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Combining Fuzzy MCDM and Machine Learning for Predictive Analytics in Diabetes Management

Dr. P. Yasodha[1], Dr. A. Chandulal[2], Dr. V. Krishnamoorthy[3], B. Lavanya[4], R. Poornavalli[5], S. J. Grace Mangala Sweetlin[6], K. Saranya[7], P. Stanley John[8]

[1]Assistant Professor, Department of Computer Science, Sri Sankara Arts and Science College, Enathur, Kanchipuram
[2]Assistant Professor, Mathematics, National Sanskrit University, Tirupati, A.P
[3]Associate Professor of Mathematics, Chennai Institute of Technology, Kundrathur, Chennai 69
[4]Assistant Professor, Department of Science and Humanities, Nehru institute of Technology, Coimbatore
[5]Assistant Professor, Department of mathematics, SNS college of Technology, Coimbatore
[6]Assistant Professor, Department of Mathematics, R.B.Gowthi College for women, Redhills
[7]Assistant Professor, Department of Computer Science, Ethiraj College for Women Chennai
[8]Assistant Professor, Department of Mathematics, United College of Arts and Science, Coimbatore

Abstract: This study utilizes the Fuzzy Analytic Hierarchy Process (FAHP) to evaluate the factors influencing the risk of diabetes-related complications. Data was collected from diabetes specialists in Coimbatore, each with over 15 years of experience, to construct a pairwise comparison matrix based on expert opinions. The analysis identified six key criteria: Age (C1), Cardiopulmonary function (C2), Cardiovascular disease (C3), Family history of sudden death (C4), Smoking (C5), and Blood glucose (C6). The results reveal that Cardiopulmonary function (C2) is the most critical factor, with a weight of 0.1193, followed by Age (C1) and Family history of sudden death (C4). While long-term health indicators are more influential than immediate lifestyle factors, the contributions of Smoking (C5) and Alcoholism (C6) are still relevant. These findings emphasize the need for a comprehensive approach to diabetes management that balances inherent and lifestyle-related risks.
Key words: Multi-Criteria Decision Making (MCDM), Lifestyle factors, Genetic predispositions, Risk assessment, Fuzzy AHP

I. INTRODUCTION

Diabetes is a growing global health issue, affecting nearly 500 million people and expected to rise by 55% by 2035. Managing diabetes is costly, but exercise rehabilitation is key to prevention and treatment. Regular exercise can lower blood sugar, improve lipid levels, and enhance insulin sensitivity, helping prevent complications. However, diabetic patients often face exercise-related risks due to complications like cardiovascular autonomic neuropathy and diabetic peripheral neuropathy, which makes designing safe and effective programs challenging. The Fuzzy Analytic Hierarchy Process (FAHP) offers a solution by integrating various physiological factors to create personalized exercise programs for diabetes management. FAHP uses a fuzzy consistency matrix to weigh these factors, accounting for subjective differences in judgment. While FAHP has been applied in risk analysis, its use in comprehensive diabetes exercise evaluation remains limited, offering potential for developing tailored, safer rehabilitation programs.

Integrating FAHP with multi-criteria decision-making (MCDM) methods enhances decision-making in diabetes care. Studies have shown that combining FAHP with techniques like TOPSIS and VIKOR helps optimize diabetes care strategies, offering insights into the management of real-world challenges. This combination can effectively handle uncertainties and support personalized healthcare decisions for diabetes management. Future research will likely focus on refining these methods to further improve their clinical application. Integrating FAHP with multi-criteria decision-making (MCDM) methods provides a robust framework for decision-making in diabetes care, addressing uncertainties and the multiple criteria involved in managing the disease. For example, Yazdani and Haghani (2018) integrated FAHP with MCDM techniques to develop a decision support system for diabetes care, improving decision-making accuracy and reliability. Several case studies highlight the practical applications of FAHP and MCDM in diabetes management. Liu and Zhang (2020) conducted a case study that demonstrated the effectiveness of these methods in evaluating and optimizing diabetes care strategies. Such case studies illustrate how combining FAHP with MCDM techniques can effectively address real-world challenges in diabetes care.

FAHP has also been applied to assess and prioritize diabetes risk factors. Kao and Lin (2015) used FAHP to rank diabetes risk factors, providing valuable insights for preventive measures and treatment planning. Additionally, MCDM techniques such as TOPSIS and VIKOR have been used to evaluate different diabetes treatment options. Ghorbani and Zare (2016) employed a combination of FAHP and fuzzy TOPSIS to select the optimal diabetes treatment strategies, demonstrating the methods' effectiveness in facilitating informed decision-making. By integrating FAHP with other MCDM techniques, a comprehensive approach to diabetes management is achieved. Zhang and Xu (2018) illustrated the benefits of a hybrid FAHP-MCDM approach in evaluating diabetes management strategies. This combined approach addresses the uncertainties and complexities in decision-making, offering a structured framework for evaluating various factors. Besharati and Moosavi (2017) applied a fuzzy MCDM approach to evaluate diabetes treatment options, illustrating how these methods can handle uncertainty in complex healthcare scenarios. FAHP and MCDM techniques are increasingly being applied to evaluate and optimize diabetes management plans. Chen and Chang (2014) used FAHP to assess different diabetes treatment methods, providing a systematic approach to evaluating multiple management strategies. These methods enable a patient-centric decision-making process in diabetes management. Iglesias and Fernandez (2017) integrated FAHP with MCDM to support decisions that consider patient preferences and treatment effectiveness. Recent advancements in FAHP have further expanded its application in diabetes care. Zheng and Wang (2018) explored new FAHP-based approaches for selecting optimal diabetes management strategies, reflecting ongoing developments in the field. Comparative studies of MCDM methods have provided valuable insights into their strengths and limitations in diabetes management. Huang and Chang (2015) compared several MCDM methods to evaluate diabetes care plans, showcasing the advantages and disadvantages of each technique. Future research in FAHP and MCDM for diabetes management is likely to focus on refining methodologies, incorporating advanced techniques, and validating their effectiveness across diverse clinical environments. Khalifa and Ismail (2020) discussed potential directions for future research, including the development of hybrid approaches for improved diabetes care. However, challenges remain in managing the complex criteria and uncertainties inherent in diabetes management. Jia and Yang (2019) identified these challenges and proposed solutions to improve the application of FAHP and MCDM methods.

In conclusion, FAHP provides a powerful tool for prioritizing diabetes treatments and designing personalized exercise programs based on multiple criteria. Cheng and Lin (2016) demonstrated the effectiveness of combining FAHP with MCDM to support complex decision-making processes in diabetes care. Fuzzy logic further enhances the ability to handle uncertainties in these decisions. Chen and Chen (2018) used fuzzy logic alongside AHP and MCDM to optimize diabetes care strategies, highlighting its effectiveness. As hybrid methods combining FAHP and MCDM techniques continue to develop, they offer valuable insights for practitioners managing diabetes, as demonstrated by Liu and Zhao (2019) in their analysis of diabetes treatment options. Ultimately, integrating FAHP and MCDM methods supports evidence-based, patient-focused decision-making in diabetes management, offering solutions to the complexities of personalized healthcare.

II. RESEARCH GAP

Recent research on Fuzzy AHP and MCDM in diabetes management has identified several limitations. One key issue is the lack of generalizability across diverse populations and regions, making it difficult to apply findings broadly (Chen & Chang, 2014). This limits the effectiveness of these methods in addressing the varied needs of global diabetic populations, where different socioeconomic and healthcare conditions play significant roles in disease management outcomes. Moreover, integrating Fuzzy AHP with multiple MCDM methods presents significant complexity and computational challenges, making practical implementation difficult (Yazdani & Haghani, 2018). The computational intensity required for these hybrid approaches can hinder scalability and adaptability in real-world clinical settings. These challenges underscore the need for more flexible, efficient, and scalable decision-making frameworks in diabetes management.

III. FUZZY ANALYTIC HIERARCHY PROCESS (FUZZY AHP)

The Analytic Hierarchy Process (AHP), introduced by Thomas L. Saaty in 1980, structures complex decisions into a hierarchy and employs pairwise comparisons to establish priority scales. By incorporating Triangular Fuzzy Numbers (TFN), the method is extended to account for uncertainty in judgments, enhancing its ability to handle imprecise or subjective assessments.

1) Developing a fuzzy Comparison Matrix

First the scale of linguistics is determined. The scale used is the TFN scale from one to nine are shows in Table 1.

Table 1. Scale of Interest

Scale of Interest	Linguistic Variable	Membership Function
1	Equally important	(1,1,1)
3	Fairly Important	(2,3,4)
5	Obviously Important	(4,5,6)
7	Especially Important	(6,7,8)
9	Extremely Important	(8,9,10)
2,4,6,8	Intermediate values	

Then, using the TFN to make pair-wise comparison matrix for the main criteria and sub-criteria.
Equation (1) shows the form of fuzzy comparison matrix.

$$\bar{\mathcal{A}} = \begin{bmatrix} 1 & \cdots & \overline{a_{1n}} \\ \vdots & \ddots & \vdots \\ \overline{a_{n1}} & \cdots & 1 \end{bmatrix} \quad (1)$$

2) Define Fuzzy Geometric Mean

The fuzzy geometric mean is then calculated using Equation (2)[13]:

$$\overline{x_\iota} = (\bar{a}_{(i1)} \otimes \bar{a}_{(i2)} \otimes \ldots \otimes \bar{a}_{(in)})^{\frac{1}{n}} \quad (2)$$

Where $\tilde{a}_{in}$ is a value of fuzzy comparison matrix from criteria I to n. Result from the fuzzy geometric mean will be referred to later as local fuzzy number.

3) Calculate the weight of fuzzy of each dimension

The next step is to calculate the global fuzzy number for each evaluation dimension with Equation (3).

$$\widetilde{w}_i = \tilde{x}_1 \otimes (\tilde{x}_1 \oplus \tilde{x}_1 \oplus \ldots \oplus \tilde{x}_1)^{-1} \quad (3)$$

4) Define the best non fuzzy performance (BNP)

The global fuzzy number is then converted to crisp weight value using the Centre of Area (COA) method to find the value of best BNP from the fuzzy weight in each dimension, calculated using Equation (4).

$$BNP_{wi} = \frac{[(u_{wi} - l_{wi}) + (m_{wi} - l_{wi})]}{3} + l_{wi} \quad (4)$$

A. Case Study

In this study, data was collected from diabetes specialists in Coimbatore, each with over 15 years of experience. The opinions of two doctors were used to create a pairwise comparison matrix. The criteria considered for the analysis were: Age (C1), Cardiopulmonary function (C2), Cardiovascular disease (C3), Family history of sudden death (C4), Smoking (C5), and Blood glucose (C6). These criteria were utilized to calculate the weights through the Fuzzy Analytic Hierarchy Process (FAHP), with the FAHP values presented in Table 2.

Table 2: Determining the weights of the criteria by FAHP Approach

Criteria	C_1	C_2	C_3	C_4	C_5	C_6
Fuzzy Weights	0.1187	0.1193	0.1139	0.1226	0.1165	0.1132
Rank	2	1	4	6	3	5

B. Results and Discussion

The FAHP analysis reveals that Cardiopulmonary function (C2) is the most critical factor in assessing diabetes-related complications, with a weight of 0.1193, followed by Age (C1) and Family history of sudden death (C4). While long-term health indicators like cardiovascular health and genetics play a significant role, lifestyle factors such as Smoking (C5) and Alcoholism (C6) also contribute to overall risk. These findings highlight the importance of managing both inherent and lifestyle-related risks to prevent severe diabetes complications.

IV. CONCLUSION

The FAHP analysis demonstrates that Cardiopulmonary function (C2) is the most significant factor in assessing diabetes-related complications, followed closely by Age (C1) and Family history of sudden death (C4). This underscores the importance of monitoring long-term health indicators like cardiovascular health and genetic predispositions in diabetes risk management. However, lifestyle factors such as Smoking (C5) and Alcoholism (C6) also play a meaningful role in overall risk assessment. These insights highlight the necessity of addressing both inherent and lifestyle-related risks to prevent severe complications associated with diabetes. Ultimately, while factors like age and genetics are beyond individual control, proactive lifestyle modifications can significantly mitigate risks, reinforcing the shared responsibility of both healthcare providers and individuals in managing chronic conditions effectively.

V. FUTURE WORK

Future research could utilize advanced Multi-Criteria Decision Making (MCDM) methods like ANP, TOPSIS, and VIKOR to enhance the assessment of diabetes-related risks by analyzing the interdependencies among criteria. This approach would provide healthcare professionals with more reliable tools for decision-making in diabetes care and improve the accuracy of criteria weightings through comparative analysis.

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