ISSN (electrónico): 1699-5198 - ISSN (papel): 0212-1611 - CODEN NUHOEQ S.V.R. 318

ARÁN

Nutrición Hospitalaria

Trabajo Original

Valoración nutricional

# Heuristic evaluation of body mass index with bioimpedance data in the Mexican population

*Evaluación heurística del índice de masa corporal con datos de bioimpedancia en la población mexicana*

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## Abstract

**Introduction:** given the problematic battle against cardio-metabolic diseases and the increase in computational power, different applications are being developed to help estimate overweight and obesity in the population.

**Objectives:** to evaluate the body mass index (BMI) formula (kg/m$^2$), taking body fat measured by bioimpedance as a reference and comparing it with variations of the same form obtained by applying algebraic transformation rules using an artificial intelligence heuristic search method.

**Material and methods:** an artificial intelligence heuristic method was applied to search for the formula that most accurately calculates people's body fat percentage. The formula was generated from body mass and stature, variables used to estimate BMI. Thousands of formulas involving body mass and stature were generated from BMI using transformation rules with algebraic variations and increased and decreased constants.

**Results:** body mass, stature, and body fat percentage data set from 142 female and 150 male participants were used. Body mass and stature were used to classify participants into two classes based on body fat percentage (excessive or adequate, with cutoff points of 30 % for women and 15 % for men). The Youden index guided the search algorithm by evaluating candidate formulas to generate new ones. Among the formulas with the maximum value of the Youden index, Body mass$^{1.1}$ / Stature$^{2.9}$, is proposed as the best candidate as an alternative formula to apply instead of the BMI conventional formula.

**Conclusions:** although BMI showed a high Youden index, the AI algorithm found that the W$^{1.1}$ / H$^{2.9}$ formula is even more efficient in assessing body fat in men and women.

**Keywords:**

Anthropometry. Best first search. Mathematical algorithms.

Received: 29/03/2024 • Accepted: 03/09/2024

*Acknowledgments: the LaNCoCoME members acknowledge the support received by Conahcyt for the year 2024.*

*Conflicts of interest: all authors declare that they have no conflicts of interest concerning this investigation and have completed the International Committee of Medical Journal Editors (ICMJE) Format for Disclosure of Potential Conflicts of Interest, available at http://www.icmje.org/disclosure-of-interest/(accessed on 29 March 2024). The funders had no role in the study's design, in the collection, analyses, or interpretation of the data, in the writing of the manuscript, or in the decision to publish the results.*

*Artificial intelligence: the authors declare not to have used artificial intelligence (AI) or any AI-assisted technologies in the elaboration of the article.*

Ramos-Jiménez A, Hernández Lepe MA, Hernández-Torres RP, Murguía-Romero M. Heuristic evaluation of body mass index with bioimpedance data in the Mexican population. Nutr Hosp 2024;41(6):1238-1245
DOI: http://dx.doi.org/10.20960/nh.05247

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## Resumen

**Introducción:** ante la problemática batalla contra las enfermedades cardiometabólicas y el aumento del poder computacional, se están desarrollando diferentes aplicaciones que ayuden a estimar el sobrepeso y la obesidad en la población.

**Objetivos:** evaluar la fórmula del índice de masa corporal (IMC) (kg/m$^2$), tomando como referencia la grasa corporal medida por bioimpedancia y comparándola con variaciones de la misma forma obtenidas aplicando reglas de transformación algebraica mediante un método de búsqueda heurística de inteligencia artificial.

**Material y métodos:** se aplicó un método heurístico de inteligencia artificial para buscar la fórmula que calcule con mayor precisión el porcentaje de grasa corporal en las personas, que se generó a partir de la masa corporal y la estatura, variables utilizadas para estimar el IMC. Se generaron miles de fórmulas que involucran la masa corporal y la estatura a partir del IMC utilizando reglas de transformación con variaciones algebraicas y constantes aumentadas y disminuidas.

**Resultados:** se utilizó un conjunto de datos de masa corporal, estatura y porcentaje de grasa corporal de 142 mujeres y 150 hombres participantes. La masa corporal y la estatura se utilizaron para clasificar a los participantes en dos clases según el porcentaje de grasa corporal (excesiva o adecuada, con puntos de corte del 30 % para mujeres y del 15 % para hombres). El índice de Youden guió el algoritmo de búsqueda evaluando fórmulas candidatas para generar otras nuevas. Entre las fórmulas con el valor máximo del índice de Youden, Masa corporal$^{1.1}$ / Estatura$^{2.9}$, se propone como la mejor candidata como fórmula alternativa para aplicar en lugar de la fórmula convencional del IMC.

**Conclusiones:** aunque el IMC mostró un índice de Youden alto, el algoritmo de IA encontró que la fórmula Masa corporal$^{1.1}$ / Estatura$^{2.9}$ es aún más eficiente para evaluar la grasa corporal en hombres y mujeres.



**Palabras clave:**

Antropometría. *Best first search.* Algoritmos matemáticos.


## INTRODUCTION

Body mass index (BMI) is a recognized anthropometric evaluation to estimate, to varying degrees, to determine calorie-nutritional problems and to classify individuals with or without risk of metabolic diseases according to their body mass-for-stature ratio (1). It is used systematically to estimate undernutrition, overweight, and obesity and is crucial in determining public health policy. The elegant and simple formula allows a straightforward interpretation of an individual's calorie-nutritional status: BMI = body mass (kg) / stature (m)$^2$.

While it is a paradigm that BMI estimates the proportion of fat mass in both men and women (2), it provides a good measure of risk for heart disease, high blood pressure, dyslipidemias, type 2 diabetes, gallstones, respiratory problems, and certain types of cancer (3). Even in women, BMI values ≥ 25 kg/m$^2$ are associated with endocrine diseases such as hyperandrogenic syndrome (4). Its widespread application has allowed comparisons of health over time in different regions and population subgroups. However, BMI has limitations; it does not directly measure body fat, and factors such as age, gender, ethnicity, and muscle mass can influence the relationship between BMI and body fat (5). For example, BMI can classify muscular individuals as overweight or obese, especially in athletes, due to the higher muscle density compared to fat mass (6). In addition, BMI does not capture information about the distribution of fat mass at different sites in the body (2). Despite these limitations, BMI remains a valuable tool for assessing potential disease risk when used with other indicators, such as waist girth, body composition (fat mass, muscle mass, bone mass), lifestyles, and genetic and hereditary factors (7). However, new anthropometric indices are suggested to be developed that more readily estimate body fat, especially central adiposity. Such indices should be equally simple to apply and understand (5). Thus, the need arises to develop accurate equations that optimize the assessment of nutritional status and risks associated with disease, considering the biological and environmental factors described above. Such a task is complex and requires the simultaneous analysis of a large amount of data, where artificial intelligence (AI) and mathematical algorithms can help us.

Mathematical algorithms are increasingly important in diagnosing and treating obesity, which is relevant to medicine (8). In this sense, AI can help identify patterns of obesity among variables that are invisible to the naked eye but clinically significant (9).

Classical search engine techniques (chatbots) and traditional applications are still helpful in finding algebraic formulas that relate and provide optimal or near-optimal estimates among multiple variables. These search methods have the characteristic that the search space is explicit, i.e., they generate possible solutions that are automatically evaluated by the heuristic function predefined by the programmer but which, in turn, are directly observable by the researcher. Such is the case of BMI, which is used to find relationships between weight and height that estimate obesity. Using an equation, BMI expresses a particular way of relating two independent variables, body mass, and stature, allowing the estimation of overweight relative to body fat. Since BMI does not correctly estimate body fat in different populations (10), we wonder if there are variations of the BMI formula that assess obesity more accurately in most populations. AI can help in this search if the algebraic transformation rules and the heuristic function that guides them are defined.

Therefore, this work aimed to evaluate the BMI formula (kg/m$^2$), taking body fat measured by bioimpedance as a reference and comparing it with variations of the same form obtained by applying algebraic transformation rules using an AI heuristic search method.

## METHODS

### ETHICS AND PARTICIPANT ELIGIBILITY

All participants were informed of the study's purpose and procedures. Their acceptance was formalized through informed consent, and their anonymity and confidentiality were strictly enforced. This study was carried out following the Declaration of Helsinki and was approved by the Universidad Autónoma de Ciudad Juárez (UACJ) Review Board (Reference number: CBE. ICB/062.09-15).

Participant eligibility, anthropometric measurements, and electric bioimpedance evaluations have been published in detail (11).

## SEARCH SPACE

The "Best First Search" (BFS) method was used to generate a search space of alternative formulas to the BMI by applying 14 transformation rules starting from the BMI formula as the initial node, i.e., all evaluated formulas start from successive transformations of the BMI. The algebraic transformation rules applied were the same as in Murguía-Romero et al. (12): the increase or decrease of the stature exponent (by one-tenth), the increase or decrease of the body mass exponent, the change of the body mass share from base to exponent, the change of the stature share from base to exponent, the increase of a constant multiplying body mass as an exponent, the increase of a regular multiplying stature as exponent, the change of the equation as quotient to a multiplication, subtraction or addition (Fig. 1).

The heuristic function to guide the search was the accuracy of the formula concerning the percentage of body fat measured by bioimpedance. The cutoff points for deciding excessive body fat, measured as the percentage of total fat, were 15 % for men and 30 % for women, corresponding to the average values of total fat measured by bioimpedance in the participants.

Sensitivity, specificity, and their 95 % errors are described, as well as the Youden index and its counterpart, the overall accuracy of the equation.

The BFS algorithm was programmed in Prolog language and ran independently for women and men. A search space of at

```
% Prolog rules
rule(r10_exp_h_increment, W/H ^ Exp_h, W/H^Exp_h1):-
     number(Exp_h),
     Exp_h< 3,
     Exp_h1 is Exp_h + 0.1.
rule(r11_exp_w_increment, W^Exp_w/ H, W^Exp_w1/H):-
     number(Exp_w),
     Exp_w<2,
     Exp_w1 is Exp_w + 0.1.
rule(r20_w_as_exponent, W ^ Exp_w /H^N, 1.1^(W*1)/H^N):-
     number(Exp_w).
rule(r21_h_as_exponent, W / H^Exp, W / 2^(H*2)):-
     number(Exp).
rule(r31_w_increment_exp, Base^(W*N)/H, Base^(W*N1)/H):-
     number(Base),
     var(W),
     N < 2,
     N1 is N + 0.1.
rule(r32_h_increment_exp, W/Base^(H*N)), W/Base^(H*N1)):-
     number(Base),
     var(H),
     N < 4,
     N1 is N + 0.1.
rule(r33_decress_exp, W/Base^(H*N)), W/Base^(H*N1)):-
     number(Base),
     var(H),
     N > 1,
     N1 is N - 0.1.
rule(r40_w_base_inc, Base^(W*N) / H, Base1^(W*N)/H):-
     number(Base),
     Base < 4,
     Base1 is Base + 0.1.
rule(r41_w_base_dec, Base ^ (W*N)/H, Base1^(W*N)/H):-
     number(Base),
     Base > 0.1,
     Base1 is Base - 0.1.
rule(r42_h_increase_base, W/Base^ H, W/Base1^H):-
     number(Base),
     Base < 3,
     Base1 is Base + 0.1.
rule(r43_h_drecrement_base, W/Base^H, W/Base1^H):-
     number(Base),
     Base > 1,
     Base1 is Base - 0.1.
rule(r51_multiply, W/H,W*H).
rule(r52_substract, W / H, W - H).
rule(r52_add, W / H, H + W).
```

**Figure 1.**

Applied transformation rules to the generation of BMI variant formulae.

least 70,000 formulae was generated. In addition to its algebraic structure, each formula's sensitivity (and its error), specificity (and its error), Youden index, and precision were obtained.

## RESULTS

This study used data on body mass, stature, and body fat percentage measured by bioimpedance in 142 women and 150 men (Table I).

The BFS search method evaluated 70,955 BMI formula variants for women and 303,095 for men (Table II). Thus, formulas with a maximum sensitivity of 87 % for women and 79 % for men were obtained. It should be noted that the BFS algorithm is guided by the heuristic function, which in this case was sensitivity, so the search tree does not represent the totality of possible formulae when applying the defined algebraic transformation rules (Fig. 1).

The formulas with the highest Youden index (0.77 for women and 0.60 for men) are mostly algebraic in structure:

$$W^{a} / b^{Hc}$$

where W is the body mass (kg), and H is the stature (m), with a, b, and c constants. The maximum value was presented by a total of 328 and 40 formulas for females and males, respectively, of which almost all have the above algebraic structure, except the following three formulae for females:

$$W / H^{2.6}$$
$$W / H^{2.7}$$
$$W^{1.1} / H^{2.9}$$

And the following three formulas for men:

$$W / H^{2.6}$$
$$W^{1.1} / H^{2.8}$$
$$W^{1.1} / H^{2.9}$$

The formula $W^{1.1} / H^{2.9}$ has two essential characteristics: a) it is expected for women and men, and b) it has the same algebraic structure as BMI; only the values of the exponents change, so it was chosen as the possible formula for BMI, and with which its efficiency as a classifier is compared (Fig. 2, Table III).

Comparing the efficiency of the formula $W^{1.1} / H^{2.9}$ with the BMI (Table III) shows that the parameters are generally very similar. For example, the difference in sensitivity is 1 % in women and 4 % in men; in specificity, 0 % (women) and 1 % (men). The difference in the Youden Index is meager, 0.01 (women) and 0.04 (men). In general, the differences in the efficiency parameters of these two formulas are higher in men than in women. Sensitivity was lower than specificity in BMI and in all variant formulae explored.

**Table I.** Anthropometric characteristics of the participants

| Statistics | Women | | | | |
|---|---|---|---|---|---|
| | **Average** | **SD** | **Minimum** | **Maximum** | **Total data *(n)*** |
| Age, yrs | 21.1 | 4.0 | 17 | 46 | 143 |
| Weight, kg | 64.8 | 13.1 | 40.53 | 117.1 | 143 |
| Stature, cm | 160.3 | 5.0 | 149 | 171 | 143 |
| BMI, kg/m$^2$ | 25.2 | 4.5 | 16.6 | 42.0 | 143 |
| WG, cm | 76.5 | 10.1 | 54.8 | 104.8 | 143 |
| Body fat, % | 30.6 | 6.1 | 18.3 | 47.4 | 143 |
| | **Men** | | | | |
| | **Average** | **SD** | **Minimum** | **Maximum** | **Total data *(n)*** |
| Age, yrs | 21.9 | 3.4 | 16 | 37 | 151 |
| Weight, kg | 72.4 | 11.8 | 47.77 | 113.58 | 151 |
| Stature, cm | 172.4 | 6.7 | 154 | 189 | 151 |
| BMI, kg/m$^2$ | 24.4 | 3.9 | 17.3 | 40.9 | 151 |
| WG, cm | 80.5 | 8.8 | 64.5 | 109.6 | 151 |
| Body fat, % | 15.3 | 5.0 | 5.3 | 34.1 | 150 |

*SD: standard deviation; BMI: body mass index; WG: waist girth.*

**Table II.** Example of formulas generated in the BFS search space. The first 15 formulas with BMI as the starting node apply the rules in figure 1

| Search generation order | Formula | Sensitivity % | Specificity % | Error s 95 % | Error e 95 % | Youden Index | Accuracy % |
|---|---|---|---|---|---|---|---|
| **Women** | | | | | | | |
| 1 | $W/H^{2}$ | 86 | 90 | 24 | 18 | 0.76 | 88 |
| 2 | $W/H^{2.1}$ | 83 | 91 | 24 | 16 | 0.75 | 87 |
| 3 | $W^{1.1}/H^{2}$ | 86 | 90 | 22 | 16 | 0.76 | 88 |
| 4 | $W^{1.1}/H^{2}$ | 79 | 86 | 49 | 22 | 0.65 | 82 |
| 5 | $W/2^{2H}$ | 85 | 91 | 24 | 18 | 0.76 | 88 |
| 6 | $W*H^{2}$ | 75 | 79 | 69 | 33 | 0.53 | 77 |
| 7 | $W^{2}-H$ | 80 | 83 | 52 | 23 | 0.63 | 82 |
| 8 | $W^{2}+H$ | 80 | 83 | 52 | 23 | 0.63 | 82 |
| 9 | $W^{1.1}/H^{2.1}$ | 86 | 90 | 22 | 18 | 0.76 | 88 |
| 10 | $W^{1.2}/H^{2}$ | 86 | 89 | 21 | 16 | 0.74 | 87 |
| 11 | $W^{1.1}/2^{2H}$ | 87 | 90 | 24 | 18 | 0.77 | 89 |
| 12 | $W^{1.1}*H^{2}$ | 75 | 79 | 66 | 33 | 0.53 | 77 |
| 13 | $W^{2}-H^{1.1}$ | 80 | 83 | 52 | 23 | 0.63 | 82 |
| 14 | $W^{2}+H^{1.1}$ | 80 | 83 | 52 | 23 | 0.63 | 82 |
| 15 | $W^{1.2}/2^{2H}$ | 86 | 90 | 22 | 16 | 0.76 | 88 |
| **Men** | | | | | | | |
| 1 | $W/H^{2}$ | 76 | 80 | 77 | 45 | 0.55 | 78 |
| 2 | $W/H^{2.1}$ | 77 | 81 | 77 | 42 | 0.58 | 79 |
| 3 | $W^{1.1}/H^{2}$ | 76 | 78 | 77 | 46 | 0.54 | 77 |
| 4 | $W^{1.1}/H^{2}$ | 69 | 71 | 84 | 61 | 0.39 | 70 |
| 5 | $W/2^{2H}$ | 77 | 81 | 76 | 42 | 0.58 | 79 |
| 6 | $W*H^{2}$ | 61 | 65 | 87 | 81 | 0.26 | 63 |
| 7 | $W^{2}-H$ | 64 | 70 | 87 | 68 | 0.34 | 67 |
| 8 | $W^{2}+H$ | 64 | 70 | 87 | 68 | 0.34 | 67 |
| 9 | $W/H^{2.2}$ | 77 | 81 | 77 | 45 | 0.58 | 79 |
| 10 | $W^{1.1}/H^{2.1}$ | 76 | 78 | 76 | 45 | 0.54 | 77 |
| 11 | $W^{1.1}/H^{2.1}$ | 69 | 71 | 84 | 61 | 0.39 | 70 |
| 12 | $W*H^{2.1}$ | 59 | 65 | 87 | 82 | 0.23 | 62 |
| 13 | $W^{2.1}-H$ | 64 | 70 | 87 | 68 | 0.34 | 67 |
| 14 | $W^{2.1}+H$ | 64 | 70 | 87 | 68 | 0.34 | 67 |
| 15 | $W/H^{2.3}$ | 76 | 81 | 77 | 44 | 0.57 | 78 |

*W: body weight (kg); H: stature (m).*

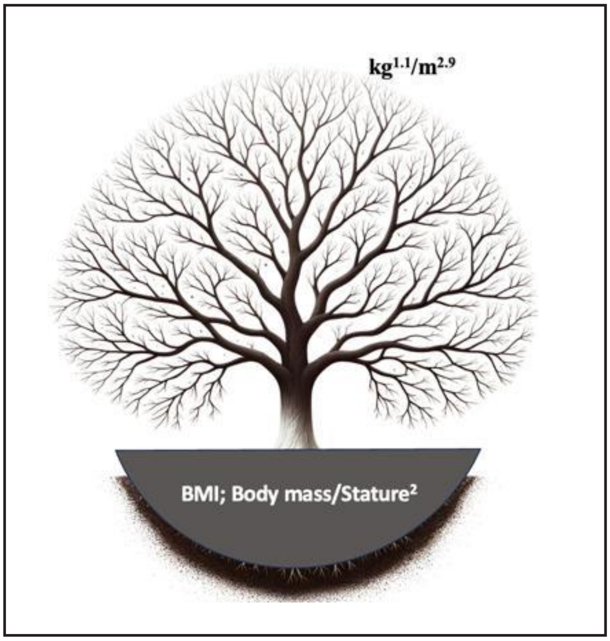


**Figure 2.** Representative structure of the applied heuristics in the search for the formula that best calculates fat percentage (body mass in $kg^{1.1}$ / stature in $m^{2.9}$). The formula was generated from BMI.

**Table III.** Efficiency characteristics of the BMI formulae and one found with maximum sensitivity

| | Women | | | Men | | |
|---|---|---|---|---|---|---|
| **Formula** | **BMI** | **W^1/H^2.9** | **Difference** | **BMI** | **W^1.1/H^2.9** | **Difference** |
| Sensitivity | 86 % | 87 % | 1 % | 76 % | 79 % | 3 % |
| Specificity | 90 % | 90 % | 0 % | 80 % | 81 % | 1 % |
| error s95 | 24 % | 22 % | -1 % | 77 % | 73 % | -4 % |
| error e95 | 18 % | 15 % | -3 % | 45 % | 46 % | 1 % |
| Youden Index | 0.76 | 0.77 | 0.01 | 0.55 | 0.60 | 0.04 |
| Accuracy | 88 % | 89 % | 1 % | 78 % | 80 % | 2 % |

*BMI: body mass index; W: body weight (kg); H: stature (m).*

## DISCUSSION

To our knowledge, this is the first work that performs a search for alternative formulas to BMI (kg/m²) using the "Best First Search" algorithm, a classical AI heuristic technique with a combinatorial approach to economically find optimal formulas from preceding nodes (13, 14). The formulas found here are variants of the BMI based on algebraic transformation rules, each generated from precursor branches, confirming a broad tree-like search space whose common root or trunk is the BMI. This work provides new knowledge in two respects. First, how the equation production system is defined, consisting of the transformation rules, the initial state of BMI (kg/m²), and the heuristic that guides the search for new formulas to detect obesity (12); it could serve as an example in the search for new classifiers of health status, such as the already known atherogenic indices of waist-hip, hypertriglyceridemia-waist, glucose-insulin, among others (1,15). Secondly, this work provides further insight into the properties of BMI in terms of its efficiency as a classifier of obesity-related health status (1). In this regard, the most important findings are that BMI is 10 % more sensitive in women than in men (86 % for women, 76 % for men), much higher than the sensitivity reported (~ 51 %) by Sommer et al. (16), and optimal when compared to its algebraic variants analyzed here. Regarding specificity, it is higher than sensitivity (90 % and 80 % for females and males, respectively) in all variants explored and slightly lower than those already reported (~ 96 %) (16). The differences may be due to the different methods used to calculate fat percentages between authors (16).

There is no doubt that BMI is a good discriminator of individuals' caloric-nutritional status, where values above 25 kg/m$^2$ are related to cardiovascular diseases, dyslipidemias, and insulin resistance (1). However, the $W^{1.1}$ / $H^{2.9}$ formula outperforms BMI as a classifier of fat percentage in both women and men and has the highest values for efficiency parameters among the many variants evaluated.

Murguía-Romero et al. (12), in a similar study and with the same methodology, compared BMI with other formulas and its relationship with metabolic syndrome. They found that the Ponderal Index is only 0.8 % more sensitive than BMI for classifying individuals at risk of metabolic syndrome. Similarly, we found two equations close to the weight index (Weight / Height$^{2.9}$), with only 1 % and 2 % more accurate than BMI for detecting obesity.

Coincidentally, the formulae $W^{1.1}$ / $H^{2.9}$ are very similar to the Ponderal Index (body mass / stature$^3$; kg/m$^3$), an index used to assess caloric-nutritional status in pregnant women, neonates, and infants and its associations with possible cardiovascular and metabolic complications (17). Ayatollahi (18) confirmed its usefulness as an indicator of fat mass in adolescents, like us, in people 17-46 years of age. However, BMI is still erroneously considered the best classification of the obesity degree (19). The low use of the Ponderal Index as an indicator of calorie-nutritional status in adolescents and adults may be because, to date, no cutoff points related to metabolic and cardiovascular diseases have been established for this index. In addition, BMI is a relatively more straightforward formula than the weight index.

The present analysis uses a dataset of 292 participants (142 women and 150 men) with total fat percentage measured by bioelectrical impedance as the independent variable. Thus, the results can be improved by increasing the number of participants, subdividing by age group, and taking visceral fat percentage instead of total fat percentage as the independent variable. Another way to improve the analysis is to increase the search space and evaluate an even more significant number of people. However, no more efficient formulas than those found here will likely be seen, as the algorithm (BFS) is very efficient.

AI-powered tools are effective in decision-making and digital health interventions for weight loss (9). AI can personalize diets and exercise programs to suit individual needs by analyzing large amounts of clinical data: blood, images, medications, stomach bacteria, reactions to certain foods, and lifestyles, among others. AI can also be used to predict and treat obesity in adults. For example, AI algorithms have been developed to predict when people will drop out of weight loss programs (20). As we are currently experiencing with ChatGPT, AI can also act as a behavioral coach, encouraging patients to follow a healthier lifestyle.

Despite advances in AI, it is essential to recognize that human interaction remains valuable in treating obesity. Research shows that AI-powered weight loss apps are most effective when used with support from healthcare professionals (21), as they can offer more personalized weight loss advice and empathetic doctor-patient interactions.

## LIMITATIONS

This analysis uses data from 143 and 150 female and male participants, respectively, so it was impossible to obtain adequate resolution to differentiate between many formulas for which the maximum value of the Youden index was obtained. Studies that involve data from more participants may yield more precise results. For the same reason, no cutoff points were proposed for the candidate formula that exceeds the BMI in the Youden index, and it was not possible to evaluate the formulas by age groups.

## CONCLUSIONS

The BMI showed a Youden index close to the formulas with the highest value, corroborating its importance in evaluating health with body mass. Although the AI algorithm found that the $W^{1.1}$/ $H^{2.9}$ formula is even more efficient in assessing body fat in men and women. In summary, AI has a great potential to aid in diagnosing and treating obesity and can be a valuable tool for nutritionists and exercise physiologists. While AI offers solutions and support to patients with obesity, it is essential to combine it with the support of healthcare professionals to obtain the best results in weight loss and obesity treatment.

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