**TITLE**

Fuzzy logic as a decision-making support system for the indication of bariatric surgery based on an index (OBESINDEX) generated by the association between body fat and body mass index.

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**ABSTRACT**

Background: A Fuzzy Obesity Index (OBESINDEX) for being used as an alternative in bariatric surgery indication (BSI) is presented. The search for a more accurate method to evaluate obesity and to indicate a better treatment is important in the world health context. BMI (body mass index) is considered the main criteria for obesity treatment and BSI. Nevertheless, the fat excess related to the percentage of Body Fat (%BF) is actually the principal harmful factor in obesity disease that is usually neglected. This paper presents a new fuzzy mechanism for evaluating obesity by associating BMI with %BF that yields a fuzzy obesity index for obesity evaluation and treatment and allows building up a Fuzzy Decision Support System (FDSS) for BSI. Methods: Seventy-two patients were evaluated for both BMI and %BF. These data are modified and treated as fuzzy sets. Afterwards, the BMI and %BF classes are aggregated yielding a new index (OBESINDEX) for input linguistic variable are considered the BMI and %BF, and as output linguistic variable is employed the OBESINDEX, an obesity classification with entirely new classes of obesity in the fuzzy context as well as is used for BSI. Results: There is gradual, smooth obesity classification and BSI when using the proposed fuzzy obesity index when compared with other traditional methods for dealing with obesity. Conclusion: The BMI is not adequate for surgical indication in all the conditions and that the fuzzy logic becomes an alternative for decision making in bariatric surgery indication based on the OBESINDEX.

Key Words: 1. Obesity 2. Bariatric and metabolic surgery 3. Body composition 4. Bioelectrical impedance 5. Fat mass 6. Body mass index 7. Bariatric surgery indication

## Introduction

The clinical conditions that are characterized as overweight (pre-obesity) and obesity are currently a universal epidemic of critical proportions. Efforts have been made to minimize this public health problem, but the prevalence of obesity is still growing in both developed and developing countries[1-6].

An excess of fat tissue (obesity) has been shown to be harmful for multiple organs and systems through trobogenic, atherogenic, oncogenic, hemodynamic, and neuro-humoral mechanisms[7-11]. Recently, obesity and related diseases (comorbidities), including *diabetes mellitus*, hypertension, coronary artery disease, cancer, sleep apnea, and osteoartrosis, have replaced tobacco use as a leading cause of death, where obesity contributes directly to the severity of the comorbities[12-15].

Therefore, a great clinical interest exists for evaluating overweight and obese patients to determine the risks inherent with these conditions, to prescribe and control conservative treatments, and to indicate when surgical treatment is needed. In the last 30 years, only the overweight and obesity rating system, which uses the body mass index (BMI), has been internationally recognized[16] (Table 1).

Guidelines for the classification of overweight and obese adults using BMI[16]

| Classification | | BMI |
|---|---|---|
| **Overweight** | | **25 to 29.9** |
| **Obesity** | **Class I** | **30 to 34.9** |
| **Obesity** | **Class II** | **35 to 39.9** |
| **Morbid Obesity** | **Class III** | **≥40** |

Table 1. *Clinical guidelines on the identification, evaluation, and treatment of overweight and obesity in adults. Washington, National Institute of Health, 1998*.

The BMI, which is also called the *Quetelet index*, is a mathematical proportionality between the individual's body mass in kilograms (W) and squared-height expressed in meters (H): BMI = $W/H^2$. It was described for the first time in 1832 by the Belgium mathematician and astronomer Adolphe Quetelet[17]. BMI determination is a mechanism to measure weight excess, is extensively used in a myriad of epidemiologic studies, and is incorporated with clinical practice because of its simplicity. However, it does not properly evaluate the body-fat (BF) proportion because the numerator fails to distinguish lean muscle mass from body fat[18]. The BF measurement has more value than global body mass measurements since the harmful factor in obesity is the accumulation of fat in the body, and lean muscle mass does not burden the individual health[19-20].

Additionally, the BMI itself is revealed as an imprecise and inaccurate method to measure the BF percentage (%BF), especially when people from different categories are considered, which happens in populations of different ages and with different body types[21-22].

In spite of these limitations, the BMI is often used in the therapeutic approach to obesity and in determination of bariatric surgery (Table 2)[13].

Indication of bariatric surgery according to the BMI and comorbidities [13]

| | **BMI >35 and <40 Kg/m$^2$** | **BMI >40 Kg/m$^2$** |
|---|---|---|
| **Without comorbidities** | **Without indication** | **With indication** |
| **With comorbidities** | **With indication** | **With indication** |

Table 2

Furthermore, the appropriate BMI cut-off point that best indicates bariatric surgery for the different populations is unclear. Evidence that patients with a BMI ≤ 32 or even ≤ 27 can benefit from other therapies, such as laparoscopic gastric bypasses, reinforcing the question of whether the universal use of the BMI as indicator for bariatric surgery is appropriate[23-24].

Therefore, overweight and obesity evaluations that are based on the body-mass type and %BF quantifications and that consider differences in age, gender, and ethnicities are more reliable and appropriate in determining a patient’s real condition compared to the BMI evaluation[25-28] (Tables 3 and 4).

**BODY FAT (%)[25]**

| | White (non-Hispanic) | Black (non-Hispanic) | Mexican-American |
|---|---|---|---|
| **Age (years)** | **Average** | **Average** | **Average** |
| **Men** | | | |
| **12 – 13.9** | **18.4** | **19.5** | **22** |
| **14 – 15.9** | **18.4** | **17.8** | **18.8** |
| **16 – 17.9** | **17.7** | **18.6** | **21.3** |
| **18 – 19.9** | **19.6** | **19.9** | **22.7** |
| **20 – 29.9** | **21.8** | **23.7** | **24.1** |
| **30 – 39.9** | **23.6** | **23.6** | **25.4** |
| **40 – 49.9** | **24.2** | **24.9** | **26.6** |
| **50 – 59.9** | **25.1** | **25.1** | **26.7** |
| **60 – 69.9** | **26.2** | **24.9** | **26.7** |
| **70 – 79.9** | **25.1** | **24.3** | **26.1** |
| **Women** | | | |
| **12 – 13.9** | **24.8** | **26.9** | **28.6** |
| **14 – 15.9** | **29.1** | **30.9** | **31.8** |
| **16 – 17.9** | **30.7** | **32.6** | **33.3** |
| **18 – 19.9** | **30.8** | **33.3** | **33.5** |
| **20 – 29.9** | **31** | **35.5** | **35.8** |
| **30 – 39.9** | **33** | **38** | **38** |
| **40 – 49.9** | **35.4** | **39.4** | **39.9** |
| **50 – 59.9** | **37.3** | **40** | **39.4** |
| **60 – 69.9** | **36.9** | **39.8** | **39.4** |
| **70 – 79.9** | **35.9** | **38.5** | **37.8** |

Table 3. Body-fat percentage according to age, gender, and ethnicity.
NHANES III, Chumlea. 2002.

**Obesity classified by %BF[28]**

| %BF | Women | Men |
|---|---|---|
| **ADEQUATE** | **<25%** | **<15%** |
| **LIGHT** | **25 – 30%** | **15 – 20%** |
| **MODERATE** | **30 – 35%** | **20 – 25%** |
| **HIGH** | **35 – 40%** | **25 – 30%** |
| **MORBID** | **>40%** | **>30%** |

Table 4**.**

Considering that the BF percentage is the most reliable indicator of obesity and that the BMI is used to prescribe surgery, it would be convenient to also consider %BF when approaching the patient and considering bariatric surgery.

However, the BMI should be included in conjunction with the %BF when evaluating the condition of the patient and determining an obesity treatment algorithm; this must be completed once the BMI reaches a level that is considered internationally overweight and obese since BMI has good specificity in identifying body-fat excess[18].

Therefore, the search for a more accurate model that evaluates overweight and obese patients with apparent body-mass excess led to the conception of a cut-off value that indicates when surgery is appropriate for these patients. This index evaluated the BMI and the %BF in the context of fuzzy logic.

According to the Boolean classification, a patient with a BMI of 39 $kg/m^2$ and another patient with a BMI of 40 $kg/m^2$ are distributed, according to the WHO, in different obesity categories[9] (class II and class III (morbid obesity), respectively) and receive different treatments. Although the patient with a BMI of 39 $kg/m^2$ is not recommended for bariatric surgery unless he has a comorbitity, the patient with a BMI of 40 $kg/m^2$ is recommended for this surgery even though the difference between them is minimal. In these cases, the patients may not present relevant differences in their clinical, biological, anatomic, or physiopathological conditions that justify discrepancies in the treatment indication.

In clinical practice and situations that are similar to reality, these rigid boundaries sometime result in an inappropriate classification of an individual in a specific condition, which deprives them from of appropriate treatment. The use of fuzzy logic aims at minimizing this misunderstanding.

Fuzzy logic was introduced by Lofti Aliasker Zadeh in 1965 and was developed to deal with the concept of partial truths with ill-defined limits, which vary from completely true to completely false and gradually leave one condition to the other. Different from the theory of classical ensembles based in the Aristotle principle of the excluded middle where the element belongs or not to a category, fuzzy sets consider that an element belongs partially, but not absolutely, to a category, and therefore, it is a powerful tool to deal with inaccurate, uncertain, or vague terms. This provides consistent, easy, and low-cost solutions to real problems[29].

These characteristics and the capacity to deal with the linguistic variables or linguistic terms, the ease understanding, and the ability to incorporate the expert's experience and the attributed values to the systems justify the increasing number of studies that use fuzzy-set theory and fuzzy logic in biomedical issues. Thus, this mathematical approach becomes an extremely applicable option for elaborating medical models in diagnosis systems, medical images, epidemiology, or public health[30-37]. Recent studies demonstrate the progressive increase of the use of fuzzy logic in several medical areas: internal medicine, cardiology, vascular surgery, intensive therapy, pediatrics, endocrinology, oncology, gerontology, plastic surgery, orthopedics, anesthesiology, dermatology, ophthalmology, ear-nose-throat, gynecology, urology, neurology, psychiatry, radiology, in imaging and laboratory data evaluation, and forensic medicine; it is also progressively used in the basic science areas: physiology, anatomy, pathology, biochemistry, pharmacology, and genetics[30-39].

Regarding a patient with a BMI of 39 $kg/m^2$, the fuzzy-set theory and fuzzy logic allow, for example, a recommendation for surgical treatment, while the set theory would not give a recommendation for surgical treatment due to its level of membership.

The division of the discourse for the sets of BMI and %BF that are developed by the fuzzy-set theory results in two sets and an overlap of categories (overlapped designations). This results in a patient that can be classified in complementary manners. This diffuse approach allows each patient to be classified in a manner that is compatible with several categories, with different degrees of membership, and with the advantage of a more realistic classification of the surgical recommendation that considers the admitted variables.

This approach was valid in a previous study where the BMI and %BF values were selected from the Medline and Medscape databank. These data were obtained from anthropometric DEXA, bioelectrical impedance analysis (BIA), or densitometry measurements of male patients, and they were evaluated with fuzzy logic. This study concluded that the BMI is not adequate for a bariatric surgery indication in all conditions and that fuzzy-set theory and fuzzy logic are an alternative for the decision to recommend bariatric surgery[40]

The search for a more accurate model to evaluate overweight and obese patients that have an excess of body mass as a whole or an isolated increase of %BF led to the creation of an index to approach these conditions. This index considers the association between the BMI and %BF in regards to fuzzy set theory and fuzzy logic. This index (OBESINDEX) must have the ability to accurately recommend which patients should be referred for bariatric surgery.

**Objectives**

General: To determine a more accurate parameter for the evaluation of obesity (OBESINDEX) that is more compatible with the degree of the disease, allows of a universal application in obesity treatment, and aims at recommending the best treatment, including the recommendation of bariatric surgery (ICB).

Specifically:

1) To evaluate the use of the Obesity Index (OBESINDEX) in a random sample.
2) To determine the validity of the Obesity Index (OBESINDEX) in indicating bariatric surgery.

## Methods

This prospective study carried out in the city hospital, "Dr. José de Carvalho Florence" (HMJCF), in São José dos Campos, São Paulo state, during the period of December of 2008 to August of 2009; it also had the approval of the Ethic and Research Commission (CEP) of the University of Taubaté (UNITAU) (Exhibit I) and the Federal University of São Paulo (UNIFESP) (Exhibit II). All participants in the study signed a informed consent form that was in accordance with Decree no. 196/96 of the National Health Council (CNS)/Health Ministry (MS) and its complements (Decrees 240/97, 251/97, 292/99, 303/00, and 304/00 of the CNS/MS) (Exhibit III).

Inclusion criteria were the following: patients from emergency and nursing rooms in the HMJCF, of either gender, and aged 18 years or older. Exclusion criteria were the following: patients who refused to take part in the study, pregnant women, patients fasting for more than 6 hours for solid food and 4 hours for liquids, and patients with kidney failure, hydroelectrical alterations, inadequate hydration, fever (T>378$^{o}$C), ascites, cirrhosis, a by-pass, or an amputation of the inferior or superior members.

The weight, height, and %BF of the patients were measured during the same day and at subsequent time points.

### BMI Calculation

To calculate the BMI, a stadiometer, which was graded at every 0.5 cm, and a digital scale, with 0.1-kg sensitivity, were used.

### %BF Calculation

To obtain %BF and fat-free mass (FFM) values, we used the body composition analyzer, a method that uses direct multi-frequency bio-impedance and the Segmental-model InBody230 (Biospace Co., Ltd. Seoul 135-784 KOREA) Tetra-polar System with 8-points. The %BF values and fat-free mass (FFM) system were obtained through the BIA from equations that were incorporated in the equipment, as described by Bedogni[41].

FFM mainly consists of an aqueous solution of ions and has a strong conductive current and a low impedance log, whereas fat mass does not conduct electricity as well and has a high impedance[42]. Therefore, the resistance of the current flow is inversely related to the fat-free mass. Hence, the BIA measures the body composition indirectly and is based on the electrical-conductivity principle and its stable relation with the body's liquid. It also uses the resistance, the reactance, and the phase angle as bioelectrical parameters[48,50-55]. Resistance is the opposition offered by the body content to the alternated electrical current and is inversely proportional to the quantity of water and electrolytes present in the tissues. In the human body, the thin tissues are high conductors since they are a substantial reservoir of water and electrolytes and represent a low resistance mean. This technique demands standard conditions when performing the measurements: namely, the individual's body position, adequate hydration, the absence of food and alcohol ingestion prior to the evaluation, and the abstention from heavy and recent physical activity. The BIA's predictive accuracy can be influenced by the degree of body fat, age, gender, ethnic characteristics, diseases that alter the body type and factors that modify the hydroelectrolytic composition[53]. In order to clarify conflicting results, we used predictive equations that were adequate to the population under study[50, 48-55].

Protocol for the evaluation:

1) The patients were instructed to refrain from drinking alcohol and to not perform heavy physical activity during the day prior to the exam.
2) Fasting of 6 h for solid food and 4 h for liquids prior to the exam.
3) The patients were instructed to use the rest room before the test.
4) The patients wore light clothes or a hospital gown.
5) The patients did not wear watches or jewelry in the vicinity of the electrodes.
6) The patients remained standing for 5 min before the exam performance.
7) The room temperature at the exam was maintained between 20 and 25ºC.

**Diffuse treatment of IMC, %BF, and OBESINDEX values:**

<u>Classical Set Theory</u> – This is based on the excluded middle principle where an element belongs or does not belong to an established set.

Fuzzy logic – This allows a relation of gradual membership of an element to a determined set[29,30].

Initially, the BMI was modified by the treatment of the crisp classes, as adopted by the WHO, in fuzzy sets. This fuzzification was extended to the %BF classes. The BMI and %BF classes were added resulting in a new index, the OBESINDEX (Figure 1).[40]

Finally, the OBESINDEX was used to classify individuals in relation to their obesity condition and establish a criterion that provides a decision-making system that can recommend bariatric surgery (Figure 2).

To implement this relationship, the approach uses a diffuse rating for the BMI values from the BIA and uses the conjugation operation between the partial values and linguistic terms related to them.

Currently, the classical set theory is used to classify obesity and to recommend a surgery treatment. It uses independent variables like “yes” or “no”, “belongs” or “does not belong” (Figure 1).

Conversely, fuzzy logic allows for allocating a patient with a BMI of 39 kg/m$^2$ in the fuzzy set with a recommendation for surgical treatment and with a specific degree of membership and also in the fuzzy set without recommendation for surgical treatment and with a different degree of membership. This provides the advantage of a more realistic classification of the surgical recommendations connecting the adopted variables (Figures 2 and 3).

A diffuse set, A, from the universe of discourse, BMI, is defined by a membership function $\mu_A(x)$, where each element is mapped to number (degree) in an interval between [0,1]. The membership function $\mu_A(x)$ can be understood as the compatibility degree among the linguistic terms slim, overweight, OI, OII, and OIII.

BMI = {slim, overweight, obesity degree I (OI), degree II (OII), degree III (OIII)}, ex., $\mu_s(x)$: X→[0,1], $\mu_{overweight}(x)$: X→[0,1], $\mu_{OI}(x)$: X→[0.1] and so on.

Therefore, the suggested index also establishes an arbitrary value between 0 and 1; thus, it produces a smooth and gradual surface for BMI classification.

Similar to the fuzzy-set BMI, the fuzzy set of the universe of discourse, %BF, is also defined by a membership function $\mu_A(x_1)$, where each element is mapped to a degree in an interval between [0,1].

%BF = {adequate, light obesity, moderate obesity, high obesity, morbid obesity}, ex., $\mu_{adequate}(x){:}X \rightarrow [0.1]$, $\mu_{light\ obesity}(x){:}X \rightarrow [0.1]$, $\mu_{moderate\ obesity}(x){:}X \rightarrow [0.1]$ and so on.

The suggested approach assumes that the value related to the BMI is a x object, and the 1st coordinate is named P; the value related to the %BF is a y object, and the 2nd coordinate is named P, where P is an ordinate pair P=(x,y). The set of all ordinate pairs (x,y), where the 1st element in each pair is a number of the universe discourse X and is associated with the BMI and the 2nd element is a member of another universe of discourse Y and is related to the %BF, produces a Cartesian product, X+Y, in the form of:

$$X+Y = \{(x,y);\ x \in X,\ y \in Y\}$$

where $X = \{x_1,.....,x_n\}$, $x_i \in$ IMC e $Y=\{y_1,....,y_n\}$, $y_i \in$ %GC.

The elements of BMI, $x_i$, and the elements of %BF, $y_i$, which are distributed in the universes of discourses X and Y, respectively, are grouped and assigned by classes or linguistic terms that are associated with BMI obesity classes (overweight, obese class I, obese class II, and obese class III) and %BF (adequate, light obesity, moderate, high, morbid). These sets are usually considered using the classical ensembles theory, where the universe of discourse is partitioned so that the Cartesian pair $(x_i,y_j)$ assumes either an unit value of 1 for each pair that belongs to the relationship or a null value of 0 for each pair that does not belong to the relationship, i.e., $\mu(x,y) = \{0,1\}$.

However, it seems to be arbitrary to assign a Boolean form or classification as the one used for the BMI and %BF. For instance, a patient with a BMI of 39 kg/m$^2$ and another patient with a BMI of 40 kg/m$^2$ would be classified into the OII and OIII groups, respectively, and getting different treatment recommendations. Although the first is not in the range for a surgical recommendation, the second is not, even if the variation from one patient to the other is minimal, i.e., ΔBMI=1 for a BMI of 39 kg/m$^2$ and 40 kg/m$^2$. In this situation, both patients may not present significant biological, anatomical, or physiopathological differences that justify such a discrepancy in the treatment recommendation.

Regarding the above scenario, the partition of the universe of discourse for the BMI and BIA sets should be accomplished using fuzzy set logic. Each Cartesian pair, (x,y) so that x Є IMC and y Є %GC, assumes an intermediary value between 0 and 1, ex, $\mu(x,y) = [0,1]$, which can produce an overlapping of classes (overlapped assignments) in a way that the patient can be classified in complementary manners.

Following the example of the two patients with a BMI of 39 kg/m$^2$ and BMI of 40 kg/m$^2$, both would be categorized either as OII as OIII. The difference exists since the first patient presents a class of OII that is higher than OIII, whereas the second patient is more in the OIII group than in the OII group. In this case, both patients have a potential to receive or not receive a recommendation for surgical treatment; this determination depends on other factors and not only the BMI value, which is improperly and perhaps inconsistently used.

When determining the value for obesity from each fuzzy set, the partition from the universe of discourse, the linguistic values (which are the BMI and the %BF), can be related through the intersection operators (∩), union (U), and complementary (¬). The intersection operation corresponds to the conjunction operation and to the logic connective “e”; the disjunction operation corresponds to the union operation and to the logic connective “or”; and the complementary operation corresponds to the logic connective of negation. The conjunction, disjunction, and complementary operators are used in the construction of implication operators, *I*: [0,1] x [0,1] → [0,1], and are used to mold the rules of the inference of type: IF <premise> THEN <conclusion>.

Fuzzy logic is essentially a system of rules of inference. This mechanism of fuzzy inference uses logic principles to establish how facts and rules have to be combined to derive new facts. An important concept is the fuzzy conditional proposition:  IF: x is A, THEN y is B, where x is the input linguistic variable, y is the output linguistic variable, A is the input linguistic term, and B is the output linguistic term; in other words, A => B, where (x is A) is the background of the rule and (y is B) is the consequent of the rule.

In this study, the input linguistic variables (premises or universe of discourse; input or backgrounds) considered are the BMI and the %BF. The output linguistic variable (consequent of the rule) considered is the evaluation of the obesity/surgical treatment indication (OBESINDEX). This relation is associated to the obesity (input) and the recommendation for surgical treatment (output).

The consequent of the rule, the obesity/surgical-treatment-indication evaluation, also originates a fuzzy set, which is partitioned in the following manner: slim (M), muscle hypertrophy (HMU), weight excess (EP), sumotori (SUT), fuzzy obese (OBFZ), and morbid obese (OBE).

These described steps embrace the mapping process that includes the following: 1) the knowledge basis, 2) the fuzzification that translates the crisp value (classical number) of the input variable into a fuzzy value, 3) the cylindrical extension, the aggregation, the conjunction, and the projection, and 4) the defuzzification that translates the output linguistic variable in a crisp value.

The input linguistic variables, or premises considered (backgrounds of the rule), were the BMI and the %BF.

To build the input variable for the BMI, the WHO classification (Table 1) was used. The fuzzy set for the BMI was partitioned into the following linguistic terms: overweight (OW), obesity class I (OI), obesity class II (OII), and obesity class III (OIII).

To build the input variable for the %BF, the NIDDK classification of overweight and obesity was used (Table 4). The fuzzy set for the %BF was partitioned into the following linguistic terms: adequate (AD), light (LI), moderate (MDE), high (HI), and morbid (MORB). The obesity/surgical-treatment-indication evaluation constituted the output linguistic variable (consequent of the rule). The fuzzy set for the obesity/surgical-treatment indication was partitioned into the following: The output in the consequent of the rule is given by obesity evaluation also related to BSI (consequent of the rule). The set of linguistic terms are thin (TH), adequate (AD), light (LI), muscular hypertrophy (MUH), excess of weight (EW), sutomori (SUT), fuzzy obesity (FZOB), and morbid obesity (MOR). The sutomori fuzzy set for obesity is introduced by the authors an there is no similar in literature. The sumo wrestlers are classified apart of the other categories since they present unique characteristics. These athletes have a muscular mass and presents a high level of %BF and due to that are usually considered as obese. However, when compared with individuals with equivalent BMI, they present lower values of %BF.The base of rules was constituted as follows:

R1) If BMI is TH and %BF is AD, then it is TH
R2) If BMI is TH and %BF is LI then it is TH
R3) If BMI is TH and %BF is MDE, then it is EW
R4) If BMI is TH and %BF is HI, then it is EW
R5) If BMI is OW and %BF is AD, then it is MUH
R6) If BMI is OW and %BF is LI, then it is MUH
R7) If BMI is OW and %BF is MDE, then it is EW
R8) If BMI is OW and %BF is HI, then it is FZOB
R9) If BMI is OW and %BF is MOR, then it is FZOB
R10) If BMI is OI and %BF is AD, then it is MUH
R11) If BMI is OI and %BF is LI, then it is MUH
R12) If BMI is OI and %BF is MDE, then it is SUT
R13) If BMI is OI and %BF is HI, then it is FZOB
R14) If BMI is OI and %BF is MOR, then it is FZOB
R15) If BMI is OII and %BF is AD, then it is MUH
R16) If BMI is OII and %BF is LI, then it is MUH
R17) If BMI is OII and %BF is MDE, then it is SUT
R18) If BMI is OII and %BF is HI, then it is FZOB
R19) If BMI is OII and %BF is MOR, then it is FZOB
R20) If BMI is OIII and %BF is MDE, then it is MOR
R21) If BMI is OIII and %BF is HI, then it is MOR
R22) If BMI is OIII and %BF is MOR, then it is MOR

The rules were restricted to those considered relevant; in other words, they were restricted to only those than can really happen (Table 5).

| | TH | OW | OI | OII | OIII |
|---|---|---|---|---|---|
| **AD** | **TH** | **MUH** | **MUH** | **MUH** | **X** |
| **LI** | **TH** | **HM** | **HM** | **HM** | **X** |
| **MDE** | **EW** | **EW** | **SUT** | **SUT** | **MOR** |
| **HI** | **EW** | **FZOB** | **FZOB** | **FZOB** | **MOR** |
| **MOR** | **X** | **FZOB** | **FZOB** | **FZOB** | **MOR** |

**Table 5**

The inference for the decision making used the minimum method of Mamdani, and for the defuzzification, the center area method was used.

The fuzzy-data evaluation used the Matlab program.

**BMI, %BF, and OBESINDEX performance to diagnose obesity and surgical treatment indication:**

We used a WHO reference standard to evaluate the obesity diagnosis performance, which was evaluated using the BMI, (Table 1). Values that were already described in the literature were used to evaluate the obesity-diagnosis performance, which was evaluated using the %BF cut-off value[28] (Table 4). To evaluate the OBESINDEX, a value defined by the defuzzification of the output variable was used, as previously described.

**Statistic analysis**

The continuous variables were presented as mean and standard deviation (DP_ and numbers and percentages as categorical variables. The Pearson coefficients of correlation and the respective intervals of confidence (IC) (95%) were estimated to compare BMI, %BF and OBESINDEX by genre. The McNe Figure 3 ed to compare the percentage of the individuals considered obese by the BMI versus %BF, BMI versus OBESINDEX and %BF and %BF versus OBESINDEX.

**Sample**

In the current study, 81 patients were evaluated, and 72 out of the 81 were evaluated by analyzing the BMI and %BF. Among the excluded patients, 7 were not fasting, a patient had consumed alcohol within 24 h prior to the test, and a patient had a fever (T=38.2$^{o}$C) at the time of evaluation.

Of the 72 patients, 42 were female and 30 were male. The mean age ± standard deviation (DP) was 39.5±11.2 years old for women and 43.5±15.8 years old for men. The mean weight ± DP was 70.0±14.5 kg for women and 79.6±25.3 kg for men. The mean BMI ± DP was 27.1±5.8 kg/m$^2$ for women and 27±7.4 kg/m$^2$ for men. The mean %BF ± DP was 38.7±6.7% for women and 26.3±7.9% for men. The demographic data are described in Table 6.

| | **Women** (n=42) | | | | **Men** (n=30) | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Minimum | Maximum | DP | Mean | Minimum | Maximum | DP |
| **Age** (years) | 39.5 | 18.0 | 60.0 | 11.2 | 43.5 | 18.0 | 76.0 | 15.8 |
| **Weight** (Kg) | 70.0 | 48.0 | 113.1 | 14.5 | 79.6 | 32.0 | 160.0 | 25.3 |
| **Height** (m) | 160.9 | 148.5 | 170.0 | 5.7 | 172.2 | 155.5 | 183.0 | 7.5 |
| **BMI** | **27.1** | **18.8** | **45.9** | 5.8 | **27.0** | **17.6** | **54.1** | 7.4 |
| **GC** (%) | **38.7** | **25.2** | **48.8** | 6.7 | **26.3** | **9.9** | **40.1** | 7.9 |

Table 6

**Results**

As Figures 7 and 8 demonstrate, a significant increasing linear correlation exists between BMI (kg/m$^2$) and BF (%) and between BMI (kg/m$^2$) and FFM  (kg).

Agreement was also found among the following values:

-BMI and body fat (BF) for females

-BMI and fat-free mass (FFM for males)

-BMI and OBESITY for both genders

The maximum and minimum BMI, %BF, and OBESINDEX values are presented in Table 7. Mean and DP values are given for BMI and %BF. Table 8 displays the Pearson linear correlation coefficients between BMI (Kg/m$^2$) and the remaining variables: %BF, MLG, and OBESINDEX for both genders.

| | **Women** (n=42) | | | | **Men** (n=30) | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Minimum | Maximum | DP | Mean | Minimum | Maximum | DP |
| **BMI** | **27.1** | **18.8** | **45.9** | 5.8 | **27.0** | **17.6** | **54.1** | 7.4 |
| **GC** (%) | **38.7** | **25.2** | **48.8** | 6.7 | **26.3** | **9.9** | **40.1** | 7.9 |
| **OBESINDEX** | | **23.9** | **91.7** | | | **23.9** | **91.7** | |

**Table 7**

| | | **Women** (n=42) | **Men (n=30)** |
|---|---|---|---|
| **BMI and %GC** | Pearson correlation | 0.831 | 0.656 |
| | Sig. (2-tailed) | <0.001 | <0.001 |
| **BMI and MLG** | Pearson correlation | 0.683 | 0.848 |
| | Sig. (2-tailed) | 0.000 | <0.001 |
| **BMI and OBESINDEX** | Pearson correlation | 0.770 | 0.617 |
| | Sig. (2-tailed) | <0.001 | <0.001 |
| **BF and OBESINDEX** | Pearson correlation | 0.905 | 0.961 |
| | Sig. (2-tailed) | <0.001 | <0.001 |

**Table 8**

The percentage of individuals that were considered obese by the %BF criteria was statistically lower than by the BMI criteria (Table 9). The percentage of obese individuals determined by the OBESINDEX criteria was statistically higher than by the BMI criteria (Table 10). The percentage of obese individuals determined by the %BF criteria was statistically higher than by the OBESINDEX criteria (Table 11).

| **BMI** >30 kg/m$^2$ | **GC** >35(women) >25(men) OBESE | NON-OBESE | |
|---|---|---|---|
| OBESE | 16 | 1 | 17 (23.6%) |
| NON-OBESE | 30 | 25 | 55 |
| TOTAL | 46 (63.9%) | 26 | 72 |

**Table 9**

| **BMI** >30 kg/m$^2$ | **OBESINDEX** >68 OBESE | NON-OBESE | |
|---|---|---|---|
| OBESE | 12 | 5 | 17 (23.6%) |
| NON-OBESE | 18 | 37 | 55 |
| TOTAL | 30 (41.7%) | 42 | 72 |

**Table 10**

| **%GC** >25 men >35 women | **OBESINDEX** >68 OBESE | NON-OBESE | |
|---|---|---|---|
| OBESE | 30 | 16 | 46(63.9%) |
| NON-OBESE | - | 26 | 26 |
| TOTAL | 30 (41.7%) | 42 | 72 |

**Table 11**

The correlation between the BMI and %BF for women was stronger than for men. When comparing BMI to MLG, the correlation was better for men. The groups show a strong correlation for all of the variables in both genders. Regarding the BMI and OBESINDEX, the correlation was strong for both women and men. The correlation between %BF and OBESINDEX was the best one for both genders.

The percentages of individuals that were considered obese by the BMI, %BF, and OBESINDEX criteria are presented in Table 12. The percentage of individuals considered obese by the %BF criteria (63.9%) was statistically higher than by the IMC criteria (23.9%) ($p<0.001$). The percentage of individuals considered obese by the OBESINDEX (41.7%) was statistically higher than by the BMI criteria (23.6%) ($p<0.001$). The percentage of individuals considered obese by the %BF criteria (63.9%) was statistically higher than by the OBESINDEX (41.7%) ($p<0.001$) (Table 12).

| | |
|---|---|
| **BMI = 23.6%**<br>>30 | **%GC = 63.9%**<br>>35(women)<br>>25(men) |
| **BMI = 23.6%**<br>>30 | **OBESINDEX = 41.7%**<br>>68 |
| **%GC = 63.9%**<br>>35 (women)<br>>25(men)<br>n=72 | **OBESINDEX = 41.7%**<br>>68 |

**Table 12** (McNemar test)[56]

## Discussion

### Use of BMI to classify obesity

Despite its limitations, the BMI is still considered the most useful measurement of the obesity level of the population. Thus, the BMI can be used to estimate the prevalence of obesity in the population and the risks associated with this condition. However, it does not elucidate the wide variation in the nature of obesity between different individuals and diverse populations.

Studies indicate that the BMI has to be adjusted for diverse ethnical groups as the WHO study of the Western Pacific Region[57] demonstrated that different cut-off values must be adapted for overweight (>23 kg/m$^2$) and for obesity (>25 kg/m$^2$). Studies evaluated the Australian aborigine population and showed that the cut-off point was >26 kg/m$^2$ for defining overweight.

The BMI accuracy in diagnosing obesity is mainly limited in intermediary ranges of BMI in men and in elders due to a failure in discriminating free-fat mass and body fat.[27]

The BMI has a high specificity for identifying obese individuals; however, it presents low sensitivity and misses the diagnosis in half of the individuals with obesity that was classified through the %BF[27]. Even though a cut-off point is not clearly defined by the WHO, several studies agree with the intervals that indicate the values that define the various degrees of obesity[27,28,57].

Several values for the BMI and %BF classify individuals in different categories with more realistic degrees of compatibility, according to the fuzzy-set theory and fuzzy logic. When comparing those indexes for obesity evaluation and surgical treatment with the Boolean classification as commonly used, the employment of OBESINDEX seems to be recommended.

The results of this study were in agreement with the data found in the literature when the performances of the BMI and %BF in diagnosing obesity were compared.[18,27,58,59] Analyzing only the BMI, 23% of the sample was considered obese, while this proportion increased to 63.9% and 41.7% when evaluating with the %BF and the OBESINDEX, respectively.

The variability between living things of the same species, inherent to the biological condition, allows a range of classification as the ones previously mentioned. However, the limits of these artificially created classes are inaccurate and badly defined.

To justify the use of fuzzy logic, which complemented the Boolean logic, in this research, we have to consider that the classical procedure for evaluating the results from research in the life-science area has been the application of descriptive statistics to the tabulation and stratification of data. Furthermore, inferential statistics have been used where probabilistic analyses are needed.

In the classical logic approach, all of the instruments aim at establishing values with a higher rate of occurrence; specific ranges of variables are directly defined as causes or modulating factors. This treatment is perfectly suited when it refers to results of exact-science studies where the objects are simple substances and the samples are homogeneous. However, this is not the case in the biological field where the disparity observed can be simply due to normal individual variation that occurs in a species population[60].

Furthermore, the unique characteristics of living things are not merely due to their physical-chemical composition but rather, attributed to their organization. In this case, the whole is greater than the sum of its parts[61]. Therefore, the physical-chemical explanations, which are ruled by laws and subject to mathematical rules, cannot clarify and foresee the biological phenomena with accuracy. When formed by concepts and historical narratives, the life sciences are fundamentally different from the exact sciences, such as physics[62].

As an alternative or complementary method to dealing with these biological data, an approach based in the fuzzy-set theory allows rational formulation using imprecise, uncertain, or vague data that may contain partial truths. This permits the simulation of human judgment when making decisions[63]. The use of fuzzy logic is progressing in the modulation of “intelligent” programs that can work with qualitative and quantitative indexes for decision making in the biomedicine field.

Fuzzy logic allows the conjugation of all variables involved in an observation, simultaneously. This is different from the Cartesian analyses that pair two variables at a time and looks for their correlations. Different from Aristotle or Boolean logic, fuzzy logic admits varied degrees of membership between the true and false or yes and no, of the elements evaluated in relation to sets that are qualitatively determined, and build relationships between the several variables in the characterization of memberships using the non-Cartesian connective. Therefore, through the study of the set of IF-THEN rules in the composition of these variables (IF P1 is Y1 and P2 is Y2 and P3 is Y3 and …Pn is Yn THEN C is W), it is possible to map how the variables are used in the decision making or how they are constituted in the production or modulation of a phenomenon. Relating these variables to the formulation of concepts that are defined by semantic terms, the different degrees of membership of an element to a status or quality can be represented. The use of the fuzzy-set theory in mapping, as in building supporting systems, to decision making (algorithms), modulating, and/or controllers seems to be more appropriate in the life-science field and can complement or even be used independently from inferential-statistic analysis. Therefore, fuzzy logic is an alternative to deal with dynamic components that cannot be described by conventional modulating methods due to a lack of accurate and formal knowledge of the system or due to the non-linear behavior of the variables.

**Conclusion**

The OBESINDEX is adequate to evaluate the obesity condition and to recommend bariatric surgery.

The OBESINDEX results are closer to the real clinical condition of obesity of the individual than either the BMI or the %BF.

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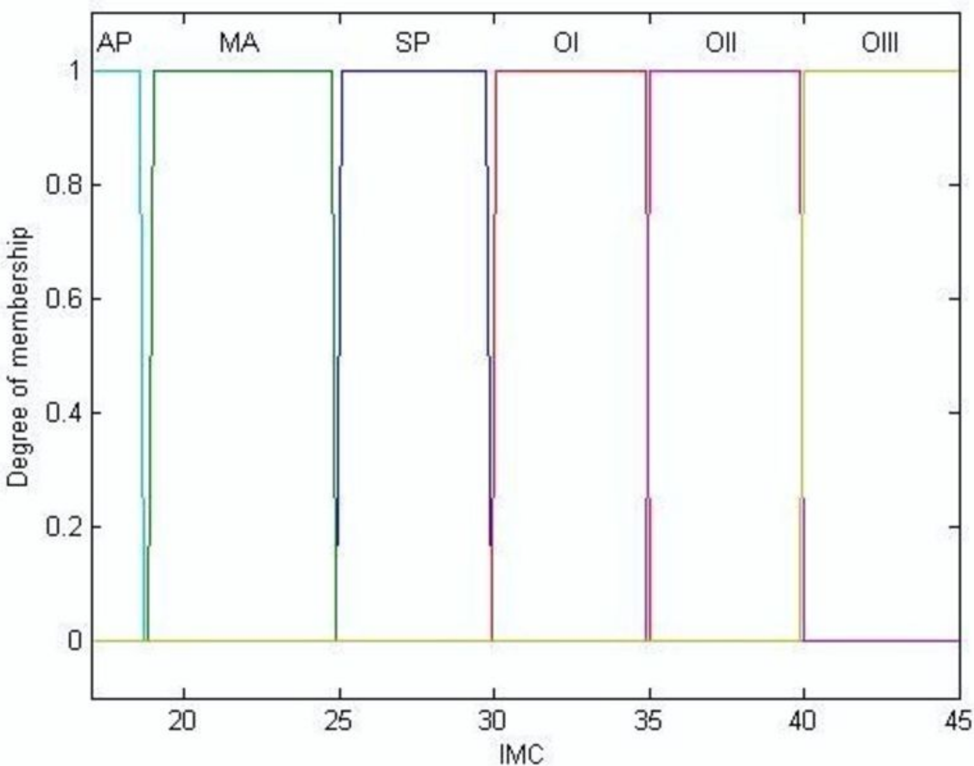

AP
MA
SP
OI
OII
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1
0.8
0.6
0.4
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0
Degree of membership
20
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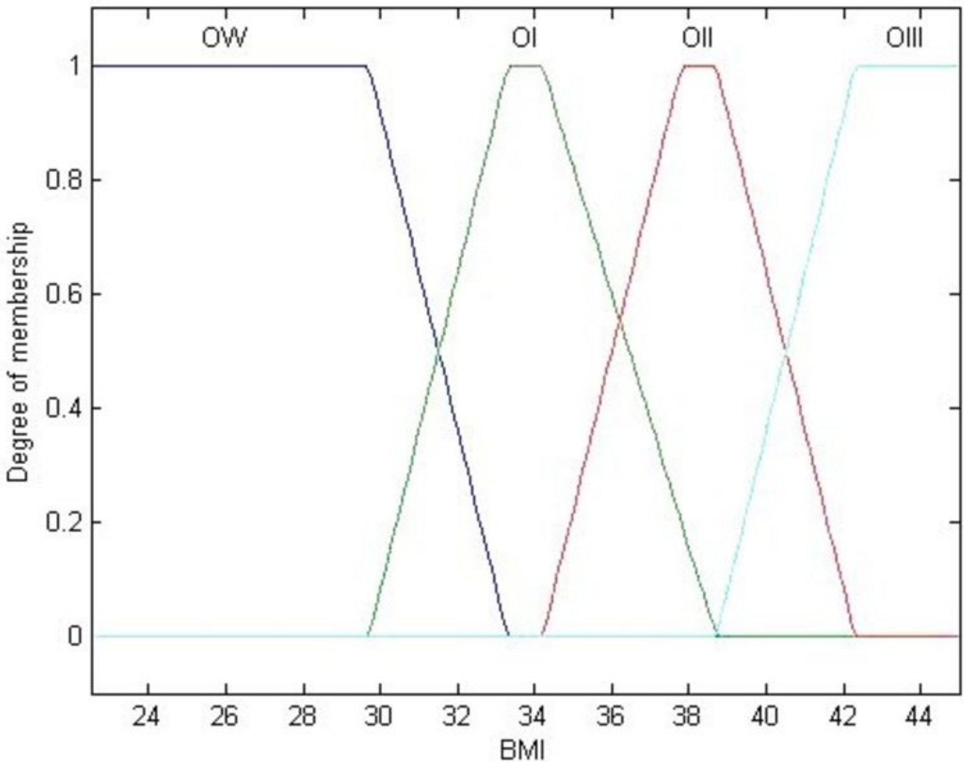
35
40
45
IMC



OW
OI
OII
OIII
1
0.8
0.6
0.4
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0
Degree of membership
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26
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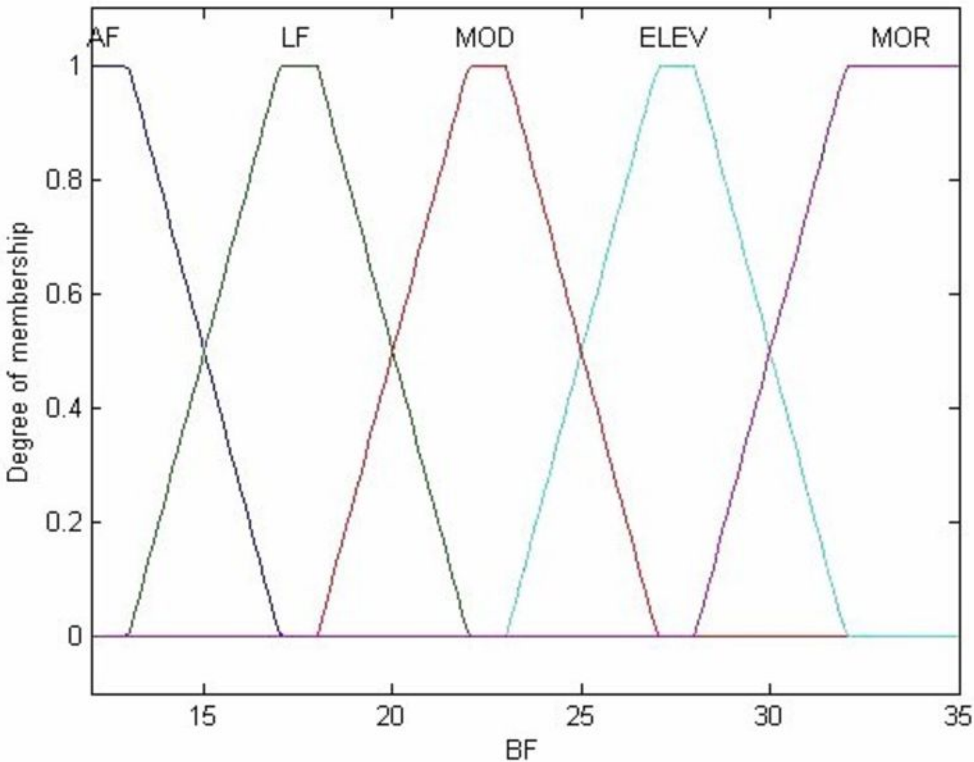
38
40
42
44
BMI



AF
LF
MOD
ELEV
MOR
Degree of membership
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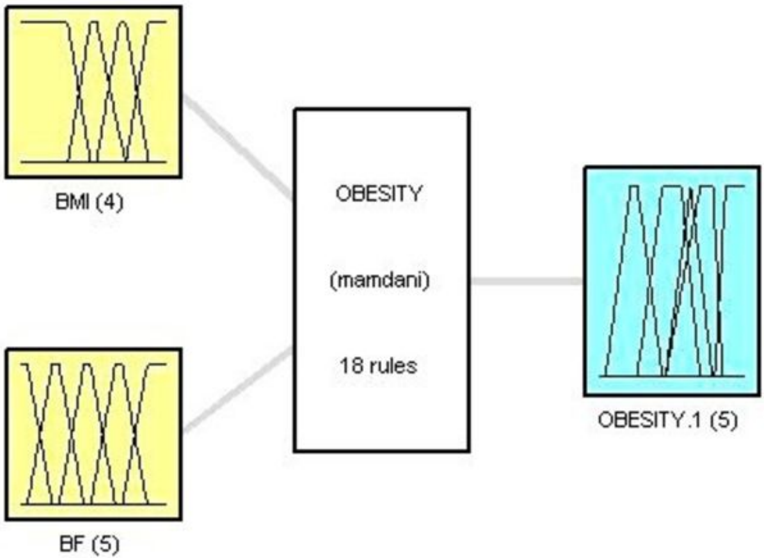
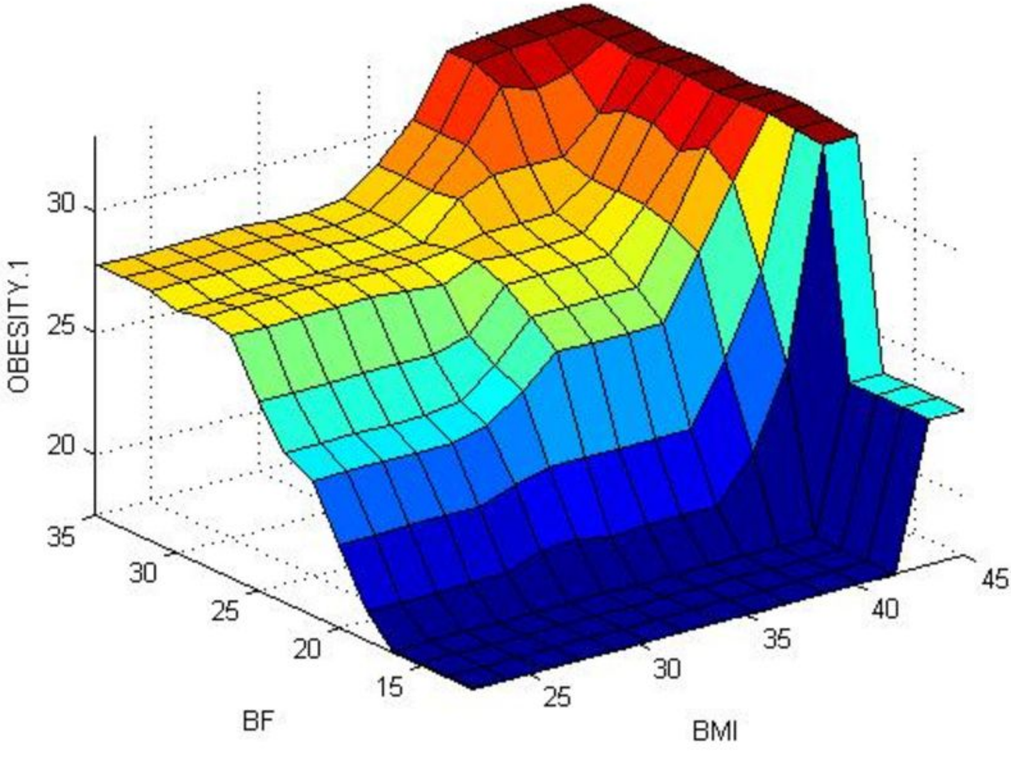
0.8
0.6
0.4
0.2
0
15
20
25
30
35
BF




System OBESITY: 2 inputs, 1 outputs, 18 rules



OBESITY.1
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20
35
30
25
20
15
BF
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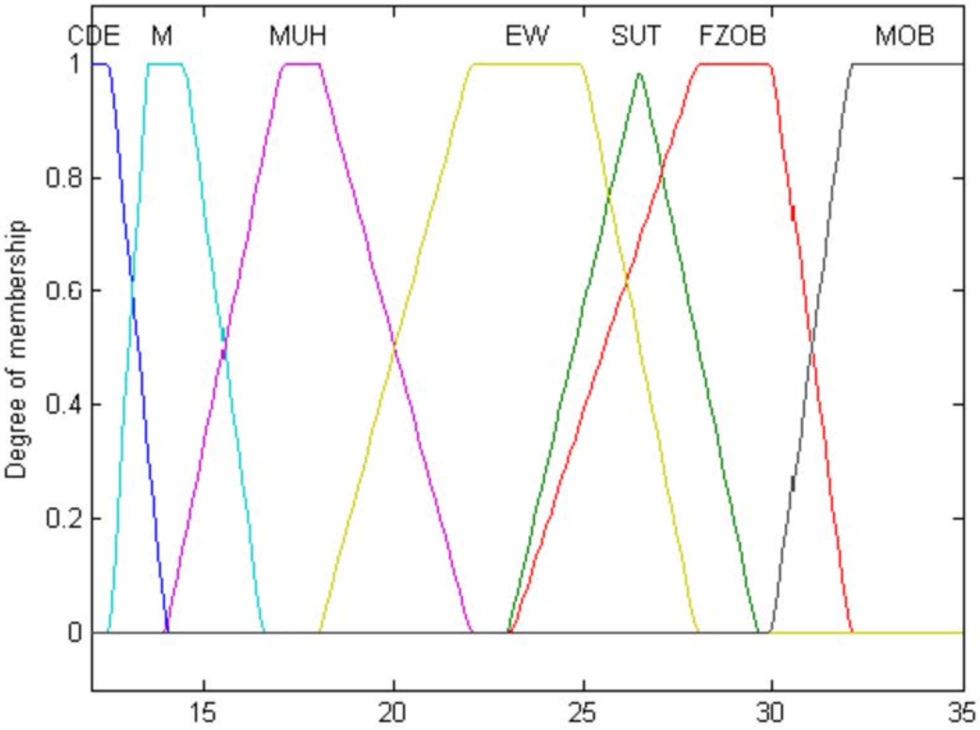
35
40
45
BMI



CDE
M
MUH
EW
SUT
FZOB
MOB
Degree of membership
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0.8
0.6
0.4
0.2
0
15
20
25
30
35

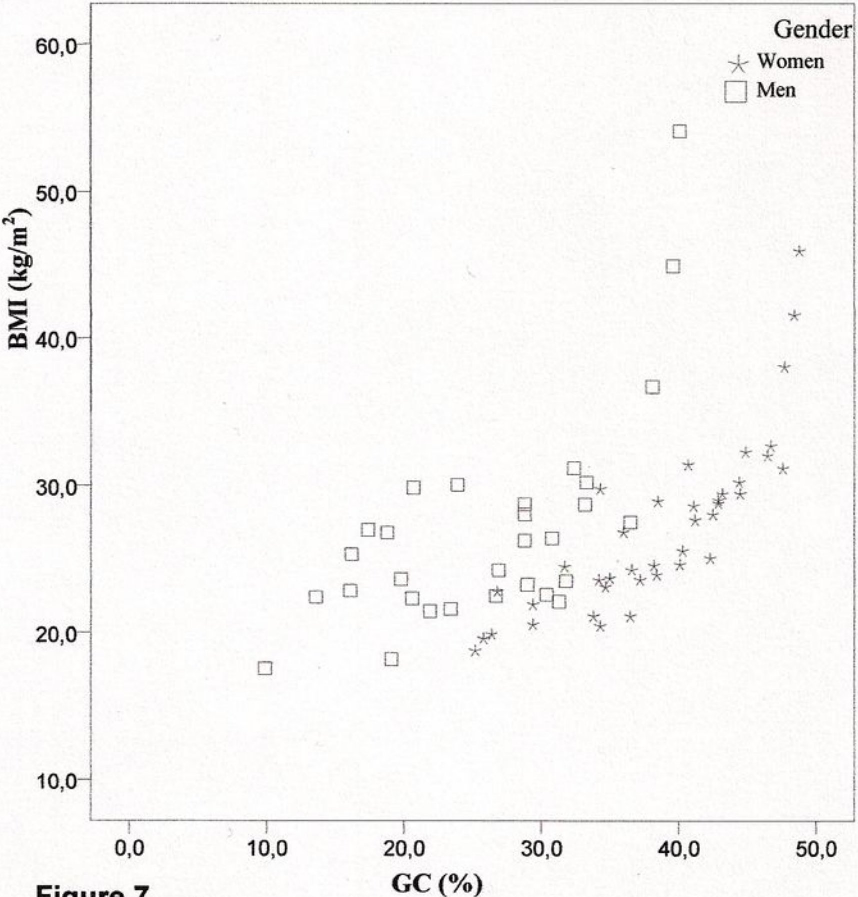
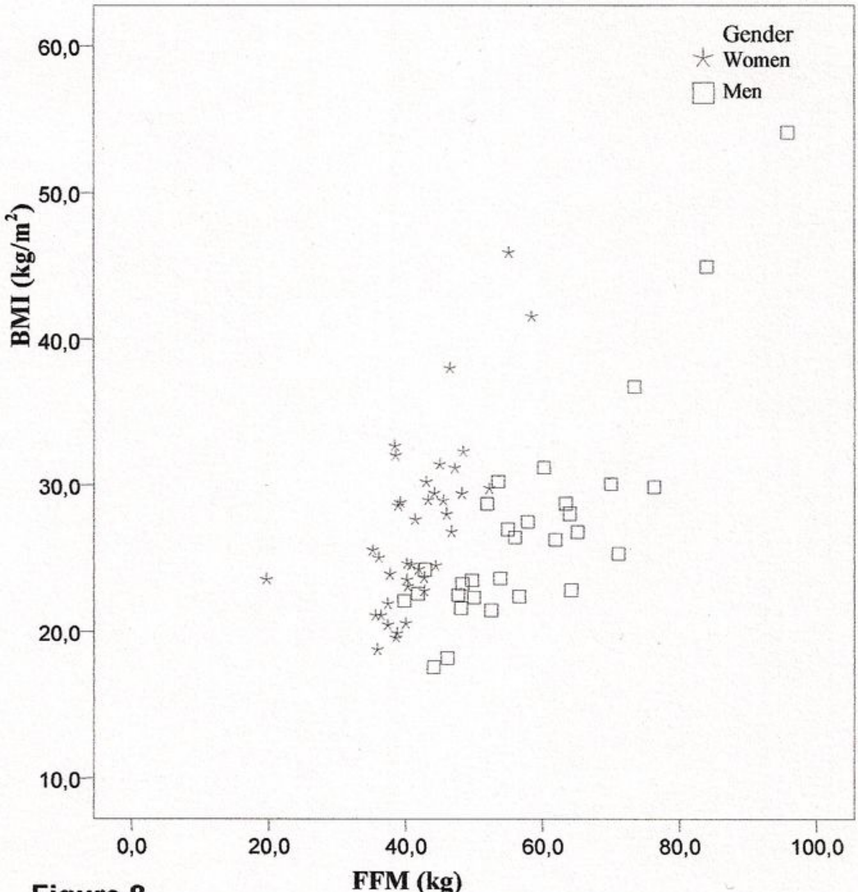

Gender
Women
Men
60,0
50,0
40,0
30,0
20,0
10,0
BMI (kg/m²)
0,0
10,0
20,0
30,0
40,0
50,0
GC (%)

Figure 7


Gender
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Men
BMI (kg/m2)
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40,0
30,0
20,0
10,0
0,0
20,0
40,0
60,0
80,0
100,0
FFM (kg)

**Figure 8**