.3 |
| 0.5 | 0.6 | 0.7 | 0.1 | 0.2 | 0.3 | 0.3 | 0.4 | 0.5 | 0.1 | 0.2 | 0.3 | 0.9 | 1 | 1 |
| 0.8 | 0.9 | 1 | 0.1 | 0.2 | 0.3 | 0.1 | 0.2 | 0.3 | 0.9 | 1 | 1 | 0.9 | 1 | 1 |
| 0.9 | 1 | 1 | 0.9 | 1 | 1 | 0.9 | 1 | 1 | 0.9 | 1 | 1 | 0.1 | 0.2 | 0.3 |

**Table 10:** Weighted normalized fuzzy decision matrix for Alternatives

| **Alter native** | **C1** | | | **C2** | | | **C3** | | | **C4** | | | **C5** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 6.93 | 8.4 | 10 | 0.87 | 1.87 | 3 | 2.6 | 3.73 | 5 | 0.87 | 1.87 | 3 | 0.87 | 1.87 | 3 |
| A2 | 5.07 | 6.6 | 8.33 | 3.17 | 4.4 | 5.83 | 5.7 | 7.33 | 8.33 | 0.63 | 1.47 | 2.5 | 0.63 | 1.47 | 2.5 |
| A3 | 2 | 3 | 4.2 | 0.4 | 1 | 1.8 | 1.2 | 2 | 3 | 0.4 | 1 | 1.8 | 3.6 | 5 | 6 |
| A4 | 5.6 | 7.2 | 9 | 0.7 | 1.6 | 2.7 | 0.7 | 1.6 | 2.7 | 6.3 | 8 | 9 | 6.3 | 8 | 9 |
| A5 | 6.6 | 8.33 | 9 | 6.6 | 8.33 | 9 | 6.6 | 8.33 | 9 | 6.6 | 8.33 | 9 | 0.73 | 1.67 | 2.7 |