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A novel approach to determining change of caloric intake requirement based on fuzzy logic methodology

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ABSTRACT

Obesity is a global epidemic. Decisions related to the consumption of high calorific food are critical because many serious health risks are associated with being overweight and obesity. This article presents a novel approach to determining the caloric intake requirement using fuzzy logic principles. The proposed fuzzy methodology effectively deals with the fuzziness of the data and subjective judgments of the person's level of physical activity, body mass index and age. The method of converting the crisp inputs to fuzzy sets, rule firing and defuzzifying the outputs of the fuzzy inference engine to a linguistic value, is illustrated with an example. The proposed methodology is important in practical terms in responding to dynamic life and work styles and related factors in today's society.

1. Introduction

Obesity is a widely concerned critical health issue globally. According to the World Health Organization [1], at least 2.8 million adults die each year as a result of being overweight or obese. In many countries, being overweight and obesity kill more people than being underweight. Obesity is now not only a health issue in the majority of developed countries, it is also a serious threat for a majority of low and middle income countries. The health risks of obesity are reflected in the common diseases it causes. Globally, 44% of diabetes, 23% of ischaemic heart disease and 7–41% of certain cancers are attributable to being overweight and obesity [1].

This article explores the application of fuzzy logic approach to determining energy intake requirements and takes into consideration the level of physical activity, age and body mass index. Clearly important factors in this are the changing nature of work, new technologies that make work itself less mobile requiring less physical effort, and changing modes of transport that require less energy intake, all of which affect the body's ability to control excessive fat accumulation. Such adaptation is quite dynamic. Fuzzy systems represent imprecise human knowledge in a logical way and do not seek precise statements [2]. Fuzzy systems rely on experts' knowledge and enable the expression of fuzzy 'inputs' in linguistic terms. They can be used effectively when some data are difficult to measure accurately or difficult to quantify numerically, for example, level of physical activity as a 'decision input'.

This paper is organized as follows: Section 2 provides the background by briefly reviewing the critical issues of obesity and goes on to review the application of a fuzzy logic approach in current health research literature. The fuzzy logic framework is developed in Section 3. Section 4 identifies the relevant decision variables of body mass index, physical activeness and age in the decision making process and presents the fuzzy logic methodology. It includes testing the fuzzy logic framework using a real data follows. Section 5 concludes with a discussion of limitations of the present study and suggestions for further study.

2. Background

The World Health Organization (WHO) reports that globally, about one billion adults are overweight and more than 300 million are obese [1]. According to the national health survey (2004–2005) in Australia, 42.1% of adult males and 30.9% of adult females were classified as overweight and 25.6% of males and 24% of females were classified as obese [3]. This obesity epidemic is not prevalent only in high income countries but is now also common in low- and middle-income countries [3].

There is much research that investigates the contributing factors of obesity. It has been argued that neither human genotype nor the energy and fat intake has changed substantially over the past two to three decades [4]. What has changed over the years

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is the lifestyle of people. They suggest that the decreasing level of physical activity or the level of energy expenditure is one of the major factors of the obesity issue. Energy intake needs to be modified to avoid health concerns. A high carbohydrate intake has been identified as producing adverse effects on lipid and glucose metabolism increasing the risk of cardiovascular diseases [5]. Such adverse effects related to carbohydrate intake are common in obesity. In other words, those who have high BMI are more vulnerable to the risk of stroke, diabetes, colon cancer, breast cancer [6,1].

The proposed model is based on fuzzy logic principles. A significant advantage of fuzzy expert systems is that the experts' knowledge is translated into rules in a language that can be understood and communicated easily [7]. The primary source of knowledge for fuzzy systems is individual experts who are familiar with the situation and know the answers to the why, what, when, where and how questions and contribute to designing the rules in the fuzzy system. In order to accommodate industry dynamics, these rules can be modified in the fuzzy reference engine design. Fuzzy logic has been used in areas as diverse as process industry, biotechnology, manufacturing, electro-mechanical systems, traffic control, avionics and biomedical systems [8–11]. However, the adoption of fuzzy logic principles in the field of health currently remains limited in the literature. Some extant literature presents the adoptability of fuzzy logic principles in breast cancer diagnosis to detect microcalcifications in very dense breast mammograms [12]; in monitoring home-based elderly people through recognizing activities by using physiological sensors; microphones, infrared sensors, debit sensors and state-change sensors [13]; for mimicry of doctors reasoning for screening adult psychosis [14]; for initial assessment of AIDs through case based reasoning [15] and also for issuing prescriptions by medical practitioners [16]. There is an opportunity to extend the application of fuzzy logic with regard to decision making around individual health sustenance that deals with fuzzy inputs in the form of imprecise and imperfect data.

3. Development of Fuzzy Integrated Framework (FIF)

In this paper, we propose a framework to assist decision making about carbohydrate intake requirements by an individual. The proposed framework integrates three input variables forming multiple decision criteria. The use of fuzzy logic principles enables the quantifying of subjective judgments of different decision criteria as interval judgments and handles the uncertainties in the decision-making process. It is based on the FIF (Fig. 1) proposed by Lau and Dwight [17] which consisted of the core fuzzy system including three stages of fuzzification, inference engine and defuzzification and the preceding stages of situation analysis, data collection, and knowledge acquisition which feed comprehensive input data into the fuzzy system.

3.1. Fuzzy logic methodology

The first stage of situation analysis seeks to match the situation with the design of the fuzzy system. Consequently, a good understanding of the situation and the context is important and a rigorous analysis of the problem is needed in order to identify the data input requirements to build a comprehensive and meaningful design of the fuzzy system. The subjective judgments of the variables form the set of linguistic values in the fuzzy system. The raw data is collected as deterministic values known as crisp values (or range of values) [18] to build the input data set. Both the size of data for a comprehensive analysis and right format of data, compatible with the fuzzy system, are important at this stage [17].

The fuzzy system is rule-based and rules are set by the domain experts who know how to respond to situations from their experience in similar situations. The knowledge acquisition stage involves obtaining this knowledge and developing explicit rules in the form of If-Then statements that are easily communicable and verifiable with multiple experts due to their linguistic nature. However, challenges arise due to the inconsistency and incompleteness of the expert knowledge and need to be managed. Methodologies for such knowledge acquisition from expert groups are discussed in the literature [19]. These rules convert the implicit knowledge using, in this case, the practitioners in the supply chain environment, and build a block of rules that determine the decision outputs.

3.1.1. Fuzzification

The first stage of the core fuzzy system is fuzzification to build fuzzy sets. This involves the conversion of crisp values to fuzzy values such as good, acceptable and unacceptable. A fuzzy set is characterized by a membership function; the numerical range of input data values is the universe of discourse and the membership function assigns a grade of membership ranging from 0 to 1 for each data set. As explained by Lau and Dwight [17], the fuzzy subset of A can be mathematically expressed as below where X is the whole data set and x is the element of subset A, $\mu_A(x_i)$ is the membership function of element x_i in the universe of discourse when the support set is a finite set, $X = \{x_1, x_2, x_3, x_4, \ldots, x_n\}$.

$$A = \sum_{i-1}^{n} \mu_A(x_i)/x_i \tag{1}$$

In the FIF model, the universe of discourse is categorized into several regions which belong to different predicate functions: significantly low (SL), relatively low (RL), neutral (N), relatively high (RH) and significantly high (SH). These predicate functions determine the fuzzy values and build the fuzzy sets. As shown in Fig. 2, these predicate functions take triangular or trapezoidal shapes.

The input fuzzy set comprises several membership values from different fuzzy inputs. The expression of membership value is shown below.

$$\mu_a = \mu_k(x)|_{x=a} = b \tag{2}$$

where a and b are real numbers, representing crisp input data and membership value respectively, $\mu_k(x)$ is the fuzzy set.

These values are the intersection of the two equations represented by the crisp input data and the function of predicate. The intersection point (x_1, y_1) shown in Fig. 3 gives the membership value relative given by the y-coordinate to the crisp input data of x-coordinate. In some cases, the crisp input equation intersects two different equations belonging to different predicate functions that can generate two membership values, such as y_1 and y_2 as shown in Fig. 4.

Age is a significant variable of caloric intake requirements and with the advancing age, the requirement of energy declines with increasing age for normally nourished adults [20]. Obesity is closely related with body mass index [1] which is an indicator of healthiness of weight relative to height. It is calculated by dividing the weight in kilograms by height in meters squared (kg/m^2). In recent times, physical inactivity is considered a major cause of obesity and chronic diseases and conditions. Irrespective of standard recommendations, the level of physical activeness needs to be adjusted according to the body weight and caloric intake on individual basis in order to prevent unhealthy weight gains [21]. Based on the effects on obesity, the three variables of age, physical activeness and body mass index are significant variables in determining the caloric requirements. Consequently, in decision-making about the required caloric intake, there are three fundamental Inputs taken into consideration: the level of physical activeness (P), age (A), body mass index (B).

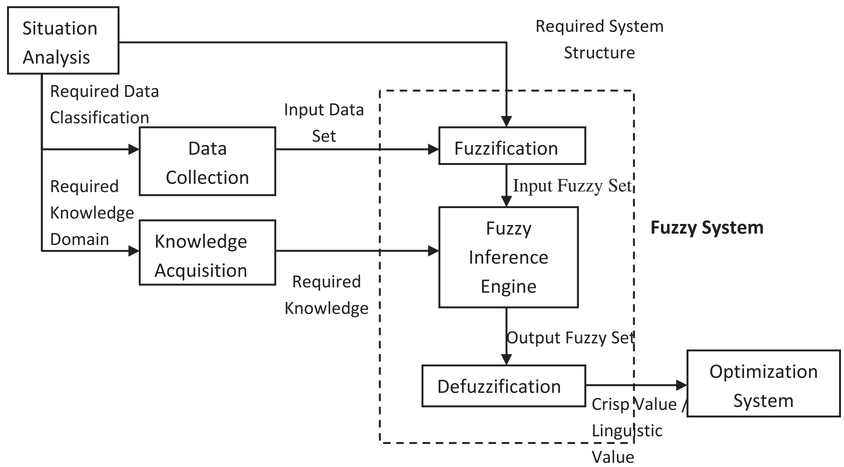


Fig. 1. A schematic diagram of the fuzzy system [17].

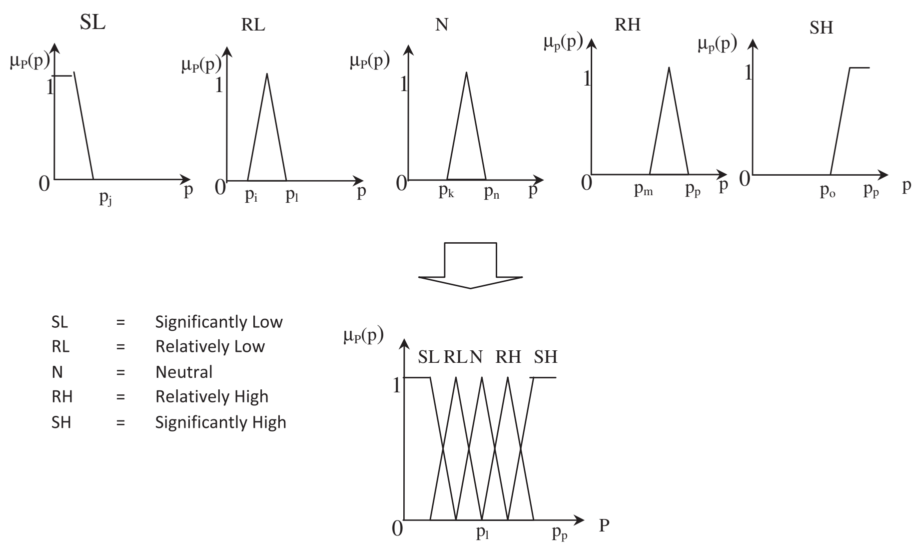


Fig. 2. The composition of fuzzy set of the decision variable of physical activeness, *P*.

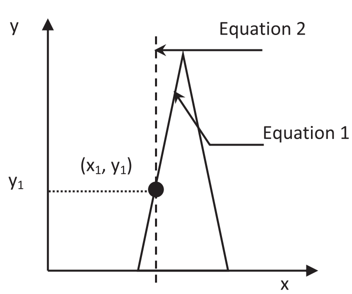


Fig. 3. The intersection with a fuzzy set.

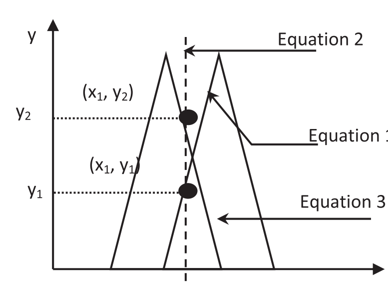


Fig. 4. The two intersection points of the fuzzy sets.

The WHO [1] defines the normal range of body mass index as 18.5–24.9 and these limits are the same for both sexes. These limits have been contested by health researchers: the body mass index limits defined by the WHO need to be adjusted based on ethnic differences as suggested from the Asian perspective that the low prevalence of obesity but high prevalence of diabetes and hypertension at lower limits of body mass index [22] and also higher fat level at low BMI levels [23]. Another limitation with the body mass index is its general misclassification as the total body fat content where tallest and shortest subjects tend to be misclassified as obese or muscular athletes may have rated obese with high value of body mass index which is caused by the muscle weight not by the fat content [22]. However, for the scope of this study, the general limits of body mass index proposed by the WHO are used to develop the model. From fuzzy terms, the body mass index (B) is a fuzzy set with b_i denoting the elements in the data set and $\mu_B(b_i)$ the membership function as in Fig. 5; and B = {VL, SIL, SLL, N, SLH, SIH, VH} where VL = very low; SIL = significantly low; SLL = slightly

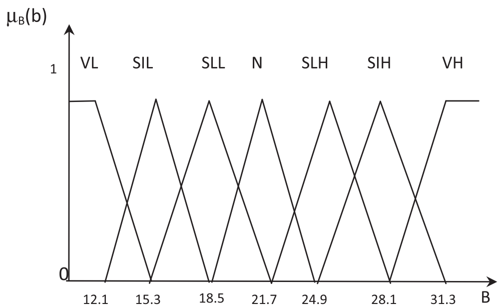


Fig. 5. The fuzzy set of μ_B(b).

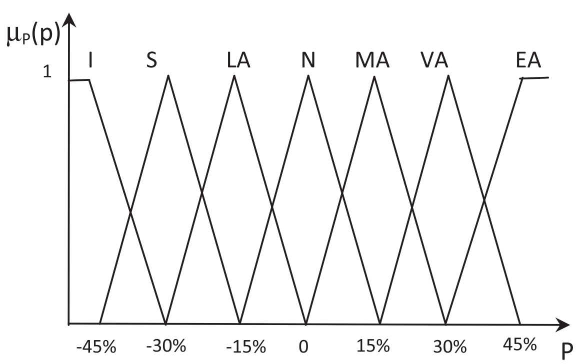


Fig. 6. The fuzzy set of μ_P(p).

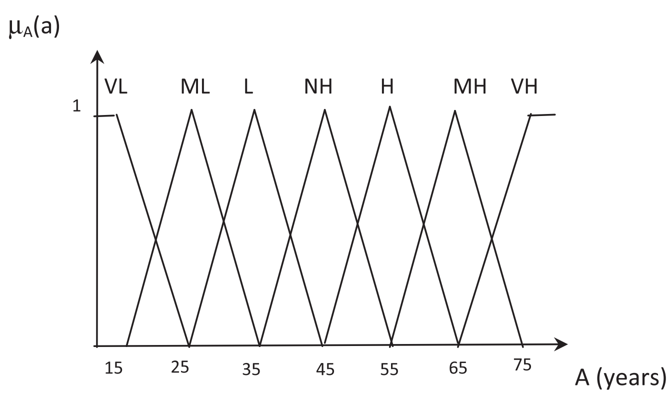


Fig. 7. The fuzzy set of μ_A(a).

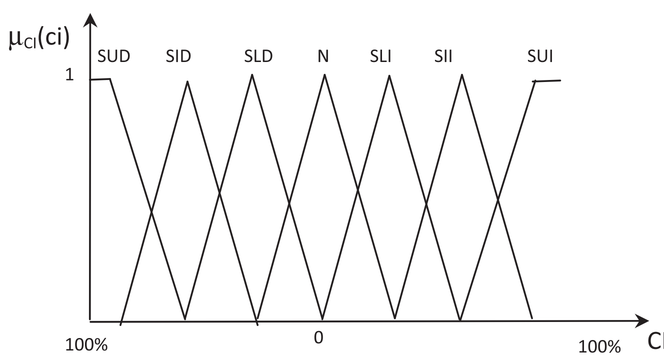


Fig. 8. The fuzzy set of μ_{CI}(ci).

low; N = neutral; SLH = slightly high; SIH = significantly high and VH = very high.

$$B = \sum_{i-1}^{n} \mu_B(b_i)/b_i \tag{3}$$

The level of physical activity is the sum of energy expenditure which is generally measured by the number of blocks walked, number of stairs climbed, recreation activities participated [24]. A person's actual expenditure of energy through the engagement of physical activities may be different from the recommended level of physical activity by a medical professional. Hence, the input variable of the level of physical activity (P) is measured as a percent of variation from the recommended value. It consists of a fuzzy set of P with p_i, the elements in the data set and $\mu_P(p_i)$ the membership function of P (Fig. 6) = {I, S, LA, N, MA, VA, EA} where I = inactive; S = sedentary; LA = lightly active; N = normally active; MA = moderately active; VA = very active; EA = extremely active.

$$P = \sum_{i-1}^{n} \mu_P(p_i)/p_i \tag{4}$$

The third input variable of age (A) is categorized relatively and the corresponding fuzzy set of A is characterized by its elements of a_i and the membership function of $\mu_A(a_i)$ (Fig. 7)

$$A = \sum_{i-1}^{n} \mu_A(a_i)/a_i \tag{5}$$

and A = {VL, ML, L, NH, H, MH, VH} where VL = very low; ML = moderately low; L = low; NH = not high; H = high; MH = moderately high and VH = very high.

The fuzzy output of change of caloric intake (CI) from the fuzzy inference engine consists of the fuzzy elements of ci_i and $\mu_{CI}(ci_i)$. The membership function of CI (Fig. 8) is:

$$\mathrm{CI} = \sum_{i-1}^{n} \mu_{CI}(ci_i)/ci_i \tag{6}$$

and CI = {SUD, SID, SLD, N, SLI, SII, SUI} where SUD = substantial decrease; SID = significant decrease; SLD = slight decrease; N = neutral; SLI = slight increase; SII = significant increase; SUI = substantial increase.

3.1.2. Fuzzy inference engine

The second stage of the core fuzzy system is the fuzzy inference engine. This engine processes the fuzzy sets of inputs and generates the fuzzy output through inference. This inference process includes rule block formation, rule composition, rule firing, implication and aggregation [17]. Rule blocks are the sets of if-then statements developed during the knowledge acquisition stage. Fig. 9 shows these rules three dimensionally for the three inputs conditions of age, BMI and the level of physical activity converted to fuzzy sets. This rule table was developed by integrating fuzzy logic expertise and nutritional expertise by considering general conditions irrespective of contextual characteristics or pre-existing health conditions of individual end users. These rules are not conclusive and used for the demonstration of the effective application of fuzzy logic approach in determining individual caloric requirements. For effective performance of the proposed model, multiple experts from the knowledge domain must be consulted and a consistent rule table must be developed, where the experts are in agreement. The challenge to this process is the need to overcome the differences of views and experiences that would lead to contradictory rule sets. The membership functions (relevant predicates for the crisp values of inputs) of the input fuzzy sets determine the applicable rules to be activated or fired. Only the selected rules (depending on the membership values) are fired and the results are then generated. There are several implication operators in use to do these implication calculations: whilst Mamdani Operator

CI	A-NH						
	B						
P	***VL***	***SIL***	***SLL***	***N***	***SLH***	***SIH***	***VH***
I	*SLI*	*SLI*	*SLI*	*N*	*SLD*	*SLD*	*SLD*
S	*SLI*	*SLI*	*SLI*	*N*	*SLD*	*SLD*	*SLD*
LA	*SLI*	*SLI*	*SLI*	*N*	*N*	*SLD*	*SLD*
N	*SLI*	*SLI*	*SLI*	*N*	*N*	*N*	*N*
MA	*SII*	*SII*	*SII*	*SII*	*SII*	*SII*	*SLI*
VA	*SUI*	*SII*	*SII*	*SII*	*SII*	*SII*	*SII*
EA	*SUI*	*SUI*	*SII*	*SII*	*SII*	*SII*	*SII*

	Age – {NH;H;MH;VH;L;ML;VL}
	BMI – {VL;SIL;SLL;N;SLH;SIH;VH}
Physical activity – {I;S;LA;N;MA;VA;EA}	Change of caloric intake - {SUD;SID;SLD;N;SLI;SII;SUI}

Legend

CI	A-H						
	B						
P	***VL***	***SIL***	***SLL***	***N***	***SLH***	***SIH***	***VH***
I	*SLI*	*SLI*	*N*	*N*	*SLD*	*SLD*	*SLD*
S	*SLI*	*SLI*	*SLI*	*N*	*SLD*	*SLD*	*SLD*
LA	*SLI*	*SLI*	*SLI*	*N*	*N*	*SLD*	*SLD*
N	*SLI*	*SLI*	*SLI*	*N*	*N*	*N*	*SLD*
MA	*SII*	*SII*	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*
VA	*SII*	*SII*	*SII*	*SII*	*SII*	*SLI*	*SLI*
EA	*SUI*	*SUI*	*SII*	*SII*	*SII*	*SII*	*SII*

CI	A- MH						
	B						
P	***VL***	***SIL***	***SLL***	***N***	***SLH***	***SIH***	***VH***
I	*SLI*	*SLI*	*N*	*N*	*SLD*	*SLD*	*SLD*
S	*SLI*	*SLI*	*N*	*N*	*SLD*	*SLD*	*SLD*
LA	*SLI*	*SLI*	*N*	*N*	*N*	*SLD*	*SLD*
N	*SLI*	*SLI*	*N*	*N*	*N*	*SLD*	*SLD*
MA	*SLI*	*SLI*	*SLI*	*N*	*N*	*SLD*	*SLD*
VA	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*	*SLD*	*SLD*
EA	*SII*	*SII*	*SLI*	*SLI*	*SLI*	*SLD*	*SLD*

	A-VH						
CI	B						
P	***VL***	***SIL***	***SLL***	***N***	***SLH***	***SIH***	***VH***
I	*SLI*	*N*	*N*	*N*	*SLD*	*SLD*	*SLD*
S	*SLI*	*N*	*N*	*N*	*SLD*	*SLD*	*SLD*
LA	*SLI*	*SLI*	*SLI*	*N*	*SLD*	*SLD*	*SID*
N	*SII*	*SII*	*SLI*	*N*	*SLD*	*SID*	*SID*
MA	-	-	-	-	-	-	-
VA	-	-	-	-	-	-	-
EA	-	-	-	-	-	-	-

CI	A-L						
	B						
P	***VL***	***SIL***	***SLL***	***N***	***SLH***	***SIH***	***VH***
I	*N*	*N*	*N*	*N*	*SLD*	*SLD*	*SLD*
S	*N*	*N*	*N*	*N*	*N*	*SLD*	*SLD*
LA	*N*	*N*	*N*	*N*	*N*	*N*	*SLD*
N	*SLI*	*N*	*N*	*N*	*N*	*N*	*SLD*
MA	*SLI*	*SLI*	*N*	*N*	*N*	*N*	*SLD*
VA	*SII*	*SII*	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*
EA	*SII*	*SII*	*SII*	*SII*	*SII*	*SII*	*SII*

CI	A- ML						
	B						
P	***VL***	***SIL***	***SLL***	***N***	***SLH***	***SIH***	***VH***
I	*SLI*	*SLI*	*N*	*N*	*N*	*SLD*	*SLD*
S	*SLI*	*SLI*	*N*	*N*	*N*	*SLD*	*SLD*
LA	*SLI*	*SLI*	*N*	*N*	*N*	*SLD*	*SLD*
N	*SLI*	*SLI*	*N*	*N*	*N*	*N*	*N*
MA	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*
VA	*SII*	*SII*	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*
EA	*SUI*	*SII*	*SII*	*SII*	*SII*	*SLI*	*SLI*

CI	A-VL						
	B						
P	***VL***	***SIL***	***SLL***	***N***	***SLH***	***SIH***	***VH***
I	*SLI*	*SLI*	*SLI*	*N*	*SLD*	*SLD*	*SLD*
S	*SLI*	*SLI*	*SLI*	*N*	*SLD*	*SLD*	*SLD*
LA	*SLI*	*SLI*	*SLI*	*N*	*SLD*	*SLD*	*SLD*
N	*SLI*	*SLI*	*SLI*	*N*	*N*	*N*	*N*
MA	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*	*SLI*
VA	*SII*	*SII*	*SII*	*SII*	*SLI*	*SLI*	*SLI*
EA	*SUI*	*SUI*	*SII*	*SII*	*SLI*	*SLI*	*SLI*

Fig. 9. The rule table for the fuzzy inference engine.

and Larsen Operator used by Union operator, Lukasiewicz Operator is used by Intersection operator. For a detailed discussion of these implication operators, see Lau and Dwight [17].

3.1.3. Defuzzification

Defuzzification is the inverse process of fuzzification. The fuzzy values are converted to crisp values or linguistic values. The most user-friendly and simple methods are Center of Area (COA) and Mean of Maximum possibilities (MOM) [17] and the application of the chosen COA method is illustrated in the calculations below.

4. Illustration of the application of the model

For anonymity, the target person of this study will be identified as X who is 38 years old with a BMI of 18. According to the advice of his medical practitioner, he needs to burn Y amount of calories per day. However, his daily routine and work related activities do not allow him engage in physical activity such as cycling, jogging, swimming resulting in an energy expenditure of 20% less than the recommended. In his scenario, the crisp values of the three input variables of age, BMI and the level of physical activity are A = 38 years; B = 18;

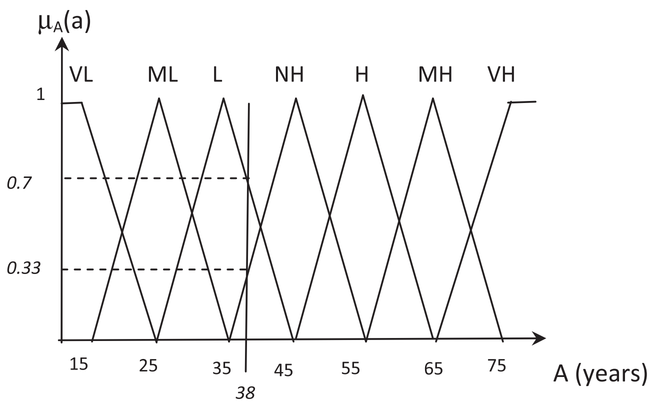


Fig. 10. Membership values for variable, *A*.

Table 1
Rule generation based on the membership values of A, B and P.

Applicable rule #	'If' clause	'Then' clause
1	If age is *not high* and BMI is *significantly low* and physical activeness is *less active*	Change of caloric requirement is slightly increase
2	If age is *not high*, BMI is *significantly low* and physical activeness is *sedentary*	Change of caloric requirement is slightly increase
3	If age is *not high*, BMI is *slightly low* and physical activeness is *less active*	Change of caloric requirement is slightly increase
4	If age is not high, BMI is slightly low and physical activeness is sedentary	Change of caloric requirement is slightly increase
5	If age is low, BMI is *significantly low* and physical activeness is *less active*	Change of caloric requirement is neutral
6	If age is low, BMI is *significantly low* and physical activeness is *sedentary*	Change of caloric requirement is neutral
7	If age is low, BMI is *slightly low* and physical activeness is *less active*	Change of caloric requirement is neutral
8	If age is low, BMI is *slightly low* and physical activeness is *sedentary*	Change of caloric requirement is neutral

Table 2
The composition results for the IF part of rules.

Rule	Composition result
Rule 1	(0.3 ^ 0.16 ^ 0.67) = 0.16
Rule 2	(0.3 ^ 0.16 ^ 0.33) = 0.16
Rule 3	(0.3 ^ 0.84 ^ 0.67) = 0.3
Rule 4	(0.3 ^ 0.84 ^ 0.33) = 0.3
Rule 5	(0.7 ^ 0.16 ^ 0.67) = 0.16
Rule 6	(0.7 ^ 0.16 ^ 0.33) = 0.16
Rule 7	(0.7 ^ 0.84 ^ 0.67) = 0.67
Rule 8	(0.7 ^ 0.84 ^ 0.33) = 0.33

and *P* = −20% respectively. These input values are fuzzified as shown in the following figures. The *A* variable cuts the *L* predicate at 0.7 and NH predicate at 0.3 as shown in Fig. 10. Similarly, the membership values of *B* and *P* variables are generated – *B* cuts the SIL predicate at 0.16 and SLL predicate at 0.84 and the *P* variable cuts the LA predicate at 0.67 and *S* predicate at 0.33.

Based on the membership values of the three variables, eight rules can be generated as shown in Table 1 from the fuzzy rules sets in Fig. 9.

Table 2 shows how the minimum membership function values are chosen for the associated rules:

These results are implicated using the Mamdani Operator selected as the implication operator to determine the output fuzzy set. This is based on the following mathematical expression,

$$\mu(x,y) = \phi[\mu_A(x), \mu_B(y)] = \mu_A(x) \wedge \mu_B \tag{7}$$

where implication operator is denoted by ϕ, input membership function by $\mu_A(x)$ output membership function by $\mu_B(y)$ and intersection function by ^. The implication results are shown in Fig. 11 and rules creating similar output results considering the predicate and the output fuzzy value are clustered together. Then these eight results are aggregated using the aggregation operator, Union ($\vee$), to generate the final fuzzy set. The front view of aggregated results is shown in Fig. 12.

In the defuzzification process, the above aggregated fuzzy values are converted to a crisp value of change of caloric requirement. The method of Center of Area is used due to its simplicity [17]. The general equation is shown below where *w*, *C*, *A* denote the weight, center of gravity and area of each individual implication result respectively.

$$Y = \frac{\sum_{j=1}^{N} w_j \overline{C_j A_j}}{\sum_{j=1}^{N} w_j \overline{A_j}} \tag{8}$$

The parameters of each polygon representing the results of each rule are shown in Table 3. An example of the calculation is given below for rule 3 and Fig. 13 shows the relevant area for calculation.

$$\tan\theta = \frac{1}{25} = \frac{0.3}{x}$$

$$x = 7.5$$

$$A = 0.3 * (50 - 2x) + \frac{1}{2} * 2 * 0.3x$$

$$\text{Area } (A) \text{ for rule } 3 = 12.75$$

Center of gravity (*C*) is at 25% and weight (*w*) is considered as 1 unit as the calculation shown in Eq. (9) has null effects on the result.

Now, by using the Eq. (2), the crisp value of the change of caloric requirement can be calculated as below.

$$\sum_{Rule1}^{Rule8} w\overline{CA} = 10.56$$

$$\sum_{Rule1}^{Rule8} w\bar{A} = 90.995$$

$$\frac{\sum_{j=1}^{N} w_j \overline{C_j A_j}}{\sum_{j=1}^{N} w_j \overline{A_j}} = 11.61\% \tag{9}$$

In summary, person *X* needs to increase his caloric requirement by 11.61% in order to stay healthy.

5. Conclusion

This study developed a methodology based on fuzzy logic approach to determine caloric intake requirements using the variables of level of physical activity, age and body mass index. As illustrated by the example, the proposed approach is useful in individual based decision-making for matching the caloric intake with lifestyle changes. The model is flexible and can be used with varying values of input variables in the form of linguistic values processed in the fuzzy inference engine. Due to the known drawbacks of fuzzy reasoning, such as inaccuracy, reliability and compactness, this methodology is not conclusive. It does show, however, how fuzzy methodology in the area of health research can contribute to integrating expert knowledge in designing if-then rules and linguistic

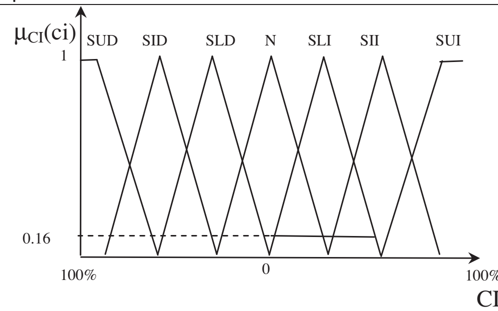
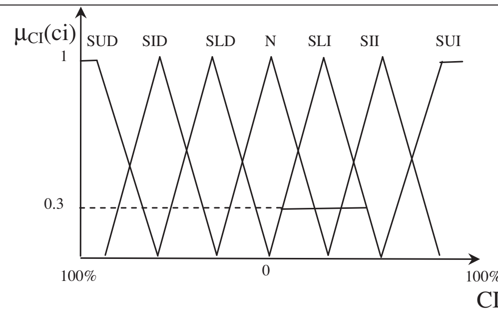
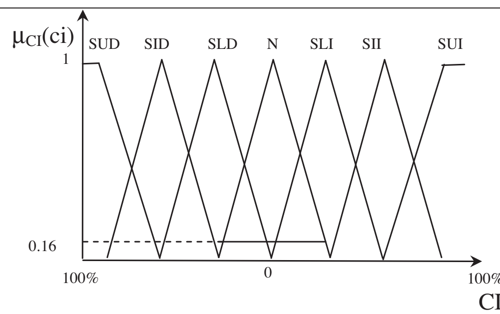
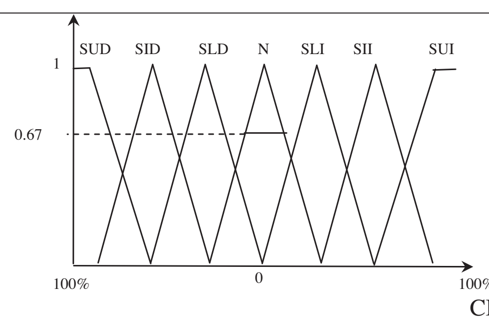
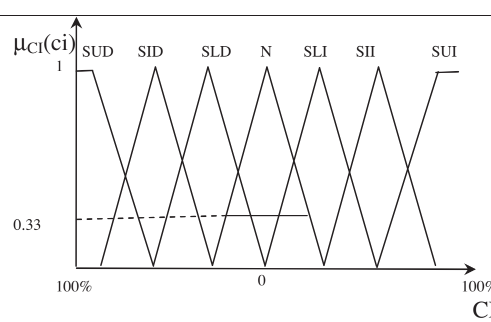
Rules	Implications
Rules 1 and 2	
Rule 3 and 4	
Rules 5 and 6	
Rules 7	
Rules 8	

Fig. 11. Implication results.

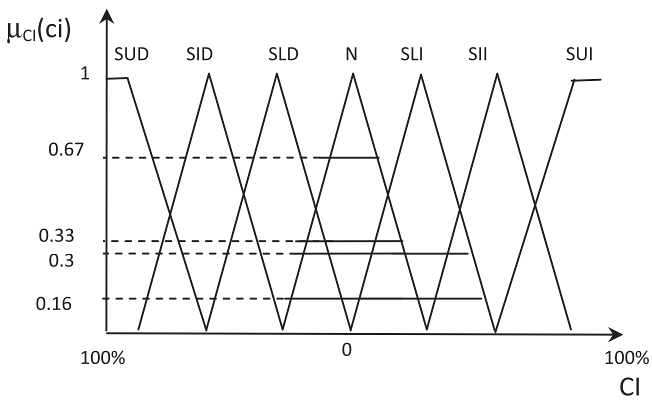


Fig. 12. The aggregated results.

Table 3
Data for defuzzification process.

Polygon	Area (A)	Center of gravity (C) (%)	Weight (w)	Product of $A*C*w$	Product of $A*w$
Rule 1	7.36	25	1	1.84	7.36
Rule 2	7.36	25	1	1.84	7.36
Rule 3	12.75	25	1	3.44	12.75
Rule 4	12.75	25	1	3.44	12.75
Rule 5	7.36	0	1	0	7.36
Rule 6	7.36	0	1	0	7.36
Rule 7	22.275	0	1	0	22.275
Rule 8	13.78	0	1	0	13.78

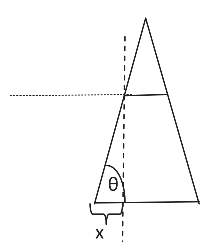


Fig. 13. The polygon for rule 3.

input data sets are systematically processed to generate linguistic output values in decision-making.

The pragmatic use of this model can be extended to a development of an integrated software application which allows individual users to enter the values for the input variables of age, body mass index and physical activeness and receive the output value for the need to change caloric intake, thus supporting real time individual decision making about dietary habits. However, a challenge in developing a good software application is to embed a robust rule table based on expert nutritionists' knowledge and synthesizing individual rule sets to build a consistent rule table for effective performance. The contextual dimension needs to be considered in developing membership functions and the input knowledge from experts on their experiences should be integrated to provide customized ranges for input variables and rule sets that will support effective performance of the model. The proposed model is scalable and able to accommodate more than three input variables. The development and presentation of the rule table become complicated when there are higher numbers of input variables and the latter can be dealt with using software.

Further research into the use of this approach has the potential to be extended to other relevant applications in health research, thus enabling systematic tapping of the tacit knowledge of multiple qualified medical practitioners and dealing with the fuzzy nature of data that feeds into the decision making process. Some potential applications in the area of health are in predicting health risks and epidemics, designing response strategies for such epidemics and in monitoring health status and diagnosing diseases.

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