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Soft Computing Decision Making System to Analyze the Risk Factors of T2DM

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Abstract. Type-2 Diabetes mellitus is one of the most alarming diseases in both developed and developing countries. The WHO predicted that 90% of people around the globe will suffer from T2DM (WHO, 2016). Most of the people are living in India without knowing that they are affected with T2DM. So, the undiagnosed T2DM leads to the complication in heart, kidney disease, eye and feet. Even though Type 2 diabetes has many risk factors associated to it, lifestyle changes play a vital role in triggering the Type 2 diabetes. Hence, the objective of the present study is to analyze and identify the most influencing risk factors of T2DM. Determining the most influencing risk factor of T2DM is not an easy task as there are lot of complexity and uncertainty involved in it. To tackle this issue, a novel decision making system is designed by combining the salient features of The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Fuzzy Cognitive Map (FCM). Eight risk factors are chosen as the input variables for the system. The proposed system elucidates that Blindness, Obesity, Physical Inactivity are the most influencing factors for the type 2 diabetes mellitus.

INTRODUCTION

The fuzzy set was introduced by Zadeh LA [25] to handle with vagueness and uncertainty of the thoughts and language in taking apt decision. To determine such vagueness, fuzzy set theory has been combined with many powerful tools of Multiple Attribute Decision Making (MADM) such as DEMATEL, VIKOR, ANP, TOPSIS etc., TOPSIS was first designed by Hwang and Yoon [9]. It is also a well-known and very simple ranking method for solving Multi Attribute Decision Making (MADM). Nowadays, the researchers concentrated on linguistic variables in solving the decision making problems [6, 7, 15, 24]. In the decision making method, experts use the linguistic terms to express his/her opinion when he/she does not have adequate information. The linguistic terms are repeatedly used as an input in decision making problem. A fuzzy number is a multi valued quantity whose value is not exact as is the case with "ordinary" numbers. It represents the value for the linguistic terms.

In the last decade, improved fuzzy TOPSIS methods have been modeled for application in different fields. Supplier selection problem in supply chain system [4, 10, 14], Taiwan's air force academy for choosing optimal initial training aircraft [22], order selection when orders exceed production [15], selecting a new information system to improve the productivity [22], evaluating environmental supplier performance [3], consumer product adoption processes in a competitive automobile market agent-based model [11], assessing alternative robots to perform a material handling [13], determining the most vulnerability region in Chennai due to rainfall [19], benefits of the practices of Islam [5].

Cognitive map and fuzzy logic were integrated by Kosco, B in 1986 [12] to design Fuzzy Cognitive Map (FCM). It is one of the simplest techniques motivated by the cognition of the human brain and it is a proficient system for decision making. FCM is a digraph connecting the concepts. The weight of the link depends on the strength of relationship between the two nodes. In order to represent the complexity of the connection strength, fuzzy weights were taken up and named as Fuzzy Cognitive Map (FCM). FCM is predominant method to capture the expert knowledge in a natural way. Simple FCM only considers the connection weights from the set {-1, 0, 1}. It is also notable that the connection weights could also be taken from [0, 1], linguistic variables or any special case fuzzy

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numbers such as triangular, trapezoidal etc. FCM also brought a lot of application in the field of Medical diagnosis, psychological problem, and engineering problem.

FCM based decision support system for medical diagnosis was designed to diagnose dyslexia (difficulty in learning). This method helps physicians on how to proceed the medical checkup and suggest proper medications to the patients [20]. Due to physicians' lack of experience, higher percentage of errors occurred around the world every year. Hence, physicians need a well equipped tool to diagnose the diseases well in advance. How FCM was used to help the physicians in decision making, prognosis, diagnosis and classification of diseases under patient's examination [1]. Multi layer FCM was proposed to diagnose the Autism in children with distinct cognitive personality using earlier symptoms such as impaired communication, restricted interests and repetitive and fixed behavior patterns [18]. In order to fine tune the FCM causal links, the Active Hebbian Learning and Nonlinear Hebbian Learning techniques have been introduced [17]. A hybrid multi-criteria decision making technique is proposed to diagnose the bipolar disorder based on FCM and TOPSIS under fuzzy situations [8]. Intuitionistic FCM was developed by an Active Hebbian Learning to perform the diagnosis procedure automatically. This method has advantage over FCM in detecting the type of diseases effectively [2]. From this review, it is observed that soft computing decision making system can be designed by integrating TOPSIS and FCM under uncertain linguistic environment to indentify the most influencing risk factors of T2DM.

THEORETICAL BACKGROUND

Definition 2.1 A fuzzy set $\tilde{A}$ is a subset of a universe of discourse *X*, which is distinguished by a membership function $\mu_{\tilde{A}}(t)$, which maps $\mu_{\tilde{A}} : X \to [0,1]$. The function value of $\mu_{\tilde{A}}(t)$ is called the membership value, which represents the degree of truth that t is an element of the fuzzy set $\tilde{A}$.

A fuzzy number is a fuzzy set on the real line that satisfies

Definition 2.2 A fuzzy number us a fuzzy set $\tilde{A}$ defined on the real line *R* and its membership function $\tilde{A} : R \to [0,1]$ satisfies the following condition,

(i) $\tilde{A}$ is convex.

(ii) $\tilde{A}$ is normal if $\max \mu_{\tilde{A}}(t) = 1$.

(iii) $\tilde{A}$ is piecewise continuous.

Definition 2.3 The α-cut of the fuzzy set $\tilde{A}$ of *X* is defined as $\tilde{A}_\alpha = \{t \in X \,/\, \mu_{\tilde{A}}(t) \geq \alpha\}$, where $\alpha \in [0,1]$.

Definition 2.4 A triangular fuzzy number $\tilde{T}$ (Figure 1) is defined as a triplet (*l*, *m*, *r*) and the membership function $\mu_{\tilde{T}}(t)$ is defined as

$$\mu_{\tilde{T}}(t) = \begin{cases} 0 & t < l \\ \left(\dfrac{t-l}{m-l}\right) & l \leq t \leq m \\ \left(\dfrac{r-t}{r-m}\right) & m \leq t \leq r \\ 0 & t > r \end{cases} \tag{1}$$

Where *l*, *m*, *r* are real numbers.

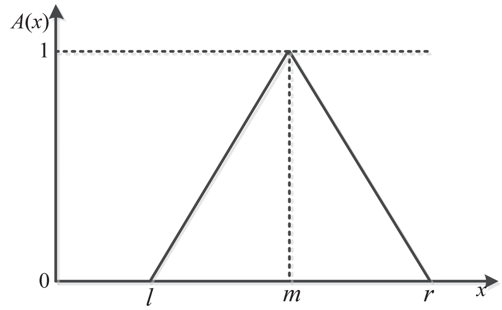

FIGURE 1. Triangular Fuzzy number

Theorem 2.5. Let $\tilde{T}_{r1} = (l_1, m_1, r_1)$ and $\tilde{T}_{r2} = (l_2, m_2, r_2)$ be two triangle fuzzy numbers. The addition, subtraction, multiplication operations of $\tilde{T}_{r1}$ and $\tilde{T}_{r2}$, denoted by, $\tilde{T}_{r1} \oplus \tilde{T}_{r2}$, $\tilde{T}_{r1} \Theta \tilde{T}_{r2}$ and $\tilde{T}_{r1} \otimes \tilde{T}_{r2}$ respectively, yield another triangular fuzzy number.

$$\tilde{T}_{r1} \oplus \tilde{T}_{r2} = (l_1 + l_2, m_1 + m_2, r_1 + r_2)$$

$$\tilde{T}_{r1} \Theta \tilde{T}_{r2} = (l_1 - r_2, m_1 - m_2, r_1 - l_2)$$

$$k \otimes \tilde{T}_{r1} = (kl_1, km_1, kr_1),\ k > 0 \text{ a crisp number}$$

$$\tilde{T}_{r1} \otimes \tilde{T}_{r2} = (l_1 \times l_2, m_1 \times m_2, r_1 \times r_2)$$

Definition2.6. A linguistic variable is a variable whose values are either words or sentences in a natural language [24].

TABLE 1. The Fuzzy linguistic scale

Linguistic terms	Linguistic values
Very Low	(0, 0, 0.25)
Low	(0, 0.25, 0.50)
Medium	(0.25, 0.50, 0.75)
High	(0.50, 0.75, 1)
Very High	(0.75, 1, 1)

Experts provide their view/opinion in the form of linguistic variables when they are lack in clear information about the problem. Therefore, the uncertain linguistic variables can be used as input parameters in the decision making techniques. Linguistic values are assigned by the fuzzy numbers for the linguistic variables.

THE PROPOSED FUZZY DECISION MAKING SYSTEM

This present study integrates the salient features of FCM and TOPSIS technique to bring it out the new hybrid technique Scenario FCM-TOPSIS through triangular fuzzy number. This technique consists of the following four stages.

Initial Fuzzification Process:

- Let $R = \{R_1, R_2, R_3, ..., R_n\}$ be a finite set of input variables for the system and classify R into linguistic term.
- Develop the membership function for each linguistic term.

FCM Process:

(i) Set up the initial linguistic uncertain direct-relation matrix.

- Let $R=\{R_1,R_2,R_3,...,R_n\}$ be a finite set of attributes and $E=\{E_1,E_2,E_3,...,E_k\}$ be the finite set of experts. Then, Experts are solicited to provide their judgments from the linguistic set *S*={*V.Low, Low, Medium, High, V.High* } for the relationship among the attributes.
- The relation matrices $D_k=[a_{kij}]_{n\times n}$ are formed from the FCM for the attributes $R=\{R_1,R_2,R_3,...,R_n\}$, where a_{kij} - causality connection weight between *i* and *j* based on *k*th expert view.

(ii) Transform the initial linguistic uncertain relation matrix $\hat{Z}_k=[\hat{z}_{kij}]_{n\times n}$ into triangular fuzzy matrix $\hat{Z}_k=[\hat{z}_{kij}]_{n\times n}$ using the triangular linguistic scale (Table-1).

(iii) Obtain the crisp direct-relation matrix $D_i,(i=1,2,\dots,m)$ through the CFCS algorithm [16].

Let $A_{ij}=(l_{ij}^k,m_{ij}^k,r_{ij}^k)$ be the degree of criteria *i* affects criteria *j*.

- Normalization

$$yr_{ij}^k=(r_{ij}^k-\min l_{ij}^k)\big/\Delta_{\min}^{\max}$$
$$ym_{ij}^k=(m_{ij}^k-\min l_{ij}^k)\big/\Delta_{\min}^{\max}$$
$$yl_{ij}^k=(l_{ij}^k-\min l_{ij}^k)\big/\Delta_{\min}^{\max}$$

Where $\Delta_{\min}^{\max}=\max r_{ij}^k-\min l_{ij}^k$

- Determine both the right and left side normalized values as follows:

$$yrs_{ij}^k=yr_{ij}^k\big/(1+yr_{ij}^k-ym_{ij}^k)$$
$$yls_{ij}^k=ym_{ij}^k\big/(1+ym_{ij}^k-yl_{ij}^k)$$

- Compute total normalizes crisp values:

$$y_{ij}^k=[yls_{ij}^k(1-yls_{ij}^k)+yrs_{ij}^k\times yrs_{ij}^k]\big/[1-yls_{ij}^k+yrs_{ij}^k]$$

- Compute crisp values:

$$x_{ij}^k=\min l_{ij}^k+y_{ij}^k\times\Delta_{\min}^{\max}$$

(iv) Construct the overall relation matrix $\tilde{F}=[\tilde{f}_{ij}]_{n\times n}$ using $[f_{ij}^1]_{n\times n}=D(I-D)^{-1},\ i,j=1,2,...,n$

Scenario Process:

(i) Take the different scenarios $S_i=\{S_1,S_2,S_3,...,S_n\}$ which are taken as the input vector and passed through the dynamical system $\tilde{F}$ for identifying hidden pattern of the system using the Sigmoid function $g(t)=1/(1+e^{-\lambda t})$, where $\lambda=5$.

(ii) The hidden pattern of the all scenario formed as matrix by $\tilde{H}=[h_{ij}]_{m\times n}$

By taking scenario output as rows formulate matrix with n columns and m rows.

(iii) Normalize the matrix $N(\tilde{H})=[h_{ij}]_{m\times n}$

TOPSIS Process:

TOPSIS method aids to rank the scenario of FCM,

(i) Calculate the initial weight $\tilde{w}_i$ of attribute C_i.

(ii) Determine the weighted normalized decision matrix $\tilde{R}=[\tilde{r}_{ij}]_{m\times n}$

(iii) Calculate the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) of $N(\tilde{H})$.

(iv) Calculate the distance of every alternative from A^+ (FPIS), and A^- (FNIS), respectively.

The distance of each alternative from A^{+} and A^{-} is given by

$$d_i^{+} = \sum_{j=1}^{n} d(\tilde{u}_{ij}, \tilde{u}_j^{+}),\ i = 1,2,...,m$$

$$d_i^{-} = \sum_{j=1}^{n} d(\tilde{u}_{ij}, \tilde{u}_j^{-}),\ i = 1,2,...,m$$

where $d(\tilde{A}, \tilde{B}) = \sqrt{(a-b)^2}$

(v) Calculate the closeness coefficient for each alternative.

$$Closeness\ Coefficient = CC_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}},\ i = 1,2,...,m$$

(vi) From the closeness coefficient value, the ranking is determined for all the alternatives.

ADAPTATION OF THE PROBLEM TO THE PROPOSED METHODOLOGY

T2DM considers not only a medical problem but also a social problem. The WHO reveals that 80% of diabetes death occur in the developing countries and predicts that such death will be doubled between 2016 and 2030 (WHO, 2018) [23]. It is also one of the most alarming diseases in both developed and developing countries. It is really a concern that the most of the people living in India are not aware that they are affected by T2DM. So, the undiagnosed T2DM leads to the complication in Neuropathy (Feet Disease), Retinopathy (Eye Disease), Nephropathy (Kidney Disease), and Cardiovascular (Heart Disease). Since Type 2 diabetes has many risk factors associated to it, this present study examines for determining the most influencing risk factors of T2DM through the proposed decision making system.

- **Initial Fuzzification:** The following risk factors of T2DM are identified RF_1-High blood glucose, RF_2-High Systolic blood pressure / RF_3-High Diastolic blood pressure, RF_4-High blood cholesterol, RF_5-Obesity, RF_6-Blindness, RF_7-Physical Inactivity, RF_8-Family history. Here, all the factors are classified into linguistic term using the available information and with the help of the medical practitioners and the suitable membership functions are defined for all the linguistic terms.

RF_1-Blood Glucose:
High blood glucose level in blood happens when either the pancreas does not produce enough insulin or the body resists insulin. It leads to the problem of heart, kidney and eye.

TABLE 2. Classification of Blood Glucose

Input	Range	Fuzzy Sets
	Below 70 mg dl	Low
Blood Glucose	(65-125) mg/dl	Ideal
	Above 130 mg/dl	High

$$\mu_{Low}(t) = \begin{cases} 1 & t \le 65 \\ \left(\dfrac{70-t}{5}\right) & 65 \le t \le 70 \\ 0 & t \ge 70 \end{cases}$$

$$\mu_{Ideal}(t) = \begin{cases} \left(\dfrac{t-65}{20}\right) & 65 \le t \le 85 \\ 1 & 85 \le t \le 105 \\ \left(\dfrac{125-t}{20}\right) & 105 \le t \le 125 \\ 0 & t \le 65\ \&\ t \ge 125 \end{cases}$$

$$\mu_{High}(t) = \begin{cases} 0 & t \le 110 \\ \left(\dfrac{t-110}{20}\right) & 110 \le t \le 130 \\ 1 & t \ge 130 \end{cases}$$

RF_2- High Systolic Blood Pressure

It refers to high pressure level for both systolic and diastolic. It can cause hardening and threatening of the arteries, which can lead to a heart attack, stroke.

TABLE 3. Classification of High Systolic Blood Pressure

Input	Range	Fuzzy Sets
Blood Pressure	Below 90	Low
	85-120	Ideal
	115-135	Near Ideal
	Above 130	High

$$\mu_{Low}(t)=\begin{cases}1 & t\le 85\\ \left(\dfrac{90-t}{5}\right) & 85\le t\le 90\\ 0 & t\ge 90\end{cases}\qquad \mu_{Ideal}(t)=\begin{cases}\left(\dfrac{t-85}{10}\right) & 85\le t\le 95\\ 1 & 95\le t\le 110\\ \left(\dfrac{120-t}{10}\right) & 110\le t\le 120\\ 0 & t\le 85 \,\&\, t\ge 120\end{cases}$$

$$\mu_{NearIdeal}(t)=\begin{cases}\left(\dfrac{t-115}{10}\right) & 115\le t\le 125\\ 1 & 125\le t\le 130\\ \left(\dfrac{135-t}{5}\right) & 130\le t\le 135\\ 0 & t\le 115 \,\&\, t\ge 135\end{cases}\qquad \mu_{High}(t)=\begin{cases}0 & t\le 125\\ \left(\dfrac{t-125}{5}\right) & 125\le t\le 130\\ 1 & t\ge 130\end{cases},$$

RF_3-High Diastolic Blood Pressure

TABLE 4. Classification of High Diastolic Blood Pressure

Input	Range	Fuzzy Sets
Diastolic Blood Pressure	Below 60	Low
	(55-85) mm Hg	Ideal
	(80-95) mm Hg	Near Ideal
	Above 90	High

$$\mu_{Low}(t)=\begin{cases}1 & t\le 55\\ \left(\dfrac{60-t}{5}\right) & 55\le t\le 60\\ 0 & t\ge 60\end{cases},\qquad \mu_{Ideal}(t)=\begin{cases}\left(\dfrac{t-55}{10}\right) & 55\le t\le 65\\ 1 & 65\le t\le 75\\ \left(\dfrac{85-t}{10}\right) & 75\le t\le 85\\ 0 & t\le 55 \,\&\, t\ge 85\end{cases}$$

$$\mu_{NearIdeal}(t)=\begin{cases}\left(\dfrac{t-80}{5}\right) & 80\le t\le 85\\ 1 & 85\le t\le 90\\ \left(\dfrac{90-t}{5}\right) & 90\le t\le 95\\ 0 & t\le 80 \,\&\, t\ge 95\end{cases}\qquad \mu_{High}(t)=\begin{cases}0 & t\le 85\\ \left(\dfrac{t-85}{5}\right) & 85\le t\le 90\\ 1 & t\ge 90\end{cases}$$

RF_4-Blood Cholesterol:

High amounts of cholesterol in the blood. It is one of the major risk factors for heart problem.

TABLE 5. Classification of Blood Cholesterol

Input	Range	Fuzzy Sets
Blood	Below 200 mg / dL	Ideal
Cholesterol	(200 to 235) mg / dL	Borderline High
	Above 230 mg / dL	High

$$\mu_{Ideal}(t)=\begin{cases}1 & t\le 195\\ \left(\frac{200-t}{5}\right) & 195\le t\le 200\\ 0 & t\ge 200\end{cases}\qquad \mu_{BorderLineHigh}(t)=\begin{cases}\left(\frac{t-200}{15}\right) & 200\le t\le 215\\ 1 & 215\le t\le 220\\ \left(\frac{235-t}{15}\right) & 220\le t\le 235\\ 0 & t\le 200\,\&\,t\ge 235\end{cases}\qquad \mu_{High}(t)=\begin{cases}0 & t\le 225\\ \left(\frac{t-225}{5}\right) & 225\le t\le 230\\ 1 & t\ge 230\end{cases}$$

RF$_5$-Obesity:
Obesity is a complex disorder which involves an excessive amount of fat accumulated in the body which is not burnt off. This condition leads to serious health problems, such as T2DM, heart disease and even cancer.

TABLE 6. Classification of Obesity

Input	Fuzzy Sets	Range
	Normal Weight	18-24
obesity	Overweight	24-28
	Obesity	26-32

$$\mu_{NORMALWEIGHT}(t)=\begin{cases}\left(\frac{t-18}{2}\right) & 18\le t\le 20\\ 1 & 20\le t\le 22\\ \left(\frac{24-t}{2}\right) & 22\le t\le 24\\ 0 & t\le 18\,\&\,t\ge 24\end{cases},\qquad \mu_{OVERWEIGHT}(t)=\begin{cases}\left(\frac{t-22}{2}\right) & 22\le t\le 24\\ 1 & 24\le t\le 26\\ \left(\frac{28-t}{2}\right) & 26\le t\le 28\\ 0 & t\le 22\,\&\,t\ge 28\end{cases}\qquad \mu_{OBESIITY}(t)=\begin{cases}\left(\frac{t-26}{2}\right) & 26\le t\le 28\\ 1 & 28\le t\le 30\\ \left(\frac{32-t}{2}\right) & 30\le t\le 32\\ 0 & t\le 26\,\&\,t\ge 32\end{cases},$$

RF$_6$-Blindness It is caused by the damage in the small blood vessels in the retina and it may lead to eye problem.

TABLE 7. Classification of Blindness

Input	Range	Fuzzy Sets
	Below 2	Blurred
Blindness	1-4	Very blurred
	3-5	Blindness

$$\mu_{Blurred}(t)=\begin{cases}1 & t\le 1\\ \left(\frac{2-t}{1}\right) & 1\le t\le 2\\ 0 & t\ge 2\end{cases}\qquad \mu_{Very\ Blurred}(t)=\begin{cases}\left(\frac{t-1}{1}\right) & 1\le t\le 2\\ \left(\frac{4-t}{2}\right) & 2\le t\le 4\\ 0 & t\le 2\,\&\,t\ge 4\end{cases}\qquad \mu_{Blindness}(t)=\begin{cases}0 & t\le 3\\ \left(\frac{t-3}{1}\right) & 3\le t\le 4\\ 1 & t\ge 4\end{cases}$$

RF_7-Physical Inactivity: An individual to spend 30 minutes brisk walking per day in a week otherwise it will lead to T2DM, heart problem

TABLE 8. Classification of Physical Inactivity

Input	Range	Fuzzy Sets
Physical Inactivity	Below 20 Minutes	Low Effective
	(15 – 55) Minutes	Ideal Effective
	Above 50 Minutes	Enormously Effective

$$\mu_{L.Effective}(t)=\begin{cases}1 & t\le 15\\ \left(\dfrac{20-t}{5}\right) & 15\le t\le 20\\ 0 & t\ge 20\end{cases}\quad \mu_{IdealEffective}(t)=\begin{cases}\left(\dfrac{t-15}{10}\right) & 15\le t\le 25\\ 1 & 25\le t\le 35\\ \left(\dfrac{55-t}{10}\right) & 35\le t\le 55\\ 0 & t\le 15\,\&\,t\ge 55\end{cases}\quad \mu_{Eno\_Effective}(t)=\begin{cases}0 & t\le 45\\ \left(\dfrac{t-45}{5}\right) & 45\le t\le 50\\ 1 & t\ge 50\end{cases}$$

RF_8-Family History:

$$\mu_{yes}(t)=\begin{cases}1, \mathit{if\ Victims\ of\ T2DM}\\ 0\end{cases}$$

- **FCM Process**

The linguistic direct relational matrix (Table-9) is designed by forming the relationship between the risk factors of T2DM with aid of medical practitioner from the linguistic set S={*V.Low, Low, Medium, High, V.High* } .

TABLE 9. Linguistic direct relational matrix

	RF_1	RF_2	RF_3	RF_4	RF_5	RF_6	RF_7	RF_8
RF_1	VL	H	H	M	L	H	L	H
RF_2	H	VL	H	L	VL	H	M	L
RF_3	H	VH	VL	L	VL	H	M	L
RF_4	VH	H	H	VL	H	M	H	VL
RF_5	VH	M	L	H	VL	L	VH	VL
RF_6	L	VL	M	VL	M	VL	VL	M
RF_7	H	M	VL	H	VH	VL	VL	VL
RF_8	M	L	L	VL	H	M	VL	VL

Next, linguistic direct relational matrix (Table-9) transformed into triangular fuzzy number using the triangular linguistic scale and then triangular fuzzy matrix changed into crisp value direct-relation matrix (Table-10) using CFCS method.

TABLE 10. Crisp value direct-relation matrix *D*

	RF_1	RF_2	RF_3	RF_4	RF_5	RF_6	RF_7	RF_8
RF_1	0	0.73	0.73	0.51	0.26	0.73	0.26	0.73
RF_2	0.73	0	0.73	0.26	0.037	0.73	0.51	0.26
RF_3	0.73	0.97	0	0.26	0.037	0.73	0.51	0.26
RF_4	0.97	0.73	0.73	0	0.73	0.51	0.73	0.037
RF_5	0.97	0.51	0.26	0.73	0	0.26	0.97	0.037
RF_6	0.26	0.037	0.51	0.037	0.51	0	0.037	0.51
RF_7	0.73	0.51	0.037	0.73	0.97	0.037	0	0.037
RF_8	0.51	0.26	0.26	0.037	0.73	0.51	0.037	0

After obtaining the crisp valued direct-relation matrix, the total relation matrix is designed using $D(I-D)^{-1}$.

TABLE 11. Overall relation matrix $\tilde{F} = [\tilde{f}_{ij}]_{n\times n}$

	RF$_1$	**RF$_2$**	**RF$_3$**	**RF$_4$**	**RF$_5$**	**RF$_6$**	**RF$_7$**	**RF$_8$**
RF$_1$	-0.649	-0.136	0.014	-0.252	-0.214	0.093	-0.350	0.241
RF$_2$	-0.167	-0.469	0.077	-0.274	-0.285	0.142	-0.201	0.081
RF$_3$	-0.190	0.027	-0.334	-0.312	-0.325	0.162	-0.229	0.092
RF$_4$	-0.221	-0.164	-0.213	-0.394	-0.187	-0.408	-0.021	-0.452
RF$_5$	-0.145	-0.229	-0.478	0.216	-0.491	-0.678	0.206	-0.601
RF$_6$	-0.158	-0.250	-0.021	-0.184	0.099	-0.309	-0.187	0.156
RF$_7$	-0.149	-0.187	-0.552	0.303	0.053	-0.786	-0.197	-0.659
RF$_8$	-0.115	-0.232	-0.187	-0.183	0.149	-0.061	-0.207	-0.233

- **Scenario Process:**

Five different scenarios $\{S_1,S_2,S_3,S_4,S_5\}$ of the risk factors are taken as the input values and then find suitable membership values for the scenario from the defined membership function at initial fuzzification process. Then, while the inputs $\{A_1, A_2, A_3, A_4, A_5\}$ are passing into the dynamical system (Overall relation matrix is treated as the dynamical system), the following outputs are obtained. With the output of the scenarios, the scenario matrix is formed (Table-), in which rows are considered to be the scenarios and columns are treated as risk factors. Then, the normalized matrix is derived from the Scenario matrix.

S_1= {(R_1, 60), (R_2, 80), (R_3, 50), (R_4, 100), (R_5, 19), (R_6, 1.5), (R_7, 17), (R_8, Yes)}
A_1= {1, 1, 1, 1, 0.5, 0.5, 0.6, 1}.
S_2= {(R_1, 100), (R_2, 80), (R_3, 63), (R_4, 232), (R_5, 23), (R_6, 3), (R_7, 30), (R_8, No)}
A_2= {1, 0.4, 0.8, 1, 0.5, 0.5, 1, 0}.
S_3= {(R_1, 130), (R_2, 85), (R_3, 60), (R_4, 230), (R_5, 25), (R_6, 4), (R_7, 10), (R_8, Yes)}
A_3= {1, 1, 0.5, 1, 1, 1, 1, 1}.
S_4= {(R_1, 120), (R_2, 90), (R_3, 70), (R_4, 220), (R_5, 27), (R_6, 2), (R_7, 15), (R_8, No)}
A_4= {0.5, 0.5, 1, 1, 0.5, 1, 0, 1}.
S_5= {(R_1, 80), (R_2, 80), (R_3, 65), (R_4, 150), (R_5, 19), (R_6, 3), (R_7, 20), (R_8, Yes)}
A_5= {0.75, 1, 1, 1, 1, 0.5, 0.5, 1}.

TABLE 12. Scenario matrix

	RF$_1$	**RF$_2$**	**RF$_3$**	**RF$_4$**	**RF$_5$**	**RF$_6$**	**RF$_7$**	**RF$_8$**
S$_1$	0.170	0.210	0.227	0.228	0.264	0.262	0.247	0.291
S$_2$	0.199	0.291	0.225	0.335	0.285	0.196	0.305	0.271
S$_3$	0.154	0.161	0.178	0.284	0.261	0.127	0.255	0.194
S$_4$	0.232	0.271	0.212	0.323	0.298	0.173	0.309	0.268
S$_5$	0.186	0.200	0.196	0.254	0.227	0.211	0.288	0.234

TABLE 13. The fuzzy normalized decision matrix

	RF$_1$	**RF$_2$**	**RF$_3$**	**RF$_4$**	**RF$_5$**	**RF$_6$**	**RF$_7$**	**RF$_8$**
S$_1$	0.401	0.406	0.487	0.355	0.440	0.589	0.391	0.512
S$_2$	0.469	0.562	0.482	0.521	0.476	0.442	0.485	0.478
S$_3$	0.363	0.311	0.383	0.442	0.436	0.286	0.405	0.342
S$_4$	0.545	0.523	0.454	0.502	0.497	0.390	0.490	0.472
S$_5$	0.437	0.386	0.421	0.395	0.379	0.474	0.456	0.412

- **TOPSIS Process:**

Next, all the risk factors are assigned weights. Then, the fuzzy weighted normalized matrix (Table-14) is obtained by multiplying scenario matrix with weights of the risk factors. Finally closeness coefficients are obtained. Based on the closeness coefficient, the ranking of risk factors are derived.

weight	0.100	0.200	0.150	0.180	0.090	0.090	0.090	0.100

TABLE 14. The fuzzy weighted normalized decision matrix

	RF_1	RF_2	RF_3	RF_4	RF_5	RF_6	RF_7	RF_8
S_1	0.040	0.081	0.073	0.064	0.040	0.053	0.035	0.051
S_2	0.047	0.112	0.072	0.094	0.043	0.040	0.044	0.048
S_3	0.036	0.062	0.057	0.080	0.039	0.026	0.036	0.034
S_4	0.054	0.105	0.068	0.090	0.045	0.035	0.044	0.047
S_5	0.044	0.077	0.063	0.071	0.034	0.043	0.041	0.041

TABLE 15. Closeness Coefficient

	RF_1	RF_2	RF_3	RF_4	RF_5	RF_6	RF_7	RF_8
d^+	1.96658	1.75042	1.85392	1.78948	1.98760	1.99181	1.98760	1.96644
d^-	0.75961	0.54345	0.64695	0.58251	0.78063	0.78484	0.78063	0.75947
$CC_i = \frac{d^-}{d^+ + d^-}$	0.27863	0.23691	0.25869	0.24558	0.28200	0.28266	0.28200	0.27861
Rank	4	8	6	7	2	1	3	5

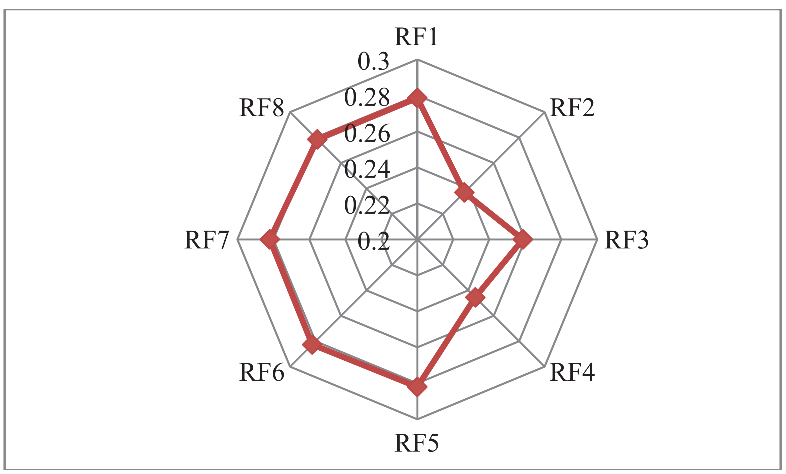

FIGURE 2. Closeness Coefficient

According to the closeness coefficient, the following ranks for risk factors are obtained **RF_6> RF_5> RF_7> RF_1> RF_8> RF_3> RF_4> RF_2.** Blindness, Obesity, Physical Inactivity are the most influencing factors for the type 2 diabetes mellitus.

CONCLUSION

This present study designed a novel decision making system by integrating the salient feature of TOPSIS and FCM. This proposed method illustrated in identifying the most influencing risk factors of T2DM. From this investigation, it is identified that the Blindness, Obesity and Physical activity are the most influencing risk factors of T2DM. Hence, the chances of developing T2DM are depending on a combination of risk factors such as genetic and lifestyle. Even though the risk factor related to gene such as family history and ethnicity cannot be changed, the factors related to lifestyle such as physical activity and obesity can be changed. The chances of developing T2DM will be reduced when adapting to the healthier lifestyle. The further research can be done in designing the hybrid models by integrating the salient features of DEMATEL-TOPSIS-VIKOR-FCM.

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