Automated and Personalized Nutrition Health Assessment, Recommendation, and Progress Evaluation using Fuzzy Reasoning

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Abstract—**Establishing a healthy lifestyle has become a very important aspect in people's lives. The latter requires maintaining a healthy nutrition by considering the type and quantity of consumed foods. It also requires maintaining an active lifestyle including the necessary amount of physical exercise to regulate one's intake and consumption of calories and nutrients. As a result, people reach out for nutrition experts to perform health assessment, whose services are costly, time consuming, and not readily available. While various e-nutrition solutions have been developed, yet most of them perform meal planning without performing health state assessment or evaluation (traditionally provided by human experts). To our knowledge, there is no existing automated solution to perform nutrition health assessment, recommendation, and progress evaluation, which are central pre-requites to the meal planning task. In this study, we introduce a novel framework titled *PIN* for Personalized Intelligent Nutrition recommendations. *PIN* relies on the fuzzy logic paradigm to simulate human expert health assessment capabilities, including weight, caloric intake, and exercise recommendations as well as progress evaluation and recommendation adjustments. It includes three essential and complementary modules: i) Weight Assessment and Recommendation (*WAR*), ii) Caloric Intake and Exercise Recommendation (*CIER*), and iii) Progress Evaluation and Recommendation Adjustment (*PERA*). This underlines the first computerized solution for nutrition health assessment. We have conducted a large battery of experiments involving 50 patient profiles and 11 nutrition expert evaluators to test the performance of *PIN* and evaluate its health assessment quality. Results show that *PIN*'s assessment and recommendations are on a par with and sometimes surpass those of human nutritionists.**

Keywords—***Nutrition health, Assessment and recommendation, Progress evaluation, Recommendation adjustment, Fuzzy logic agents, Fuzzy reasoning.***

1. Introduction

Nowadays, establishing a healthy lifestyle has become a very important aspect in people's lives. The latter requires maintaining a healthy nutrition by considering the type and quantity of consumed foods, as well as maintaining an active lifestyle including the necessary amount of physical exercise to regulate one's intake and consumption of calories and nutrients (Orji R. and Mandryk R. 2014, Parker A. G. and Grinter R. E. 2014). Poor nutrition and a lack of physical activity tend to increase the risks of dangerous complications such as obesity, diabetes, and other health issues (Ayoub J. *et al.* 2015, Mattar L. *et al.* 2015). As a result, people reach out for nutrition experts to help them achieve healthy lifestyles. In this context, a few obstacles come to play: i) the cost of seeking an expert's help which is recurring and non-trivial, ii) the need to attend regular meetings with the expert which might not be always practical, and iii) the need for readily accessible health services which might be difficult to provide by a human expert. An alternative approach is to use electronic solutions, such as mobile applications and websites that are highly available and provide basic health and nutrition services. While many solutions exist, yet most of them share the following weaknesses: i) lack of a completely automated process, where most existing solutions require manual tuning and a certain level of nutrition expertise to be utilized properly, e.g., (Livestrong Foundation 2021, Evans D. 2017, El-Dosuky M. A. *et al.* 2012), ii) providing limited health assessment by considering certain (less informative) health indicators (e.g., BMI[1]) and disregarding others (e.g., BFP[2]) (MyNetDiary Inc. 2021, SparkPeople Inc. 2021), and iii) performing meal planning or meal plan evaluation without performing health state assessment and progress evaluation (MakeMyPlate Inc. 2021, Noor S. *et al.* 2018, Petot G. J. *et al.* 1998), which are central pre-requites to the meal planning task. In fact, to our knowledge, there is no existing automated solution to perform nutrition health state assessment, recommendation, and progress evaluation.

The main goal of this study is to create a framework that provides the same quality of services offered by a human nutrition expert albeit doing it through a readily available, fully automated, and cheap e-solution. Our framework aims at providing: i) an assessment of the patients' nutrition health state: whether they should *gain*, *lose*, or *maintain* weight (based on multiple nutrition-health indicators), ii) a recommendation to strike a good balance between food intake (how much the patient should eat) and

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[1] The Body Mass Index is evaluated as the patient's weight divided over the patient's height (cf. Section 2.1).
[2] The Body Fat Percentage (BFP) is computed as the ratio of the patient's body fat weight over the total body weight (cf. Section 2.1).

physical exercise (how much the patient should exercise), and iii) a progress monitoring and adjustment of the patient's health indicators and weight. To achieve the latter services, we develop a new framework titled *PIN* for Personal Intelligent Nutrition recommendations. It includes three main agents designed using the fuzzy logic paradigm to simulate the "human common sense" thought process involved in nutrition health assessment and recommendation; i) Weight Assessment and Recommendation (*WAR*) agent: evaluates the weight state of a patient based on various inputs (age, gender, height, weight, and BFP) and then recommends a target BFP and weight (an early version of this agent is described in (Salloum G. *et al.* 2018)), ii) Caloric Intake and Exercise Recommendation (*CIER*) agent: estimates Caloric Intake (CI) and exercise recommendations based on the physical activity level of the patient and the patient's target BFP and weight produced by the *WAR* agent, and iii) Progress Evaluation and Recommendation Adjustment (*PERA*) agent: monitors and evaluates the progress of the patient toward the target BFP and weight, and adjusts the CI and exercise recommendations when required (i.e., when the patient is not making the expected progress). *PERA* is specifically important since patients' bodies do not always evolve regularly or the same way, even when following the same nutrition recommendations. *CIER* and *PERA*'s recommendations are required to perform meal plan generation[3].

We have conducted a large battery of experiments involving 50 patient profiles and 11 nutrition experts to test the performance of *PIN*. Various experimental tasks and metrics were designed with the help of 2 elect experts[4] to evaluate each of *PIN*'s three agents: *WAR*, *CIER*, and *PERA*. Inter-tester correlations were evaluated and matched with *PIN*'s scores to account for human expert (dis)agreement. Results show that *PIN*'s assessment quality and recommendations are on a par with and sometimes surpass those of human nutritionists.

The remainder of this paper is organized as follows. Section 2 presents the background and motivations of our study. Section 3 briefly reviews the related works and existing e-solutions revolving around nutrition health assessment. Section 4 describes the *PIN* framework and its components. Section 5 describes our experimental evaluation and results. Finally, Section 6 concludes with future directions.

2. Background and Motivations

The first step to performing nutrition health assessment requires collecting input information regarding the patient: i) gender, ii) age, iii) height, iv) weight, and v) Body Fat Percentage (BFP). Based on the latter, the human nutritionist's main task consists of: i) evaluating the patient's current BFP and weight, ii) recommending the patient's target BFP and weight, and iii) evaluating the patient's BFP and weight progress to adjust the recommendation accordingly. Based on the latter information and evaluations, the nutritionist can recommend a meal plan allowing the patient to reach her/his target BFP and weight.

In this section, we briefly review basic nutrition and health related concepts targeting the above tasks, and highlight the challenges and motivations of our study. Note that we omit the discussion of meal plan generation and evaluation tasks form this paper and describe them in a dedicated study (Salloum G. and Tekli T. 2021). We also provide a brief description of the preliminaries of the fuzzy logic paradigm.

2.1. BFP and Weight Assessment and Recommendation

A common approach for nutrition health assessment relies on the usage of *height-weight tables* (Kathleen M. and Janice R. 2017) as a tool for mapping patients' heights to recommended weights. Several *ideal weight formulas* can be used to recommend the weight of a person based on her/his height, while sometimes considering other parameters such as gender and age (Pai M. P. and Paloucek F. P. 2000). For instance, Body Mass Index (BMI) (Kathleen M. and Janice R. 2017) is a well-known health metric that considers both the current weight and height of the patient, and is computed following Formula 1:

$$BMI = \frac{Weight(Kg)}{Height^2(m^2)} \quad \textbf{(1)}$$

$$BFP = \frac{Body\ Fat\ Weight\ (Kg) \times 100}{Total\ Body\ Weight\ (Kg)} \quad \textbf{(2)}$$

While BMI and similar formulas can provide a target (*ideal*) weight recommendation based on the patient's height (if the target BMI is known in advance), they disregard the current weight of the patient (i.e., the weight of the patient at the time of the recommendation), and more importantly they disregard the patient's body fat composition. For instance, the author in (Khan A. S. and Hoffmann A. 2003) demonstrated in a study of 486 subjects, that about 87% of the patients classified as *normal* and *overweight* following BMI were actually *obese* according to their Body Fat Percentage (BFP). BFP is a commonly used health metric that is computed as the ratio of the patient's body fat weight over the total body weight following Formula 2. It is an indicator of the patient's body fat composition which is essential to perform accurate health assessment (Kathleen M. and Janice R. 2017). In our study, we adopt the BFP classification suggested by the American College of Sports Medicine (Khan A. S. and Hoffmann A. 2003), which is commonly used in nutrition health literature. The latter classifies patients as *underweight*, *healthy weight*, *overweight*, or *obese* based on their BFPs, taking into account their gender and age.

[3] Meal plan generation and evaluation tasks are supported by *PIN*. Yet, we omit them from this paper and describe them in a dedicated study (Salloum G. and Tekli T. 2021).

[4] The following elect experts assisted the authors in reviewing certain nutrition-related aspects in the study. They will be referred to as "elect experts" in the remainder of the paper: i) Dr. Maya Bassil, Associate Professor of Human Nutrition in the Department of Natural Sciences at LAU, and ii) Ms. Eva-Maria Kahwaji, M.Sc. in Physiology and Nutrition of Sport and Exercise at Loughborough University.

Once the patient's BFP is identified (through a simple test that can be performed at a specialized clinic or pharmacy), the expert nutritionist can decide on the target BFP and weight of the patient using a experiential reasoning process, which brings us to the first challenge motivating our study:

Motivation 1: There is no algorithmic or mathematical procedure to compute the target BFP and the target weight of a patient. Our literature review and discussions with professional nutritionists indicate that BFP and weight recommendations are "fuzzy" tasks which usually rely on the experience and expertise of the nutritionist.

Once the target BFP and weight are identified, the nutritionist needs to determine the daily Caloric Intake (CI) required to reach those targets, considering the patient's Caloric Expenditure (CE) and exercise habits. In fact, weight change comes down to the gap between CI and CE, i.e., the difference between the amount of energy acquired from food and the energy consumed by the human body, both measured in Kilocalories (Kcal). If the daily CI is larger than the daily CE, the patient will gain weight in the long run, and vice versa (Min W. *et al.* 2019). In this context, several mathematical formulas exist to identify CE, considering the Basic Metabolic Rate (BMR) and the Total Energy Expenditure (TEE) of the patient (Kathleen M. and Janice R. 2017). Also, various guidelines exist regarding how to ensure a steady and healthy weight loss[5]. In this study, we aim to provide personalized recommendations while abiding by standard health guidelines, e.g., (ODPHP 2015, Hall K. D. et al. 2011, Hall K. D. 2008).

2.2. Caloric Intake (CI) Recommendation

Another service provided by a nutrition expert is determining the CI of the patients while considering their target weights and Total Energy Expenditures (TEE). When determining CI, three general guidelines are usually adopted: i) if the goal set for the patient is to *maintain weight*, CI should be equal to TEE; ii) if the goal is to *gain weight*, CI must be greater than TEE; and iii) if the goal is to *lose weight*, CI must be lower than TEE, which brings us to our second motivating challenge:

Motivation 2: There is no algorithmic or mathematical procedure to compute CI reduction. Our literature review and discussions with nutritionists indicate that it is a "fuzzy" process which requires common-sense decision making.

2.3. Exercise Recommendation

In addition, daily physical exercise can contribute in increasing the TEE, and thus affects CI recommendation accordingly. In certain cases, exercise is the only way to lose weight without recommending an excessively low and unhealthy CI. However, the exercise caloric expenditure is relative to body weight, and general guidelines are difficult to apply to every case (ODPHP 2015). Exercise recommendation relies on: i) CI, ii) TEE, iii) general exercise guidelines, and iv) the patient's exercise preferences, which highlights our third motivation:

Motivation 3: There is no algorithmic or mathematical procedure to compute the amount of exercise needed to reach a target CI reduction rate. Our literature review and discussions with nutritionists indicate that it is a "fuzzy" process requiring common-sense decision making.

2.4. Progress Evaluation and Recommendation Adjustment

Progress monitoring and re-evaluation are common practice in health nutrition (Kathleen M. and Janice R. 2017), allowing a nutritionist to adjust the patient's CI and exercise recommendations when small or no BFP and weight progress are being made - despite the patient's adherence to the nutritionist's previous recommendations, which brings us to our fourth motivating challenge:

Motivation 4: There is no algorithmic or mathematical procedure to evaluate the progress of the patient's BFP and weight, and there are no clear guidelines to determine how much progress is acceptable when the patient is not losing (or gaining) the expected weight. Our literature review and discussions with nutritionists indicate that it is a "fuzzy" and subjective process requiring common-sense decision making which might significantly differ from one nutritionist to the other.

2.5. Preliminaries of Fuzzy Logic

Fuzzy logic is a multivalued logic that allows the definition and usage of intermediate values between conventional evaluations like *true*/*false*, *yes*/*no*, *gain*/*loose/maintain weight*, etc. It is a paradigm for processing data by using partial set membership, where an element can be part of one set and its compliment albeit with varying membership degrees (e.g., 70% *true* and 30% *false*). It incorporates a condition-action rule-based *IF X AND Y THEN Z* approach rather than attempting to model a system mathematically (Ross T. J. 2016). The model and its fuzzy membership functions are defined empirically, and rely on the designer's experience

[5] A healthy *weight loss* rate should not amount to more than 1 pound (0.45 kilograms) per week (Hall K. D. *et al.*, 2011), where a cumulative energy deficit of 3500 kcals is the equivalent of the loss of 1 pound per bodyweight (Hall K. D. *et al.*, 2011, Hall K. D., 2008). This translates into a daily 500 Kcals deficit. A slower rate of half a pound per week can be achieved by a daily 250 Kcals deficit, while faster rates of a pound and a half or two pounds per week can be achieved by 750 or 1000 Kcals daily deficits respectively. The same concept is applied to *weight gain*: a caloric surplus of 500 Kcals per day is associated with a *weight gain* of 1 pound per week.

and understanding of the system and its environment (Vlachos I. K. and Sergiadis G. D. 2007). For example, rather than dealing with weight recommendation in terms of CI=1500 kcals, BMI = 21.2, and BFP = 17.5, expressions like *IF Overweight*(*BMI*) *AND Fair*(*BFP*) *THEN Good*(*BFP*) are used. While they seem imprecise, yet such expressions can be very descriptive and provide a necessary level of abstraction on top of the crisp data values, allowing to guide the decision making process.
A typical fuzzy logic agent consists of 4 main components (Ross T. J. 2016, Kuncheva L. 1995, Zadeh L. A. 1984): i) fuzzification, ii) inference, iii) aggregation, and iv) defuzzification. Fuzzification consists in transforming input crisp values (received from sensors) into fuzzy membership scores associated with a set of linguistic variables (e.g., *normal*, *underweight*, *obese*) defined by the system designer (e.g., BMI = 21.2 is transformed into 87% *normal* and 13% *underweight*). Inference consists in applying a set of designate condition-action rules on the fuzzified data in order to produce fuzzy outputs. Multiple rules can produce different outputs, and need to be aggregated in order to produce one single fuzzy output function. The fuzzy output function is consequently defuzzified in order to produce crisp values as the final output of the agent (sent as commands to the actuators).

In this study, we adopt the fuzzy logic paradigm in order to automate the "human common sense" thought process involved in nutrition health assessment and recommendation.

3. Existing E-Solutions

Computerized applications related to nutrition health are becoming more and more available for users on different platforms. They can be organized in two main categories: i) calorie tracking tools and ii) meal planning tools. Most of them disregard nutrition health assessment, recommendation, and progress evaluation.

3.1. Calorie Tracking Tools

Calorie tracking tools, e.g., (MyNetDiary Inc. 2021, Evans D. 2017, Hall K. D. et al. 2011, Hall K. D. 2008), assist patients in monitoring their daily caloric intake (CI) and consumed macronutrients by accepting as input the patient's consumed foods, and producing/calculating as output the amount of calories and macronutrients contained in the consumed foods. One such tool is MyFitnessPal (Evans D. 2017), a mobile application that accepts as input the patient's consumed foods selected from a predefined food database, and then produces as output the required CI per day and the distribution of macronutrients necessary to reach the destination weight. The application also calculates and keeps track of the CI and macronutrient grams consumed by the patient, and offers additional functionality related to training and workout logs. The tool requires the patient to provide basic health information (e.g., age, weight, height, and physical activity level), as well as more technical nutrition health information (e.g., target weight, daily CI, and macronutrient distribution) which are usually determined by a nutrition expert. Another similar tool is MyPlate (Livestrong Foundation 2021) which collects the patient's basic health information (e.g., gender, age, height, weight) and requires the patient to determine her own target weight. The tool then estimates CI levels based on the patient's target weight and total energy expenditure (TEE). No exercise recommendations are suggested in the case of low TEE to compensate for the recommended low CI. Other similar tools such as MyNetDiary (MyNetDiary Inc. 2021) and SparkPeople (SparkPeople Inc. 2021) are also available on the Web. In short, the above mentioned tools i) require technical inputs which might be difficult to provide by non-expert users (e.g., target weight and macronutrient distribution), and ii) perform calorie consumption tracking based solely on the patient's weight and height (without considering the patient's BFP) which do not always produce accurate recommendations (due to the lack of distinction between fat mass and muscle mass, cf. Section 2).

3.2. Meal Planning Tools

Meal planning tools, e.g., (EatThisMuch Inc. 2021, Fitness Meal Planner 2021, MakeMyPlate Inc. 2021), generate daily meal plans based on patient provided CI requirements. One such tool is MakeMyPlate (MakeMyPlate Inc. 2021), a mobile application that recommends daily pre-defined meal plans fulfilling user specified CI levels. It allows the patient to replace a meal with an existing meal stored in the database, without verifying whether the replacement meal is calorically equivalent to the original one (which might result in surpassing or dropping below the recommended CI and macronutrient amounts). Another solution is EatThisMuch (EatThisMuch Inc. 2021), which accepts as input the patient's basic health information (e.g., gender, age, height, weight, and physical activity level) in addition to the BFP. It also accepts as input the patient's target weight in textual from (i.e., *maintain weight*, *lose weight*, *gain weight*, and *gain muscle*), the preferred diet type (e.g., Mediterranean, vegetarian), as well as patient food preferences. The application then produces as output daily meal plans. While powerful, yet this solution does not make any recommendation or decision regarding the health state of the patient (i.e., it does not generate a target weight or a CI recommendation). Fitness Meal Planner (Fitness Meal Planner 2021) is yet another online application sharing most of the functionalities as well as the limitation of the latter solution. The authors in (Yang L. *et al.* 2017) describe an online framework to monitor foods consumed by the patient, using food image recognition through machine learning. The system learns patient preferences by allowing the patients to select their favorite foods by uploading pictures of them. Then, image analysis is performed through a dedicated convolutional neural network to recognize the foods in the picture, allowing the system to recommend similar foods from a pre-defined food database. The aim of the study is to improve the recommendations of survey-based systems (where food preferences are learned through manual patient surveys) by using image analysis-based preference learning. Yet, the study in (Yang L. *et al.* 2017) does not aim to produce target weight or CI recommendations, nor does it produce meal plans that meet the nutrition requirements of a patient. In (Rabbi M. et al. 2015), the authors introduce another machine learning algorithm called Multi-Armed Ban (MAB) to cluster the physical activities and food logs of the patient, and provide personalized suggestions such as recommended meals or increasing the patient's physical activity. Yet, similarly to (Yang L. *et al.* 2017), the solution does not perform nutrition health assessment, and does not produce target weight or CI recommendations. Few knowledge-based approaches have been developed to evaluate meal plans, e.g., (Lertkrai P. *et al.* 2016, Wang M.H. *et al.* 2016, El-Dosuky M. A. *et al.* 2012, Lee C.S. *et al.* 2010, Wang M. H. 2009), using food ontologies constructed by domain experts and coined with fuzzy inference rules. Yet, most approaches in this category focus on evaluating existing meal plans suggested by the patient, rather than performing automatic nutrition health assessment, recommendation, and progress evaluation. The reader can refer to (Tran T. *et al.* 2020, Valdez A.C. *et al.* 2016) for comprehensive reviews of recommender systems for health informatics.

3.3. Discussion

To sum up, most existing nutrition health e-solutions share the following limitations: i) lack of a completely automated process for health assessment and meal planning, requiring domain expert intervention at different stages of the recommendation process (e.g., identifying target weight and macronutrient distribution), ii) most solutions address the meal planning problem while disregarding nutrition health assessment, recommendation, and progress evaluation, iii) those few solutions which partly perform health assessment, e.g., (Livestrong Foundation 2021, MyNetDiary Inc. 2021, SparkPeople Inc. 2021, Evans D. 2017), provide "coarse" assessments considering basic indicators (such as gender and weight) rather than using a more informative nutrition measurements such as BFP which would produce more accurate results (due to the distinction between fat mass and muscle mass). We address all the above limitations in our current solution.

4. Proposal

We introduce a framework titled Personal Intelligent Nutritionist (or *PIN*) which aims at automating the health assessment and recommendation services offered by a nutrition expert. *PIN*'s general architecture is shown in Figure 1. First, the patient provides initial health information (e.g., gender, age, weight, height, and BFP) to the Weight Assessment and Recommendation (*WAR*) agent who determines the patient's destination BFP and weight. *WAR*'s selected output is then fed as input to the Caloric Intake and Exercise Recommendation (*CIER*) agent to determine the patient's recommended CI and amount of physical exercise. One or more "healthy" recommendations can be generated (e.g., the same patient could be recommended to maintain her/his healthy weight and CI even though the target BFP is not reached, or to lose some weight by either reducing CI or increasing the amount of physical exercise – in order to reach the target BFP). Most importantly, and at any point in time, the patient can input her/his updated BFP and weight to the Progress Evaluation and Recommendation (*PERA*) agent who assesses the progress of the patient and adjusts the recommendations accordingly. The above three agents are designed based on the fuzzy logic paradigm in order to automate the "human common sense" thought process involved in nutrition health assessment and recommendation. *CIER* and *PERA*'s outputs are subsequently used to perform meal plan generation[6].

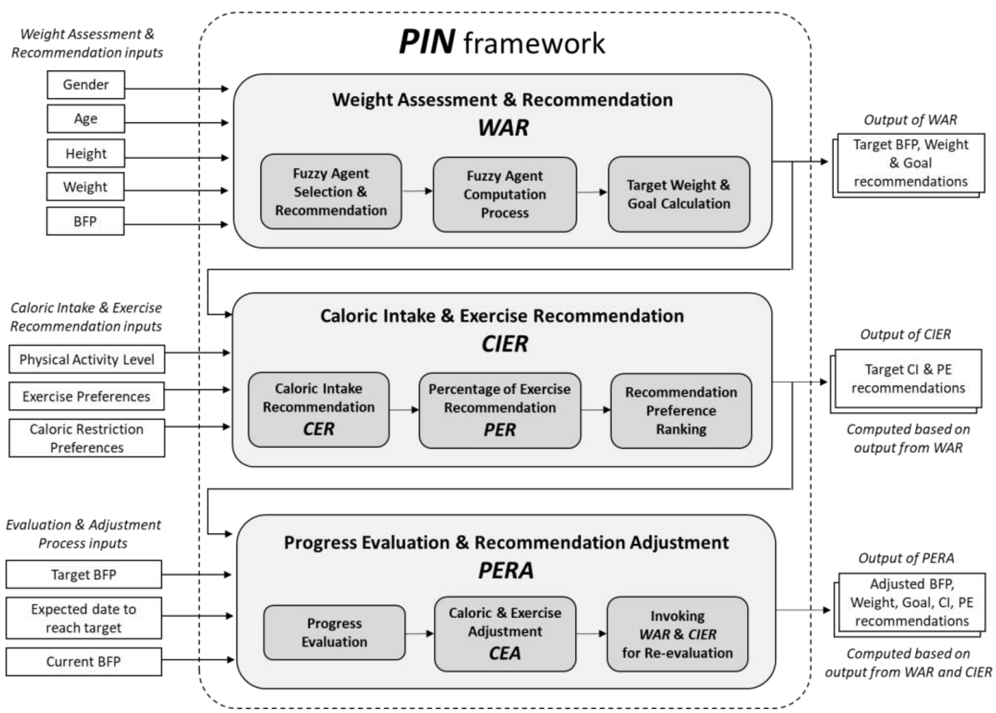


Figure 1. Simplified diagram describing *PIN*'s overall architecture

[6] Meal plan generation and evaluation tasks are supported by *PIN*, Yet we omit them from his paper and describe them in a dedicated study (Salloum G. and Tekli T. 2021).

4.1. Weight Assessment and Recommendation (*WAR*) agent

The *WAR* agent's overall process is shown in Figure 2. It accepts as input the patient's BMI and BFP, and provides as output: i) the target BFP, ii) the target weight, and iii) the recommendation goal (i.e., *loose*, *gain*, or *maintain* weight). *WAR* considers both BMI and BMF metrics as input since their combination allows for a more accurate assessment of the patient's weight state, versus only considering the patient's weight or BMI (as discussed in Section 2.1). More specifically, *WAR* consists of a set of fuzzy agents carefully designed following well established crisp value BMI and BFP classifications (Kathleen M. and Janice R. 2017, Dalleck L. C. and Tischendorf J. S. 2012). The appropriate fuzzy agent is selected based on the patient's age and gender, and is then run on the input BMI and BFP of the patient in order to produce the recommended **target BFP** as output. Recall that there is no algorithmic or mathematical process that allows determining a target weight based on a starting BFP and weight (cf. *Motivation 1* in Section 2.1). The *BFP Recommendation* agents are described in more detail in the following sub-section.

After the target BFP is computed, the next step is to estimate the patient's target weight. Following our review of the nutrition literature, there is no agreed upon mathematical procedure to determine the percentage of fat loss out of the total weight loss. In addition, the literature lacks a clear definition on how much of the lost weight is attributed to fat loss (cf. Section 2). Hence, after many discussions with our elect nutrition experts, we adopt the following assumption: *weight loss is only due to fat loss*. The fat loss is the difference between the old fat mass and the new fat mass, which is represented by the BFP multiplied by the body weight (the same logic is applied in the case of *weight gain*). As a result, we compute the **target weight** as follows:

$$w' = w - (w * \frac{p}{100} - w' * \frac{p'}{100}) \quad \textbf{(3)} \qquad \text{which simplifies to:} \qquad w' = w * \frac{\left(1 - \frac{p}{100}\right)}{\left(1 - \frac{p'}{100}\right)} \quad \textbf{(4)}$$

where *w* and *w'* represent the current and target weights respectively, and *p* and *p'* represent the current and target BFP respectively. The current body weight (*w*) and current BFP (*p*) are acquired inputs. The target BFP (*p'*) is computed by the corresponding fuzzy *BFP Recommendation* agent. Consequently, the target weight (*w'*) is computed using Formula 4.

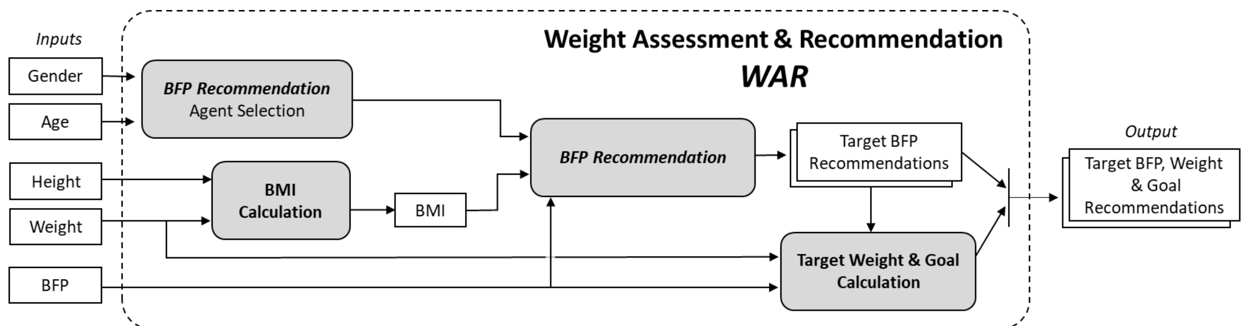


Figure 2. Simplified diagram describing the general process of the *WAR* agent

As a result, more than one "healthy" option can be recommended (e.g., maintain a healthy weight even though the target BFP is not exactly reached, or slightly lose some weight to perfectly reach the target BFP) allowing the patients to choose the option that best fits their preferences. These options are produced following the condition-action rules that are activated by the agent when processing the patient's inputs. Finally, the **recommendation goal** is determined based on the weight recommendation: i) if the target weight is larger than the current weight, the goal is to *gain* weight, ii) if the target weight is lesser than the current weight, the goal is to *lose* weight, iii) if the difference between the target and current weights is within ±0.5 kilograms, the goal is to *maintain* the current weight. Ts.

4.1.1. BFP Recommendation agent(s)

The *BFP Recommendation* agent's overall process is shown in Figure 3. First, the input BMI and BFP scalar values are fuzzified, producing linguistic values associated with fuzzy membership degrees (e.g., BMI 21.2 becomes 87% *normal* and 13% *underweight* after fuzzification following Figure 4.a). We carefully craft the BMI fuzzy partitions following the WHO (World Health Organization) BMI crisp value classification (Kathleen M. and Janice R. 2017)[7]. BFP fuzzy partitions are crafted based on the classification suggested by the American College of Sports Medicine (Dalleck L. C. and Tischendorf J. S. 2012)[7]. In contrast to BMI classification that is applied for both adult females and males, BFP classification is both *age* and *gender* specific, and consists of 6 different female age categories, and 6 different male age categories (cf. Figure 4.b and c). As a result, we define 12 separate

[7] We translate the crisp BMI categories into fuzzy sets using normalized triangular and trapezoidal functions (which are commonly adopted in fuzzy logic literature, e.g., (Ross T. J., 2016, Kuncheva L., 1995)). The fuzzy set boundaries are defined following the reference crisp categories, and they serve as the intersection points between the fuzzy membership functions. The functions intersect each other with a membership score = 0.5. For example, BMI=18.5 is the boundary between *underweight* and *normal* fuzzy sets and has a 0.5 membership in each of the mentioned sets. Maintaining a 0.5 score for all fuzzy set intersections is crucial to produce a normalized fuzzy system where the sum of all membership functions at any BMI data point is always =1. A similar process is adopted to produce the BFP partitions.

agents: i) a *female BFP Recommendation* agent for each female age categories and ii) a *male BFP Recommendation* agent for each male age category. The fuzzy partitions for all agents are available online[8].

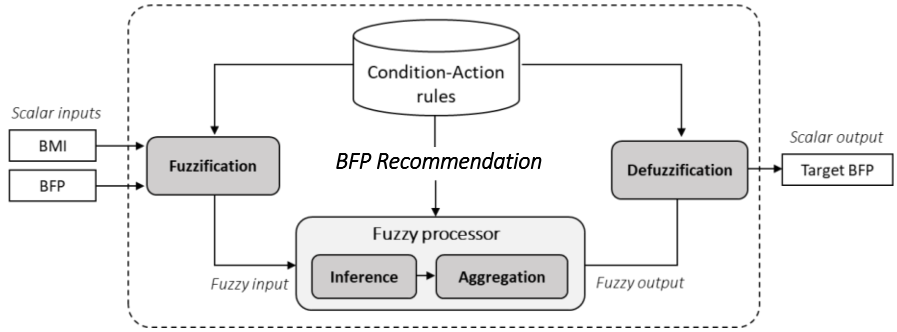
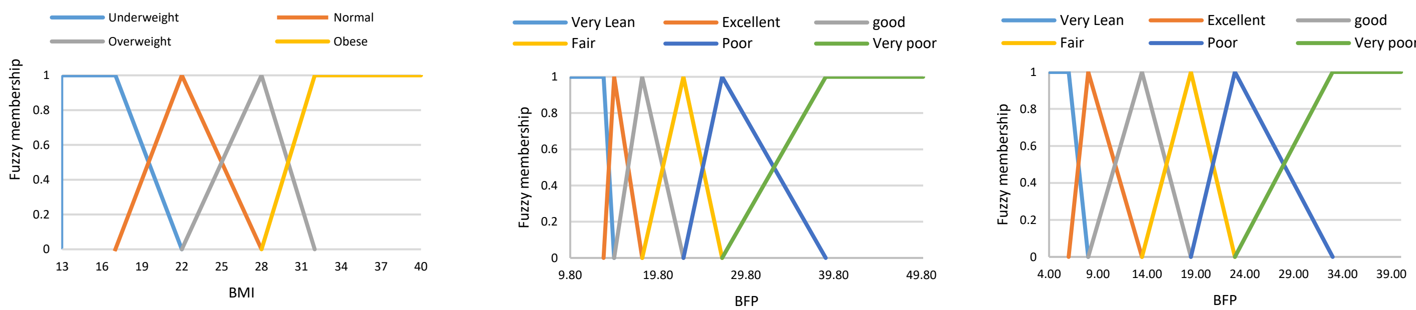


Figure 3. Simplified diagram describing the *BFP Recommendation* agent's fuzzy control logic

As for the agent's condition-action rules, they reflect the common sense logic applied by a human nutrition expert to determine a target BFP based on the patient's current BMI and BFP. We provide in Table 1 a set of condition-actions rules that we defined with the help of our elect nutrition experts (to our knowledge, such rules are not explicitly defined in the literature). Note that the same condition-action rules, inference mechanism, aggregation and defuzzification functions are adopted in all 12 BFP recommendation agents.



a. BMI fuzzy sets **b.** BFP fuzzy set for females between 20 and 29 **c.** BFP fuzzy set for males between 20 and 29

Figure 4. BMI fuzzy partitions, and sample BFP partitions for female and male patients between 20 and 29 years old

Table 1. *BFP Recommendation* agent(s)' condition-action rules

BFP\BMI	Underweight	Normal	Overweight	Obese
Very Lean	R1: BFP is Excellent	R7: BFP is Excellent	R13: BFP is Excellent	R19: BFP is Excellent
Excellent	R2: BFP is Good	R8: BFP is Good	R14: BFP is Good	R20: BFP is Good
Good	R3: BFP is Good	R9: BFP is Good	R15: BFP is Good	R21: BFP is Good
Fair	R4: BFP is Fair OR Good	R10: BFP is Fair OR Good	R16: BFP is Good	R22: BFP is Good
Poor	R5: BFP is Fair	R11: BFP is Fair	R17: BFP is Fair	R23: BFP is Fair
Very Poor	R6: BFP is Poor	R12: BFP is Poor	R18: BFP is Poor	R24: BFP is Poor

The rules in Table 1 can be reduced to the following set of composite rules without any loss of expressiveness:

- R_a: Very Lean(BFP) ⇒ Excellent (BFP) summing up rules R1, R7, R13, and R19
- R_b: Excellent(BFP) ∨ Good(BFP) ⇒ Good (BFP) summing up rules R2, R3, R8, R9, R14, R15, R20 and R21
- R_c: Poor(BFP) ⇒ Fair (BFP) summing up rules R5, R11, R17, R23
- R_d: Very Poor(BFP) ⇒ Poor (BFP) summing up rules R6, R12, R18 and R24
- R_4: Underweight(BMI) ∧ Fair(BFP) ⇒ Fair(BFP) ∨ Good(BFP)
- R_{10}: Normal(BMI) ∧ Fair(BFP) ⇒ Fair(BFP) ∨ Good(BFP)
- R_{16}: Overweight(BMI) ∧ Fair(BFP) ⇒ Good(BFP)
- R_{22}: Obese(BMI) ∧ Fair(BFP) ⇒ Good(BFP)

We adopt *Mamdani's implication* operator as the inference function (Formula 5), *maximization* as the aggregation function (Formula 6), and *center of gravity* as the defuzzification function (Formula 7) given the latter's common usage in the literature (Bouchon-Meunier B. *et al.* 2003, Kuncheva L. 1995) and their empirical performance in our study, i.e., they produced better target

[8] http://sigappfr.acm.org/Projects/PIN/

BFP recommendations compared with alternative functions. Note that our framework is flexible in allowing users to apply other fuzzy inference, aggregation, or defuzzification functions of their choosing.

Mamdani's implication:

Given fuzzy sets f_1, f_2:

$$f_1 \Rightarrow_{\text{Mamdani}} f_2 \equiv f_1 \wedge f_2 \equiv \min(f_1, f_2) \quad \textbf{(5)}$$

where $\wedge$ is the AND fuzzy logic operator[9]

Maximization aggregation:

Given fuzzy sets $f_1, f_2, \ldots, f_n$:

$$F_{agg} = F_{Max} = max(f_1, f_2, \ldots, f_n) \quad \textbf{(6)}$$

Center of gravity defuzzification:

Given aggregate fuzzy set F_{Agg}:

$$x = \frac{\int x \times F_{agg}(x) \times dx}{\int F_{agg}(x) \times dx} \quad \textbf{(7)}$$

The same condition-action rules, inference mechanism, aggregation and defuzzification functions are adopted in all agents. The difference between them relies in the BFP input classification and fuzzy membership functions.

4.1.2. Computation Examples

We consider in Table 2.a three running examples describing three patient cases extracted from our experimental dataset: i) a male with a good BFP, ii) a female with a high BFP, and iii) a male with a very low BFP. Table 2.b shows the results of the *WAR* agent produced for each of the three cases. The detailed computation process for *case 1* is described in Figure 5. Similar computation processes for *case 2* and *case 3* are provided in (Salloum G. and Tekli J. 2020). For *case 1*, two options are recommended by the agent: i) *maintain* the current weight, or ii) *lose* almost 2/3 of a kilogram. Since the patient's BFP is considered *good* based on his age and gender, the two recommended options are valid (following expert nutritionist feedback, cf. experiments in Section 5) allowing the patient either to maintain his current *good* BFP state and "healthy" weight, or to slightly reduce BFP and lose a small amount of extra weight. For *case 2*, considering the patient's age and gender, BFP is considered to be *very poor*. Here, *WAR*'s recommendation is to drop the BFP and weight in order to reach a *poor* BFP as a first step, since the agent aims to help the patient reach the *good* BFP state in a healthy step-by-step process. As for *case 3*, the patient's BFP is in the *excellent* category following his age and gender. Here, *WAR*'s recommendation is to gain some additional weight in order to increase the BFP toward the *good* state. Note that the *good* BFP state is the recommended state for non-athlete patients who do not exercise, whereas the *excellent* state is recommended for athletes or patients who regularly exercise (this will be further discussed in the following section).

Table 2. Patient cases extracted from the experimental dataset

a. Input data provided in the patient profiles

Patients	Gender	Age	Height	Weight	BMI	BFP
Case 1	Male	32	1.77 m	66.94 Kg	21.2	17.7 %
Case 2	Female	28	1.59 m	57.6 Kg	22.82	34.4 %
Case 3	Male	23	1.83	71.88	21.34	9.4 %

b. Output produced by the WAR agent

Goal	Target BFP	Target Weight
Maintain weight **Lose weight**	**17.14 %** **16.90 %**	**66.49**[10] **66.28**
Lose weight	**28.07 %**	**52.53**
Gain weight	**13.32 %**	**75.13**

4.2. Caloric Intake and Exercise Recommendation (*CIER*) agent

While the *WAR* agent computes the patient's target BFP, target weight, and the goal (*lose*, *gain*, or *maintain* weight), the *CIER* agent computes both the caloric intake (CI) and the amount of exercise (or percentage of exercise, PE) that the patient should perform to reach her/his target weight recommended by *WAR*. As discussed in Section 2, the first step in a caloric assessment is determining the basic metabolic rate (or BMR) of a patient, based on gender, age, height, and weight. Then the total energy expenditure (TEE) is determined based on the BMR and the physical activity level of the patient[11]. As a result, CI is determined based on two main factors (cf. Background in Section 2.2): the goal of the patient (*lose*, *gain*, or *maintain* weight) and the patient's TEE. Here, three main possibilities arise: i) if the goal of the patient is to *maintain* weight, CI should be equal to TEE, and hence no decision making is required in this case, ii) if the goal is to *gain* weight, CI must be greater than TEE, and iii) if the goal is to *lose* weight, CI must be lower than TEE. In addition to the above, a nutritionist could provide exercise recommendations (ER) for the patient to remain in a healthy state. Yet, CI and PE recommendations are by nature fuzzy processes that involve "common sense" human reasoning considering multiple factors such as, patient preferences, general guidelines, and the expertise of the nutritionist, etc. (cf. *Motivations 2* and *3* in Section 2)

In order to automate these processes, we design two dedicated fuzzy agents: i) caloric intake recommendation (*CIR*) agent and ii) percentage of exercise recommendation (*PER*) agent. The first agent is responsible for producing CI recommendations based on the TEE of the patient. The second agent produces the percentage of (the BMR to be added as physical) exercise, PE, based on the patient's caloric gap (i.e., the difference between TEE and the recommended CI). *CIER*'s overall process is shown in Figure 6. We further describe each of its constituent fuzzy agents in the following subsections.

[9] The AND fuzzy logic operator can be any t-norm function, including *min* which is commonly adopted in the literature.

[10] If the difference between the target and current weights is within ±0.5 kilograms (such as in this case), the goal would be to *maintain* the current weight.

[11] BMR is computed as follows (Kathleen M. and Janice R. 2017): $BMR_{Female} = 10\times weight + 6.25\times height - 5\times age - 161$ and $BMR_{Male} = 10\times weight + 6.25\times height - 5\times age + 5$. The patient's physical activity level (PAL) is then considered to compute $TEE = BMR \times PAL_{factor}$ where PAL_{factor} varies between 1.2 (sedentary, i.e., little to no exercise) to 1.9 (extremely active, i.e., hard daily exercise of physical job).

1. <u>Fuzzification:</u> Given *case 1*'s input data, namely BMI and BFP, we compute its fuzzy membership values:

- For BMI, given Figure 4.a, $f_{normal}(21.2) = 0.87$, $f_{underweight}(21.2) = 0.13$, membership =0 in all other sets
- For BFP, given Figure 4.b, $f_{fair} = 0.05$, $f_{good} = 0.95$, and membership =0 in all other sets

2. <u>Condition-Action rules:</u> Based on the input membership values, the following condition-action rules are invoked:

- R_b: Excellent(BFP) ∨ Good(BFP) ⇒ Good (BFP),
- R_4: Underweight(BMI) ∧ Fair(BFP) ⇒ Fair(BFP) ∨ Good(BFP)
- R_{10}: Normal(BMI) ∧ Fair(BFP) ⇒ Fair(BFP) ∨ Good(BFP)

Given that the output functions include different OR combinations, the condition-action rules will result in four different outputs:

	Output 1	**Output 2**	**Output 3**	**Output 4**
R_b: Excellent(BFP) ∨ Good(BFP) ⇒	Good (BFP)	Good (BFP)	Good (BFP)	Good (BFP)
R_4: Underweight(BMI) ∧ Fair(BFP) ⇒	Fair(BFP)	Good(BFP)	Fair(BFP)	Good(BFP)
R_{10}: Normal(BMI) ∧ Fair(BFP) ⇒	Fair(BFP)	Fair(BFP)	Good(BFP)	Good(BFP)

3. <u>Inference</u>: By applying *Mamdani*'s inference mechanism (we omit output 3 since it produces a result identical to output 2)

Output 1:

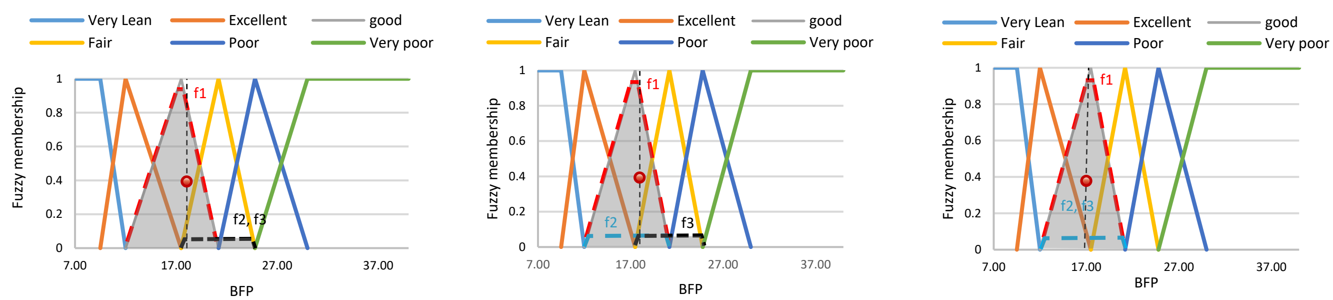
$$R_b: f_1 = \min(0.95, f(x)_{good}^{BFP\ out})$$
$$R_4: f_2 = \min(\min(0.15, 0.05), f(x)_{fair}^{BFP\ out}) = \min(0.05, f(x)_{fair}^{BFP\ out})$$
$$R_{10}: f_3 = \min(\min(0.87, 0.05), f(x)_{fair}^{BFP\ out}) = \min(0.05, f(x)_{fair}^{BFP\ out})$$

Output 2:

$$R_b: f_1 = \min(0.95, f(x)_{good}^{BFP\ out})$$
$$R_4: f_2 = \min(\min(0.15, 0.05), f(x)_{fair}^{BFP\ out}) = \min(0.05, f(x)_{good}^{BFP\ out})$$
$$R_{10}: f_3 = \min(\min(0.87, 0.05), f(x)_{fair}^{BFP\ out}) = \min(0.05, f(x)_{fair}^{BFP\ out})$$

Output 4:

$$R_b: f_1 = \min(0.95, f(x)_{good}^{BFP\ out})$$
$$R_4: f_2 = \min(\min(0.15, 0.05), f(x)_{fair}^{BFP\ out}) = \min(0.05, f(x)_{good}^{BFP\ out})$$
$$R_{10}: f_3 = \min(\min(0.87, 0.05), f(x)_{fair}^{BFP\ out}) = \min(0.05, f(x)_{good}^{BFP\ out})$$



4. <u>Aggregation and Defuzzification</u>: By applying the *maximization* aggregation function, the agent produces the fuzzy coverage areas subsumed by the inference membership functions (represented in transparent grey color in the above graphs). The *center of gravity* defuzzification function is then applied on each fuzzy coverage area to compute the corresponding center of gravity point (represented as a red dot in each of the above graphs), and then identify the corresponding BFP value (on the *x* axis) as the agent's output:

Output 1, 2, and 3: BFP =17.14 Output 4: BFP =16.90

5. <u>Results</u>: The agent produces two final BFP outputs, which values are used to compute the target weights following Formula 4:

- Outputs 1-3 are identical, i.e., target **BFP = 17.14 %**, producing target **weight = 66.49 Kg**. And given that the difference between the target weight and the current weight (66.94 Kg) is within 0.5 Kg, *WAR*'s recommended **goal** is ***maintain*** **weight**.
- Output 4 is very close to the latter, i.e., target **BFP = 16.90 %**, producing target **weight = 66.28 Kg**. And given that the target weight is less than the current weight, *WAR*'s recommended **goal** is ***lose*** **weight.**

Figure 5. *WAR*'s fuzzy computation process when applied to *case 1* of our running example (cf. Table 2.a)

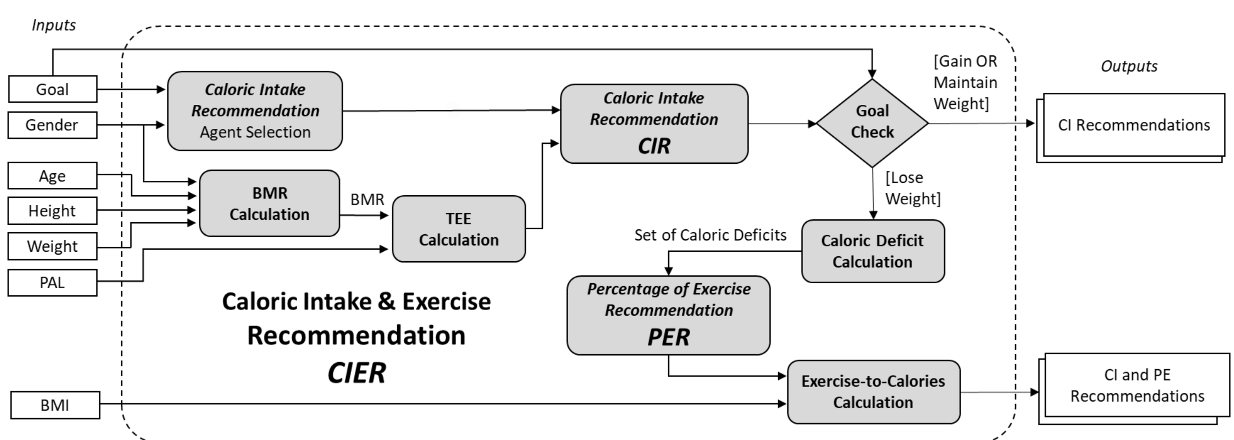


Figure 6. Simplified activity diagram describing the general process of the *CIER* agent

4.2.1. Caloric Intake Recommendation (CIR) agent(s)

This CI recommendation agent accepts as input the TEE of the patient, and produces as output a set of possible CI recommendations. Based on the ODPHP[12] guidelines (ODPHP 2015), CI is gender specific where different CI recommendation guidelines are provided for females and males. For instance, the CI estimations for adult females and males range between 1600-to-2400 and 2000-to-3000 Kcals respectively, whereas the minimum recommended healthy intakes for females and males are 1200 Kcals and 1500 Kcals respectively. Table 3 shows the CI classification which we define based on (ODPHP 2015). The same classification can be adopted for TEE. The corresponding CI and TEE fuzzy sets are produced using the same logic adopted with the WAR agent (cf. Section 4.1.1) and are shown in Figure 7 and Figure 8 respectively[13].

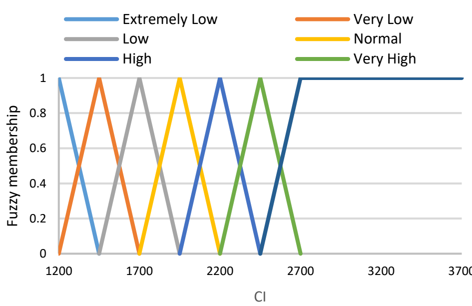
In addition to the gender specific classification, the CI decision making process differs if the goal is to *lose*, *gain*, or *maintain* weight, leading to different sets of condition-action rules for every case. Thus, we introduce 4 fuzzy agents for CI recommendation: 1) female *weight gain* agent, 2) female *weight loss* agent, 3) male *weight gain* agent, and 4) male *weight loss* agent. Both *weight gain* agents (1 and 3) and both *weight loss* agents (2 and 4) share the same condition-action rules as shown in Table 5. The condition-action rules are designed following the nutrition guidelines discussed in Section 2. We adopt *Mamdani's implication* operator as the inference function, and *maximization* as the aggregation function. The *right most* defuzzification function is adopted for the *weight loss* agents whereas the *center of gravity* defuzzification function is used with the *weight gain* agents. The latter functions were adopted following a battery of empirical results[14] (cf. experiments in Section 5). Recall that our framework is flexible in allowing users to apply any other inference, aggregation, or defuzzification function of their choosing.

Table 3. CI classifications[15]

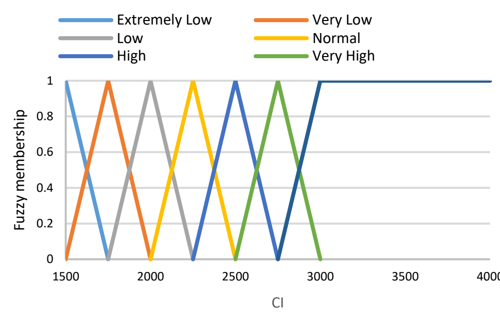
Category	**a.** Female classes Range (Kcals)	**b.** Male classes Range (Kcals)
Extremely Low	950-1200	1250-1500
Very Low	1200-1450	1500-1750
Low	1450-1700	1750-2000
Normal	1700-1950	2000-2250
High	1950-2200	2250-2500
Very High	2200-2450	2500-2750
Extremely High	2450+	2750+

Table 4. TEE classifications (ODPHP 2015)

Category	**a.** Female classes Range (Kcals)	**b.** Male classes Range (Kcals)
Extremely Low	950-1200	1250-1500
Very Low	1200-1450	1500-1750
Low	1450-1700	1750-2000
Normal	1700-1950	2000-2250
High	1950-2200	2250-2500
Very High	2200-2450	2500-2750
Extremely High	2450+	2750+



a. Female fuzzy sets



b. Male fuzzy sets

Figure 7. CI fuzzy sets defined based on the classification in Table 3[16]

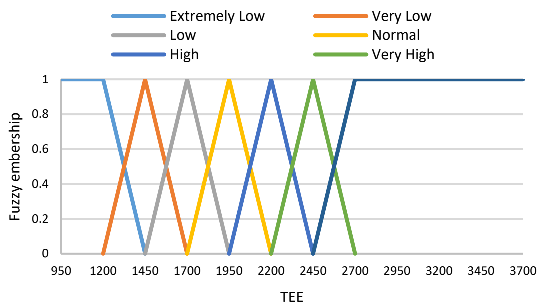
[12] American Office of Disease Prevention and Health Promotion

[13] We produce normalized triangular and trapezoidal functions to transform the crisp CI and TEE categories into fuzzy sets. The fuzzy set boundaries are defined following the reference crisp categories in Tables 3 and 4. The fuzzy functions intersect each other with a membership score = 0.5, producing a normalized fuzzy system where the sum of all membership functions at any CI and TEE data point is always =1. Note that for the *extremely low* CI category, we define the fuzzy membership between [1, 1200], [0,1450] so that the minimum CI does not drop below 1200 Kcal. This ensures that no recommendation will be performed below the minimum healthy CI threshold.

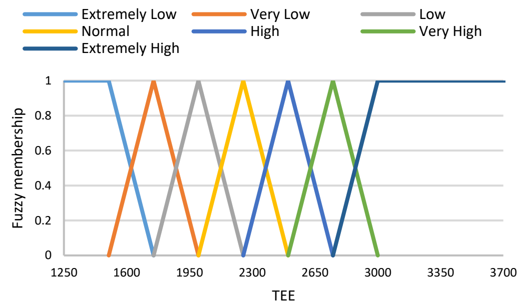
[14] For example, for an expenditure of 2531 Kcals, i) *right most* defuzzification produces the following possible recommendations: 1780, 2030, and 2280 Kcals while ii) *left most* defuzzification produces similar recommendations that are slightly lower in CI values: 1720, 1970, and 2220 Kcals. Based on discussions with experts, 60 kcals is not a significant difference, thus selecting either one of these two approaches would not make a great difference. As for iii) *center of gravity*, it provides a total of nine different recommendations which were considered redundant by the experts: 1791, 1841, 1847, 1895, 1999, 2041. 2097, 2249 and 2280 Kcals. Hence, we adopt *right most* deffuzification in our case. For the case of weight *gain* agents, the rules are defined to increase CI. Here, i) adopting the *right most* defuzzification produces very large intake recommendations. For instance, considering a male patient with a 2600 Kcals expenditure and who needs to *gain* weight, a 4000 Kcal intake is computed by the agent. The resulting caloric surplus of 1400 is very large and defies the maximum recommended surplus of 1000 Kcals. Considering ii) *Left most* defuzzification, the agent produces minimal increments resulting in a recommendation of around 2800 Kcals. Hence, after various experiments and empirical tests, we realized that the iii) *center of gravity* defuzzification function seems to produce better results: increasing the intake in a reasonable fashion, i.e., by 3300 Kcals and 3400 Kcals for the above mentioned patient case.

[15] Increments of 250 Kcals are adopted since 250 Kcals is the equivalent of losing half a pound per week as previously discussed. This is the minimum recommended deficit, thus to maintain precision, it was adopted as the increment between ranges. Since the agent deduces the CI based on the TEE, the TEE will be adopted as the input of the agent, and the output will be one or multiple healthy recommended intakes. The intake is computed by considering a surplus or a deficit from the TEE, if the goal is to *gain* or *lose* weight respectively. Thus the same classification can be adopted for TEE.

[16] As previously discussed, the minimum recommended CI for females and males are 1200 and 1500 Kcals respectively. Thus we define the fuzzy partitions for the CI by excluding values lower than the minimum recommendations. This insures that the agent produces healthy recommendations.



a. Female fuzzy sets



b. Male fuzzy sets

Figure 8. TEE fuzzy sets defined based on the classification in Table 4

Table 5. *CIR* agent(s)'s condition action rules

a. *Weight loss* agent condition-action rules

TEE	Rules
Extremely Low	R1: CI is Extremely Low
Very Low	R2: CI is Very Low OR Extremely Low
Low	R3: CI is Very Low OR Extremely
Normal	R4: CI is Low OR Very Low OR Extremely Low
High	R5: CI is Normal OR Low OR Very Low
Very High	R6: CI is High OR Normal OR Low
Extremely High	R7: CI is Very High OR High OR Normal

b. *Weight gain* agent condition-action rules

Rules
R1: CI is Very Low OR Low OR Normal
R2: CI Low OR Normal OR High
R3: CI is Normal OR High OR Very High
R4: CI is High OR Very High OR Extremely High
R5: CI is Very High OR Extremely High
R6: CI is Extremely High
R7: CI is Extremely High

Note that the recommended CI value will be always comprised within the suggested thresholds. Nonetheless, when TEE is *extremely low* or *very low*, one of the output options is to have CI equal to TEE, since very low CI values are not recommended. The issue of extremely high/low TEE will be later tackled with the *PER* agent described in the following section. Note that if the weight goal of the patient is to *maintain* the current weight, CI is set equal to the caloric expenditure (CE), and thus no additional exercise recommendations are required (i.e., no fuzzy processing in required in this case).

4.2.2. Computation Example

Consider our running example patient cases reported in Table 6. The computation process for patient *case 1* is shown in Figure 9.

Table 6. Patient cases from our running example, including the inputs and output of the *CIR* agent

	a. Input data provided in the patient profile						**b.** Target weight produced by *WAR* agent			**c.** Resulting BMR and TEE required as **input** for *CIR* agent		**d. Output** of *CIR* agent
Patient	**Gender**	**Age**	**Height**	**Weight**	**BMI**	**BFP**	**Goal**	**Target BFP**	**Target Weight**	**BMR**	**TEE**	**Recommended CI**
Case 1	Male	32	1.77 m	66.94 Kg	21.2	17.7%	Lose	16.90 %	66.28 Kg	1620.65 Kcals	1944.78 Kcals	**1555 Kcals** **1804 Kcals**
Case 2	Female	28	1.59 m	57.6 Kg	22.8	34.4%	Lose	28.07 %	52.53 Kg	1268.75 Kcals	1744.53 Kcals	**1244 Kcals** **1495 Kcals**
Case 3	Male	23	1.83 m	71.88	21.34	9.4%	Gain	13.32 %	75.13	1752.55 Kcals	2409.75 Kcals	**2653 Kcals** **2750 Kcals** **3211 Kcals** **3413 Kcals**

The patients' target weights produced by the *WAR* agent are shown in Table 6.b. The resulting BMR and TEE computed based on the target weight[17] are provided in Table 6.c, where TEE is required as input to the *CIR* agent. The recommended CI output is provided in Table 6.d. The detailed computation process for *case 1* is described in Figure 9, and similar computation processes for *case 2* and *case 3* are provided in (Salloum G. and Tekli J. 2020). For *case 1* where the patient's target is to *lose* weight, two options are recommended by the agent: i) reduce CI to 1555 Kcals, which leads to a *weight loss* rate of around 0.39 Kilograms per week, and ii) reduce CI to 1804 Kcal, which leads to slower *weight loss* of around 0.15 kilograms per week. This patient can select the option that best fits his preference depending on the amount of daily CI reduction that he is willing to sustain daily. Similarly for *case 2*, two options are recommended for the patient with caloric deficits of approximately 500 Kcals and 250 Kcals respectively. Note that in both cases, the first being a male and the second being a female, the minimum recommended (gender-specific) CI of 1500 Kcal and 1200 Kcal respectively are well respected. For *case 3* where the patient's target is to *gain* weight,

[17] BMR is computed as follows (Kathleen M. and Janice R. 2017): $BMR_{Female} = 10 \times weight + 6.25 \times height - 5 \times age - 161$ and $BMR_{Male} = 10 \times weight + 6.25 \times height - 5 \times age + 5$. The patient's physical activity level (PAL) is then considered to compute $TEE = BMR \times PAL_{factor}$ where PAL_{factor} varies between 1.2 (sedentary, i.e., little to no exercise) to 1.9 (extremely active, i.e., hard daily exercise or physical job).

four different CI options are recommended providing a range of caloric surplus options to reach the target weight, based on the daily caloric surplus (i.e. the additional amount of food) that the patient desires to consume.

Based on the patient profile the **male *weight loss* fuzzy agent** is adopted for this case.

1. <u>Fuzzification:</u> Given *case 1*'s scalar TEE, we compute its fuzzy membership value following Figure 8:

- $f_{Very\ Low}(1994.78) = 0.22$ and $f_{Low}(1994.78) = 0.78$

2. <u>Condition-Action rules:</u> Based on the input TEE membership values, the following condition-action rules are invoked:

- R_2: Very Low(TEE) ⇒ Very Low (CI) ∨ Extremely Low (CI)
- R_3: Low(TEE) ⇒ Very Low (CI) ∨ Extremely Low (CI)

Given that the output functions include different OR combinations, the condition-action rules will result in four different outputs:

	Output 1	Output 2	Output 3	Output 4
R_2: Very Low(TEE) ⇒	Very Low (CI)	Very Low (CI)	Extremely Low (CI)	Extremely Low (CI)
R_3: Low(TEE) ⇒	Very Low (CI)	Extremely Low (CI)	Very Low (CI)	Extremely Low (CI)

3. <u>Inference</u>: By applying *Mamdani*'s inference mechanism (we omit outputs 3 and 4 since they produce results identical to outputs 1 and 2 respectively)

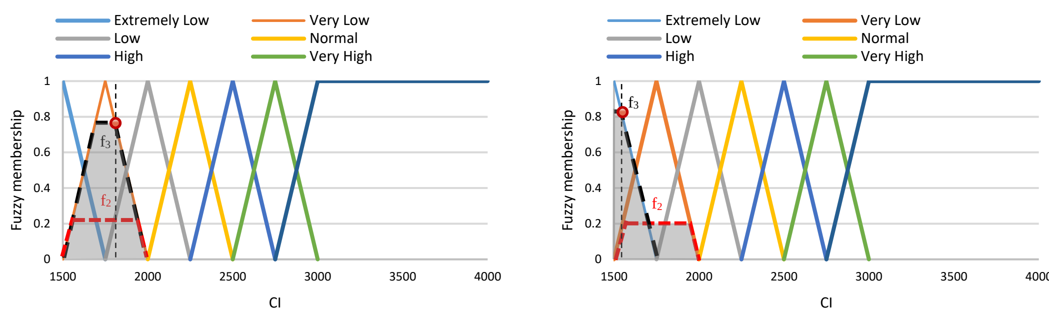
Output 1:

- $R_2: f_2 = \min(0.22, f(x)^{cal\ intake}_{very\ low})$
- $R_3: f_3 = \min(0.78, f(x)^{cal\ intake}_{very\ low})$

Outputs 2:

$R_2: f_2 = \min(0.22, f(x)^{cal\ intake}_{very\ low})$

$R_3: f_3 = \min(0.78, f(x)^{cal\ intake}_{Extremely\ Low})$



4. <u>Aggregation and Defuzzification</u>: By applying the *maximization* aggregation function, the agent produces the fuzzy coverage areas subsumed by the inference membership functions (represented in transparent grey color in the above graphs). The *right most* defuzzification function is then applied on each fuzzy coverage area to compute the corresponding defuzzification point (represented as a red dot in each of the above graphs), and then identify the corresponding CI value (on the *x* axis) as the agent's output:

Outputs 1 and 3: CI = 1,805 kcals Outputs 2 and 4: CI = 1,555 kcals

5. <u>Results</u>: The agent produces two final CI outputs: **CI = 1,805 kcals** and **CI = 1,555 kcals**, both leading to *weight loss* but at different loss rates. The patient chooses the preferred option based and how much to reduce the CI (food consumption) per day or how fast (in number of days) to reach the target weight.[18]

Figure 9. *CIR* agent's fuzzy computation process when applied on *case 1* of our running example (cf. Table 6.a)

4.2.3. Percentage of Exercise Recommendation (PER) agent

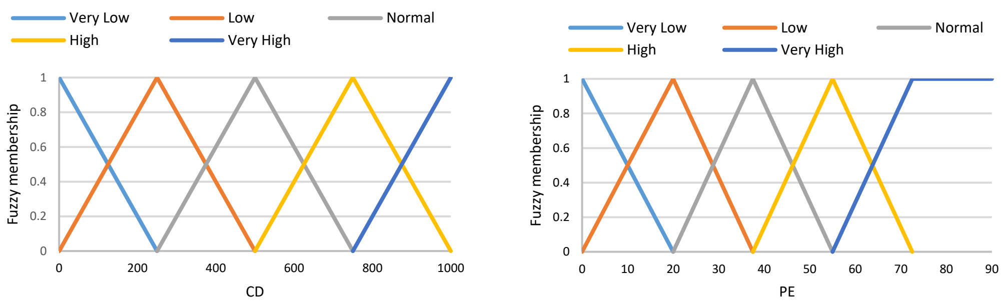
In addition to CI recommendations, exercise recommendations also need to be considered when the patient's goal is to *lose* weight. The *PER* agent is designed to meet this purpose. It receives as input the daily caloric deficit (CD), i.e., the difference between TEE and the recommended daily CI produced by the *CIR* agent. It then produces as output an exercise recommendation value representing the percentage of the BMR to be added as physical exercise: which we refer to as percentage of exercise (PE) for short. The PE recommendation is determined based on the amount of CD: i) if CD is small, exercise must be added to achieve a larger difference between TEE and CI, and ii) if CD is large, then PE should be minimal. In Table 7.a and b, we adopt commonly used classifications for CD and PE from (Hall K. D. et al. 2011) and (Kathleen M. and Janice R. 2017) respectively. The corresponding fuzzy sets are shown in Figure 10. Note that this agent is only applied on *weight loss* cases. Also, the same classifications in Table 7 apply for both male and female patients since a single fuzzy agent is needed for *PER*[19].

[18] Note that our system only presents the CI recommendations to the patient after generating the corresponding exercise recommendations (produced by the *PER* agent). In other words, both CI and exercise recommendations are coupled and presented simultaneously to the patient, since it only makes sense to estimate the time needed to reach the target weight once both CI and exercise recommendations are calculated.

[19] Recall that PE represents a percentage of the BMR dedicated for physical exercise, where BMR is specific and personalized for every case.

Table 7. Daily caloric deficit (CD) and percentage of exercise (PE) classifications, and corresponding condition-action rules

Category	**a.** Caloric deficit (CD)	**b.** Percentage of exercise (PE)	**c.** Condition-action rules
Very Low	0-250 Kcals	0 – 20 %	R1: Exercise percentage is High OR Normal
Low	250-500 Kcals	20 – 37.5 %	R2: Exercise percentage is Normal OR Low
Normal	500-750 Kcals	37.5 – 55 %	R3: Exercise percentage is Low OR Very Low
High	750-1000 Kcals	55 – 72.5 %	R4: Exercise percentage is Low OR Very Low
Very High[20]	1000+ Kcals	55 – 90 %	R5: Exercise percentage is Low OR Very Low



a. Caloric deficit (CD) fuzzy sets **b.** Percentage of exercise (PE) fuzzy sets

Figure 10. CD and PE fuzzy sets, defined based on the crisp classification boundaries from Table 7

The agent's condition-action rules in Table 7.c are defined with the help of our elect nutrition experts. They supply small CD with high PE (in order to compensate them with exercise alternatives); and supply very high CD with either no or small PE. In other words, if the CI is close to the TEE and thus the CD is small, the agent uses physical exercise as an alternative to increase the TEE and thus increase the *weight loss* rate accordingly. The defined rules allow multiple possible (PE) outputs, allowing patients to choose the ones most adapted to their needs. We adopt *Mamdani's implication* operator as the inference function, *maximization* as the aggregation function, and *center of gravity* as the defuzzification function (given the latter's empirical performance). Yet, any other inference, aggregation, and defuzzification function can be applied.

4.2.4. Computation Example

Consider the three patient cases from our running example, reported in Table 8.a. The patient's weight target (computed by the *WAR* agent), as well as the recommendation CI (computed by the *CIR* agent) and the resulting CD are provided in Table 8.b. CD is required as input to the *PER* agent. The recommended PE output is provided in Table 8.c.

Table 8. Patient cases from our running example, including the inputs and output of the PE recommendation agent

a. Input data provided in the patient profile; **b.** Resulting weight goal, CI, and CD, where CD is required as input to the PER agent; **c. Output** of PER agent

Patient	**Gender**	**Age**	**Height**	**Weight**	**BMI**	**BFP**	**Activity**	**Goal**	**BMR**	**CI**	**CD**	**PE (% of BMR)**	**PE's caloric equivalent**	**Days to target**[21]
Case 1	Male	32	1.77m	66.94Kg	21.2	17.7%	Sedentary	Lose	1620.65 Kcals	1555 Kcals	389.78 Kcals	11.23%	182 Kcals	8
												0 %	0 Kcals	12
										1804 Kcals	140.78 Kcals	11.25 %	184 Kcals	15
												29.79 %	484 Kcals	8
Case 2	Female	28	1.59m	57.6Kg	22.8	34.4%	Light activity	Lose	1268.75 Kcals	1244 Kcals	500.53 Kcals	0%	0 Kcals	78
												19.94%	253 Kcals	52
										1495 Kcals	249.53 Kcals	19.94%	253 Kcals	78
												37.52%	476 Kcals	54
Case 3	Male	23	1.83m	71.88Kg	21.34	9.4%	Light activity	Gain	1752.55 Kcals	2653 Kcals	-243.25 Kcals	0%	0 Kcals	102
										2750 Kcals	-340.25 Kcals	0%	0 Kcals	73
										3211 Kcals	-801.25 Kcals	0%	0 Kcals	31
										3413 Kcals	-1003.25 Kcals	0%	0 Kcals	24

The detailed computation process for patient *case 1* is described in Figure 11. Similar computation processes for *case 2* and *case 3* are provided in (Salloum G. and Tekli J. 2020). The outputs for all three cases include different CI and PE recommendations, all

[20] Based on the previously defined *CIR* agent, the maximum possible healthy CD is 750 Kcals. Yet in some rare cases, an expert might recommend a 1000 Kcals CD, thus it is included in the classification under the *very high* category.

[21] As mentioned in Section 2.1, a cumulative energy deficit of 3500 kcals is the equivalent of the loss of 1 pound per bodyweight. Following nutrition literature, e.g., (Hall K.D. et al., 2011, Hall, 2008), the advised rate of weight change (in gain or loss) is estimated at 1 pound per week, and can be achieved through a 500 kcals variation (in surplus or deficit) per day. As a result, the expected number of days to reach the target weight can be calculated as follows (Hall K. D. *et al.* 2011, Hall K. D. 2008): $n = \frac{7 \times |W - W'|}{\frac{G}{500}}$ where *n* is the number days needed to reach the target, *W* is the current weight, *W'* is the target weight, and *G* is the caloric gap between the total CI and TEE per day.

leading to the target weight albeit in different time durations. For *case 1* for instance, outputs 1 and 2 include low CI with small or no PE, whereas outputs 3 and 5 include large CI recommendations with small or large PE recommendations. Notice that the minimum CI recommendation is 1555 Kcals and does not drop below the minimum 1500 Kcals CI recommendation for males. Similar observations can be made for *case 2*. As for *case 3*, four different CI outputs are provided, each increasing the CI in an amount that leads to reaching the target weight in a different time duration. Also, no additional PE is recommended for *case 3* since the target is to *gain* weight.

1. Fuzzification: Given *case 1*'s scalar CD, we compute its fuzzy membership value following Figure 10.a:

- $f_{Very\ Low}(140.78) = 0.44$ and $f_{Low}(140.78) = 0.56$

2. Condition-Action rules: Based on the input CD membership values, the following condition-action rules are invoked:

- R_1: Very Low(Deficit) ⇒ High (Exercise %) ∨ Normal (Exercise %)
- R_2: Low(Deficit) ⇒ Normal (Exercise %) ∨ Low (Exercise %)

Given that the output functions include different OR combinations, the condition-action rules will result in four different outputs:

	Output 1	Output 2	Output 3	Output 4
R_1: Very Low(Deficit) ⇒	High (Exercise %)	High (Exercise %)	Normal (Exercise %)	Normal (Exercise %)
R_2: Low(Deficit) ⇒	Normal (Exercise %)	Low (Exercise %)	Normal (Exercise %)	Low (Exercise %)

3. Inference: By applying *Mamdani*'s inference mechanism (we omit outputs 3 and 4 since they produce results identical to outputs 1 and 2 respectively)

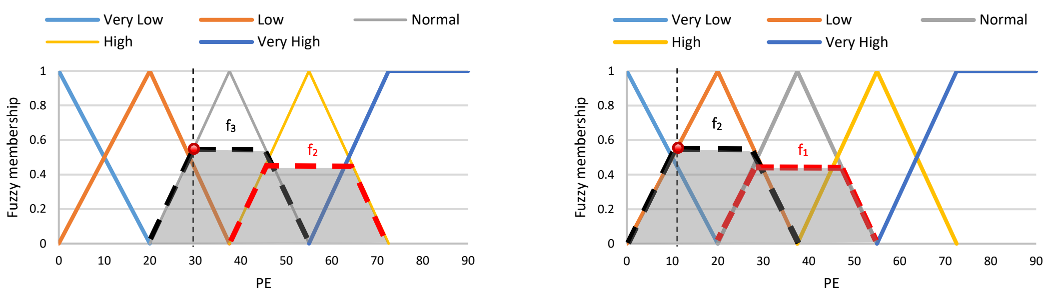
Output 1:

- $R_2: f_2 = \min(0.44, f(x)_{high}^{exercise\ \%})$
- $R_3: f_3 = \min(0.56, f(x)_{normal}^{exercise\ \%})$

Output 2:

$R_1: f_1 = \min(0.44, f(x)_{normal}^{exercise\ \%})$

$R_2: f_2 = \min(0.56, f(x)_{low}^{exercise\ \%})$



4. Aggregation and Defuzzification: By applying the *maximization* aggregation function, the agent produces the fuzzy coverage areas subsumed by the inference membership functions (represented in transparent grey color in the above graphs). The *left most* defuzzification function is then applied on each fuzzy coverage area to compute the corresponding defuzzification point (represented as a red dot in each of the above graphs), and then identify I the corresponding PE value (on the *x* axis) as the agent's output:

Outputs 1 and 3: PE = 29.79%   Outputs 2 and 4: PE = 11.25%

5. Results: The agent produces two final outputs: **PE = 29.79%** of the BMR, which comes down to **484 Kcals** daily, and **PE = 11.25%** of the BMR which comes down to **184 Kcals** daily. The first output involves a higher PE given a CD = 628 Kcals, whereas the second output involves a lower PE given a lower CD = 324 Kcals. Both outputs will lead to the same target weight albeit with different *weight loss* rates and time durations, depending on the patient's preference toward performing more or less physical exercise.

Figure 11. *PER* agent's fuzzy computation process when applied on *case 1* of our running example (reported in Table 8)

Once the CI and PE are known, deducing the expected number of days for the patient to reach the target weight can be calculated accordingly[22]. Recall that TEE varies proportionally to the weight, which highlights the need for regular monitoring and adjustment of the CI even if the patient is making good progress. We present in the following section our mechanism for monitoring progress evaluation and recommendation adjustment.

4.3. Progress Evaluation and Recommendation Adjustment (*PERA*) agent

Patient progress monitoring and evaluation are essential parts of the nutrition care cycle, especially when the patient is abiding by the nutrition recommendations but not making the expected process. Based on our review of the nutrition literature and various discussions with our elect nutrition experts, we adopt a three-week monitoring timeframe for progress monitoring, where an evaluation occurs at the three-week mark to evaluate the progress of the patient and adjust the recommendations accordingly. Weight change depends on energy expenditure, which itself depends on the changing body weight. Even though weight change is not linear over a long period of time, yet we assume that *weight change is linear within the early three-week timeframe* (which is an acceptable assumption following our discussion with the elect nutrition experts). Here, progress evaluation and adjustment are

[22] The expected number of days to reach the target weight can be calculated as $7 \times \frac{|W-W'|}{\frac{CD}{500}}$ where *W* is the patient's current weight, *W'* is the patient's target weight, and *CD* is the daily caloric deficit (Hall K.D., 2011, Pai M. P. and Paloucek F. P., 2000).

mostly needed in the case of *weight loss*, since a patient should not face *weight gain* issues if abiding by the recommended CI[23]. At each three-week mark, the CI is adjusted to account for the non-linear nature of *weight loss*.

The overall architecture of our Progress Evaluation and Recommendation Adjustment (*PERA*) agent is shown in Figure 12. We describe its components and computational processes in the following sub-sections.

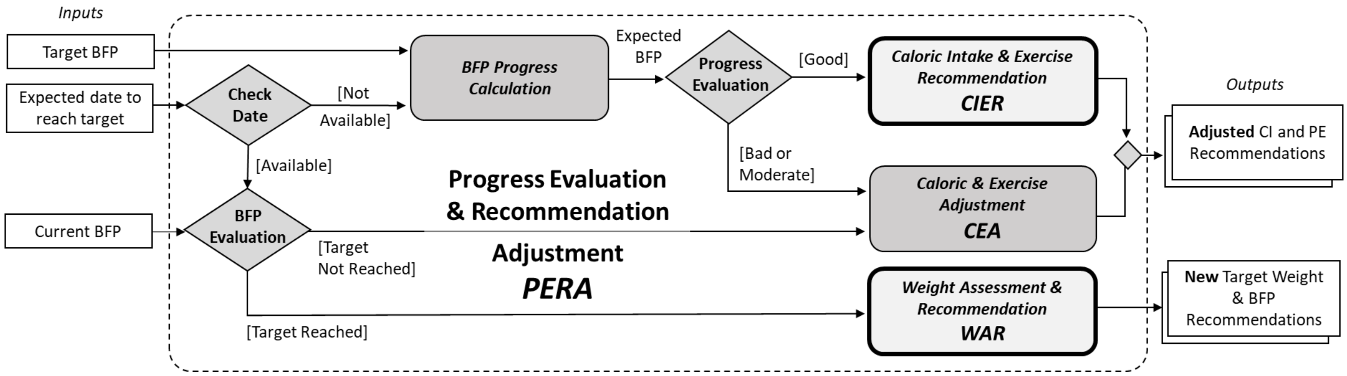


Figure 12. Simplified diagram describing the general process of the *PERA* agent

4.3.1. Progress Evaluation

PERA includes two stages of progress evaluation: i) evaluating if the final target goal is reached based on the expected date determined at the caloric assessment stage, and ii) evaluating BFP progress three weeks after the last assessment.

Evaluating the final goal: following our literature review, there is no clear methodology that nutrition experts adopt to adjust recommendations based on the patient's progress (cf. *Motivation 4* in Section 2.4). In fact, progress evaluation involves "common sense" decision making, where experts use different classifications of whether a certain amount of progress is *good*, *moderate*, or *bad*, based on their background and experience. As a result, different experts might recommend different adjustments for the same patient. In our study, we adopt the following approach when a patient is having difficulty losing weight: i) reduce the CI, and ii) increase PE in a reasonable fashion, while abiding by standardized recommended guidelines. This is performed under the assumption that the patient is abiding by the recommended CI and PE without reaching the target BFP and weight. Here, we define BFP progress (weight progress follows accordingly):

$$BFP_{progress}(\%) = \frac{BFP_{old} - BFP_{current}}{BFP_{old} - BFP_{target}} * 100 \qquad \textbf{(8)}$$

where BFP_{old} is the BFP recommendation provided in the previous assessment, $BFP_{current}$ is the one provided in the current assessment, and BFP_{target} is the one expected to be reached after the current assessment.

While even the slightest progress in *weight loss* introduces health benefits, yet the nutrition literature does not provide a clear classification of progress levels. As a result, we introduce the classification for progress in Table 9 with the help and vetting of our elect nutrition experts. To our knowledge, this is the first attempt at classifying BFP progress in the literature.

Table 9. BFP progress percentage classification

Category	$BFP_{Progress}$ range	Description
Good	[70 – 100] %	The progress is significantly close to the expected progress
Moderate	[40 – 70[%	Progress is good enough to be considered but is still far from target
Slow	[0 – 40[%	No significant progress

Following *PERA*'s final goal evaluation process (cf. Figure 12), the following behaviors might take place: i) if the patient progress qualifies as *good*, the next step is to re-evaluate the weight state of the patient to determine the next target weight. For example, the result might be to *lose* more weight, or to *maintain* the current weight if a healthy state is reached. Otherwise, ii) if the progress is *slow* or *moderate*, then the caloric recommendation should be adjusted accordingly. The latter is performed through a dedicated fuzzy agent which is described in the following sub-section. Note that a negative progress means that the patient is not abiding by the CI and PE recommendations. In this case, the process is reset by the *WAR* agent to re-compute a new target BFP and weight for the patient, and then re-evaluate the CI and PE recommendations accordingly.

Evaluating BFP progress: As mentioned previously, *PERA* evaluates the patient's BFP progress every three weeks to perform recommendation adjustment when needed. Once a patient is evaluated, the target BFP is determined by the *WAR* agent, followed by the *CIER* agent who determines the expected number of days, noted *n*, for the patient to reach the target BFP. Here, we compute BFP progress at the three-week mark as follows:

[23] CI is increased during *weight gain* to adjust for the increasing TEE of the patient as weight is gained.

$$BFP_{3-week-progress} = \frac{(BFP_{old} - BFP_{current})}{(BFP_{old} - BFP_{target}) * \frac{\alpha}{n}} * 100 \quad \textbf{(9)}$$

where α (=21 in this case) represents the number of days between the initial assessment and the subsequent assessment when $n > \alpha$. The expected difference in BFP (i.e., $BFP_{old} - BFP_{target}$) is scaled by the number of days from the last assessment over the expected number of days to reach the target. This gives an approximation of the difference in BFP to be achieved after α days.

As a result, the following behaviors might take place following *PERA*'s progress evaluation process (cf. Figure 12): i) if BFP progress is *good*, the agent considers that the patient is on track even if the BFP target is not reached. In this case, CI and PE recommendations are updated through the *CIER* agent (since TEE is dependent of the changed weight of the patient). Otherwise, ii) if BFP progress is *slow* or *moderate*, then the caloric recommendation should be adjusted accordingly. The latter is performed through a dedicated fuzzy agent which is described in the following sub-section.

4.3.2. *Caloric and Exercise Adjustment* (*CEA*) *agent*

Similar to the initial CI and PE recommendation processes described through *CIER* in Section 4.2, CI and PE recommendation adjustments require human-like decision making which we emulate through the Caloric and Exercise Adjustment (*CEA*) agent. Recall that there is no mathematical process to perform CI and PE adjustments (cf. *Motivation 4*).

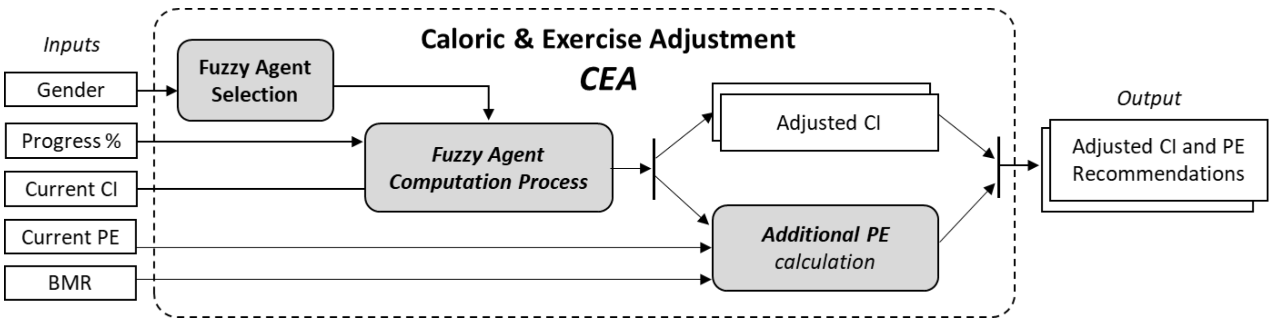
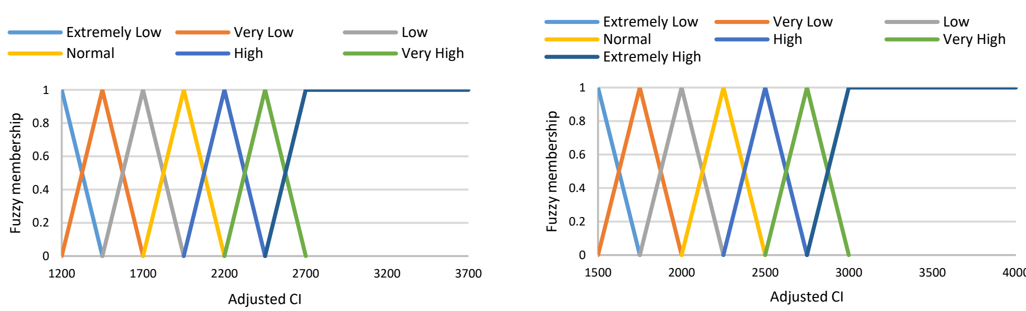


Figure 13. Simplified diagram describing the general process of the *CEA* agent

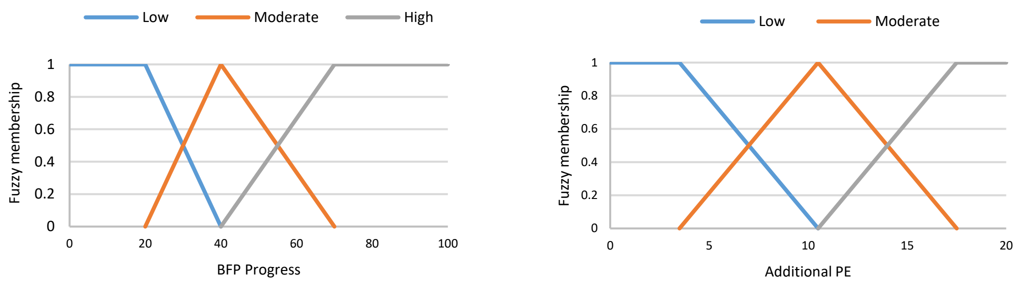
CEA's overall architecture is shown in Figure 13. It receives two inputs: i) the current CI and ii) the BFP progress percentage, and produces two outputs: i) the adjusted CI, and ii) the additional PE to be added to the current PE recommendation. Similar to the *CIER* agent (Section 4.2) where the CI classifications differ based on gender, we define two *CEA* fuzzy agents (for female and male patients) accordingly. As previously discussed, the minimum recommended CI for females and males are 1200 and 1500 Kcals respectively. Thus, we define the fuzzy partitions for the adjusted CI in Figure 14 by excluding values lower than the minimum recommendations, ensuring that the agent always produces healthy recommendations. The fuzzy sets for BFP progress and additional PE are presented in Figure 15[24].



a. Female fuzzy sets **b.** Male fuzzy sets

Figure 14. Male and female adjusted CI fuzzy sets

[24] We design the fuzzy sets as normalized triangular and trapezoidal functions similarly to the previous WAR and CIER agents. Recall that the initial PE classification from CIER provides exercise recommendations as a percentage from the BMR, varying between 0 and 90% (cf. Table 7). To avoid excessively large Additional PE recommendations, we bound the range of additional PE percentage to the *very low* category in the PE classification, which lies between 0 and 20%. This means that Additional PE will be increased in a minor fashion compared with the initial PE recommendation by CIER. For example, consider the 1600 Kcals BMR example presented above, the maximum possible addition is 20%, which is equivalent to a reasonable daily exercise expenditure of 320 Kcals.



a. BFP progress percentage fuzzy sets **b.** Additional PE fuzzy sets[25]

Figure 15. BFP progress and additional PE fuzzy sets

The condition-action rules in Table 10 are designed to generate adjusted CI recommendations following nutrition guidelines, aiming to reduce or maintain CI based on the patient progress. They are defined with the help of our elect nutrition experts based on the following premises: i) if the patient is making *slow* BFP progress, CI must be reduced and PE must be increased. Otherwise, ii) if the patient is making *moderate* BFP progress, two options arise: CI is reduced while PE remains the same, or CI remains the same while PE is increased[26]. Patients can choose the preferred option based on their personal preferences. Here, we adopt *Mamdani*'s inference, *maximization* aggregation, and the *left most* defuzzification functions when running the *CEA* agent due to their good performance based on empirical results. Yet, users can apply other inference, aggregation, or defuzzification functions.

Table 10. CEA fuzzy agent's condition action rules

CI \ **BFP progress**	Slow	Moderate[27]
Extremely Low	R1: Adjusted CI is Extremely Low AND additional PE is High	R8: Adjusted CI is Extremely Low AND additional PE is Moderate
Very Low	R2: Adjusted CI is Extremely Low AND additional PE is Moderate	R9: (Adjusted CI is Very Low AND additional PE is Moderate) OR (Adjusted CI is Extremely Low AND exercise is Low)
Low	R3: Adjusted CI Very Low AND additional PE is Moderate	R10: (Adjusted CI is Low AND additional PE is Moderate) OR (Adjusted CI is Very Low AND exercise is Low)
Normal	R4: Adjusted CI is Low AND additional PE is Moderate	R11: (Adjusted CI is Normal AND additional PE is Moderate) OR (Adjusted CI is Low AND additional PE is Low)
High	R5: Adjusted Intake is Normal AND exercise is Moderate	R12: (Adjusted Intake is High AND exercise is Moderate) OR (Adjusted Intake is Normal AND exercise is Low)
Very High	R6: Adjusted Intake is High AND exercise is Moderate	R13: Adjusted Intake is High AND exercise is Low
Extremely High	R7: Adjusted Intake is Very High AND exercise is Moderate	R14: Adjusted Intake is Very High AND exercise is Low

4.3.3. Computation Example

Consider the patient *weight loss* cases[28] from our running example, reported in Table 11.a. *PERA*'s recommendation adjustments are shown in Table 11.c. The detailed computation process for patient *case 1* is described in Figure 16. A similar computation process for *case 2* is provided in (Salloum G. and Tekli J. 2020).

We consider different scenarios for every case to highlight *PERA*'s adjusted recommendations accordingly. Given *case 1* for instance, we consider two scenarios *A* and *B* assuming a 15 day re-evaluation period for both scenarios. In *scenario A*, we consider that the reached BFP is 17.5% and the reached weight is 66.80 Kg, resulting in a BFP progress percentage of 25%. Here, *PERA* would recommend an adjusted CI of 1500 Kcals (versus the original 1804 Kcals CI recommendation), an adjusted PE caloric equivalent of 324 Kcals (versus the original 184 Kcals recommendation), and 4 remaining days to reach the target (versus the original 0 remaining days). Note that CI is reduced and PE is increased within the acceptable "healthy" recommendations. In *scenario B*, we consider that the reached BFP is 17.3% and the reached weight is 66.60 Kg, resulting in a BFP progress percentage of 50%. Here, *PERA* would recommend two options: i) reducing the CI (from 1804 Kcals) to 1500 Kcals while maintaining the same PE (at 184 Kcals); or ii) reducing the CI (from 1804 Kcals) to 1688 Kcals while increasing PE (from 184 Kcals) to 314 Kcals. Both options require a 2-day remaining time to reach the goal (versus 4 days with *scenario A*).

[25] To avoid excessively large additional exercise recommendations, we define the classification for the additional PE (i.e., *low* for [0, 7[%, *moderate* for [7, 14[%, and *high* for [14, 20[%) to cover the *very low* category in the original PE classification (cf. Table 7), which lies between PE = [0, 20[%. This allows the exercise recommendation to be increased in a minor and healthy fashion, preventing the patient from having to perform a large amount of intense daily exercise. Consider for instance the case of a male patient with BMR=1600 Kcals and a previous PE=50%, which amounts to a daily exercise expenditure of 800 Kcals, the maximum possible addition is 20% of the BMR, which is the equivalent of a reasonable additional daily exercise expenditure of 320 Kcals.

[26] In the special case where CI reaches the minimum recommended intake, it remains the same while PE is increased.

[27] Recall that the *CEA* agent is not invoked when BFP progress is *good*, which means that the patient is on track in making the required progress and does not require adjustment.

[28] Recall that *PERA* is only applied for *weight loss* cases since a patient should not face *weight gain* issues if abiding by the recommended CI.

Given *case 2*, we also consider two scenarios *A* and *B* assuming a 51-day re-evaluation period for both scenarios, where the first assessment occurs after the first 21 days (considering *PERA*'s three-weak evaluation window). In *scenario A*, we consider that the reached BFP is 33.9% and the reached weight is 57.17 Kg, resulting in a BFP progress percentage of 19.2%. Here, *PERA* recommends an adjusted CI of 1200 Kcals (versus the original 1244 Kcals CI recommendation), an adjusted PE caloric equivalent of 459 Kcals (versus the original 253 Kcals recommendation), and 35 remaining days to target (versus the original 30 remaining days). Note that CI is not reduced less than 1200 Kcals to avoid going below the minimum "healthy" recommendation of 1200 Kcals for females. Hence, *PERA*'s only option in this case is to increase PE. As for *scenario B*, we consider that the reached BFP is 33.3% and the reached weight is 56.22 Kg, resulting in a BFP progress percentage of 42%. Here, *PERA* recommends decreasing CI (from 1244 Kcals) to 1200 Kcals, increasing PE (from 253 Kcals) to 396 Kcals, and adjusting the number of remaining days (from 52) to 31 days to reach the target. While CI remains at its minimum "healthy" bound of 1200 Kcals for a female patient, yet in contrast with *scenario A*, PE is not increased as much since the patient is closer to reaching her goal compared with *scenario A*. Recall that *CEA* adjustments to CI and PE are larger/smaller depending on the patient's slower/faster progress.

When a patient reaches the target BFP and weight, the latter are re-assessed by the *WAR* and *CIER* to verify whether the patient is currently at a good weight state or needs to further *lose* (or *gain*) more weight, continuously adjusting to the patient's state.

Table 11. Patient *weight loss* cases from our running example

a. Input data provided in the patient profile — **b.** Recommendations of the *WAR* and *CIER* agents[29]

Patient	Gender	Age	Height	Weight	BMI	BFP	Goal	Target BFP	Target weight	BMR	TEE	CI	PE caloric equivalent	Days to target
Case 1	Male	32	1.77m	66.94 Kg	21.2	17.7%	Lose	16.90 %	66.28 Kg	1620.65 Kcals	1944.78 Kcals	1804 Kcals	184 Kcals	15
Case 2	Female	28	1.59m	57.6 Kg	22.8	34.4%	Lose	28.07 %	52.53 Kg	1268.75 Kcals	1744.53 Kcals	1244 Kcals	253 Kcals	52

c. Status of patient after 15 days (considering multiple scenarios per patient) — **d.** Output of the *PERA* agent

Patient	Scenario	Reached BFP	Reached weight	BFP progress	Adjusted CI	Adjusted PE caloric equivalent	Remaining Days to target
Case 1	A	17.5 %	66.80 Kg	25%	1500 Kcals	324 Kcals	4
	B	17.3 %	66.60	50%.	1500 Kcals	182 Kcals	2
					1688 Kcals	314 Kcals	2
Case 2	A	33.9 %	57.17 Kg	19.2%	1200 Kcals	459 Kcals	35
	B	33.3 %	56.22 Kg	42%.	1200 Kcals	369 Kcals	31

4.4. Recommendation Preference Ranking

As described previously, *PIN*'s fuzzy agents are designed in a flexible manner that offers the patient a wide variety of "healthy" options to choose from, similarly to a human nutritionist's way of recommending multiple healthy solutions. Yet, providing various options could become confusing for the patient, if not presented properly. To address this issue, we introduce a function to rank the recommendations based on patient preferences considering: i) the size of the daily caloric deficit (CD, i.e., the amount of food the patient would like to abstain from) and ii) the amount (percentage) of exercise PE that the patient would like to perform. Our ranking function accepts as input the patient's preferences in terms of desired CD and PE in the form of linguist qualifiers following the linguistic variables previously defined in Section 4.2 (e.g., CD and PE share the same qualifiers: {*very low*, *low*, *normal*, *high*, and *very high*}). Allowing the patients to express their preferences using linguistic qualifiers is easier than asking them to provide scalar CD and PE inputs. Consequently, we compute the preference score for a recommendation in terms of the corresponding CD and PE membership scores, as follows:

$$S_{Pref} = \alpha * S_{CD} + \beta * S_{PE} \quad \in [0, 1] \qquad \textbf{(10)}$$

where S is the total normalized preference score, S_{CD} the fuzzy CD score, S_{PE} the fuzzy PE score, and α and β the CD and PE score weights such as $\alpha, \beta \geq 0$ and $\alpha + \beta = 1$. The weight factors can be fine-tuned based on the patient preferences in terms of underdoing a more severe caloric restriction or doing more exercise.

The fuzzy CD score (S_{CD}) and PE score (S_{PE}) are computed based on: i) the fuzzy sets corresponding to the linguistic qualifiers selected by the patient, and ii) the scalar CD and PE values recommended by the system (i.e., by *CIER* when making initial recommendations, and by *PERA* when making recommendation adjustments). To do so, we take the system generated recommendations and compute their membership values in terms of the patient selected fuzzy sets, and then we average the membership values greater than zero. The fuzzy scores are computed as follows:

$$S_{CD} \text{ or } S_{PE} = \sum_{j=1}^{n} \frac{m_j}{n} \quad \in [0, 1] \qquad \textbf{(11)}$$

[29] We consider one possible output per patient case, among the different possible outputs generated by the *WAR* and *CIER* agents (cf. Table 8).

where n is number of fuzzy sets selected by the patient where the membership is greater than 0, and m_i is the membership of the fuzzy value recommended in fuzzy set j. If the patient does not select any preference, all recommendation scores will be set to the minimal value of 0. Note that the patient can also make more than one selection/preference (e.g., the patient's selected PE levels could be *low* and *very low*, meaning that the patient desires performing a *low* or a *very low* amount of exercise). If the patient selects all possible options as *acceptable* values, all recommendations will score the highest possible membership value of 1.

Given *case 1*, we consider the CI and PE recommendations by the C*IER* agent: CI= 1805 Kcals PE's caloric equivalent = 140 Kcals. Also, we consider *scenario A* where the status of the patient after 15 days of the recommendation is as follows: reached BFP = 17.5% and the reached weight = 66.45 Kg, resulting in a BFP progress = 25%.

1. Fuzzification: Given *case 1*'s scalar CI and BFP progress, we compute its fuzzy membership values following Figure 14.a and Figure 15.a:

- for CI: $f_{very\ low}$= 0.78 and f_{low} = 0.22
- for BFP progress: $f_{slow}(25\%)$ = 0.75 and $f_{Moderate}(25\%)$ = 0.2

2. Condition-Action rules: Based on the input CI and BFP progress membership values, the following condition-action rules are invoked:

- R_2: Very Low(Intake) ∧ Slow (Progress %) ⇒ Extremely Low (Adjusted Intake) ∧ Moderate (Exercise %)
- R_3: Low(Intake) ∧ Slow (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Moderate (Exercise %)
- R_9: Very Low(Intake) ∧ Moderate (Progress %) ⇒ (Very Low (Adj. Intake) ∧ Moderate (Exercise %) ∨ (Ext. Low (Adj. Intake) ∧ Low (Exercise %))
- R_{10}: Low(Intake) ∧ Moderate (Progress %) ⇒ (Low (Adjusted Intake) ∧ Moderate (Exercise %) ∨ (Very Low (Adjusted Intake) ∧ Low (Exercise %))

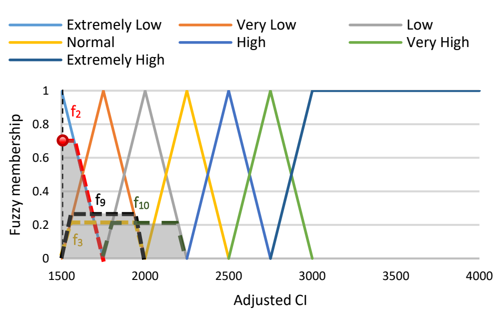
Given that the output functions include different OR combinations, the condition-action rules will result in four different outputs:

	Output 1	**Output 2**	**Output 3**	**Output 4**
R_2: Very Low(Intake) ∧ Slow (Progress %) ⇒	Extremely Low (Adjusted Intake) ∧ Moderate (Exercise %)	Extremely Low (Adj. Intake) ∧ Moderate (Exercise %)	Extremely Low (Adj. Intake) ∧ Moderate (Exercise %)	Extremely Low (Adj. Intake) ∧ Moderate (Exercise %)
R_3: Low(Intake) ∧ Slow (Progress %) ⇒	Very Low (Adjusted Intake) ∧ Moderate (Exercise %)	Very Low (Adj. Intake) ∧ Moderate (Exercise %)	Very Low (Adj. Intake) ∧ Moderate (Exercise %)	Very Low (Adj. Intake) ∧ Moderate (Exercise %)
R_9: Very Low(Intake) ∧ Moderate (Progress %) ⇒	Very Low (Adjusted Intake) ∧ Moderate (Exercise %)	Very Low (Adj. Intake) ∧ Moderate (Exercise %)	Extremely Low (Adj. Intake) ∧ Low (Exercise %)	Extremely Low (Adj. Intake) ∧ Low (Exercise %)
R_{10}: Low(Intake) ∧ Moderate (Progress %) ⇒	Low (Adjusted Intake) ∧ Moderate (Exercise %)	Very Low (Adj. Intake) ∧ Low (Exercise %)	Low (Adj. Intake) ∧ Moderate (Exercise %)	Very Low (Adj. Intake) ∧ Low (Exercise %)

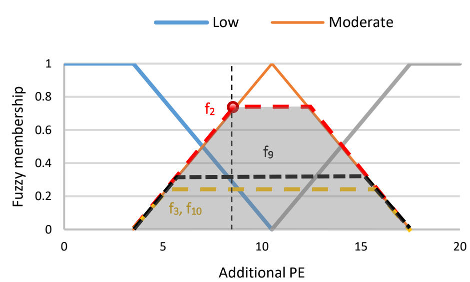
3. Inference: By applying *Mamdani*'s inference mechanism:

Output 1 (Similar inference results are produced for outputs 1, 2, and 3):

- R_2: $f_2 = \min(\min(0.75, 0.784), \min(f(x)^{Adjusted\ Intake}_{Extremely\ Low}, f(x)^{Exercise\ \%}_{Moderate}))$
- R_3: $f_3 = \min(\min(0.216, 0.75), \min(f(x)^{Adjusted\ Intake}_{Very\ Low}, f(x)^{Exercise\ \%}_{Moderate}))$
- R_9: $f_9 = \min(\min(0.249, 0.784), \min(f(x)^{Adj.\ Intake}_{Very\ Low}, f(x)^{Exercise\ \%}_{Moderate}))$
- R_{10}: $f_{10} = \min(\min(0.249, 0.216), \min(f(x)^{Adj.\ Intake}_{Low}, f(x)^{Exercise\ \%}_{Moderate}))$



Adjusted CI inference for output 1



Additional PE inference for output 1

4. Aggregation and Defuzzification: By applying the *maximization* aggregation function, the agent produces the fuzzy coverage areas subsumed by the inference membership functions (represented in transparent grey color in the above graphs). The *left most* defuzzification function is then applied on each fuzzy coverage area to compute the corresponding defuzzification point (represented as a red dot in each of the above graphs), and then identify the corresponding Adjusted CI and Adjusted PE values (on the *x* axis) as the agent's outputs:

Outputs 1, 2, 3, and 4: Adjusted CI = 1561 Kcals, and Additional PE = 8.5%

5. Results: The agent produces four identical outputs, amounting to one single recommendation for *case 1*. This is due to adopting *maximization* aggregation and the *left most* defuzzification approach. For instance, adopting the *center of gravity* approach would have resulted in three different (yet very similar) *additional PE* outputs: 9.31%, 9.47%, and 10.5%.

Figure 16. *CEA* agent's fuzzy computation process when applied on *case 1* of our running example (cf. Table 11)

Consider for instance a patient with BMR=1770 Kcals, TEE= 2434 Kcals, and goal = *lose* weight. Here, we consider two patient preferences presented in Table 12: i) *high* CD and *low* PE, and ii) *low* CD and *high* PE.

Table 12. Recommendation ranking examples following patient preferences

a. High CD and low PE

	CD preference	PE preference
	Normal *or* High	Very Low *or* Low
	Resulting recommendations ranking	
Rank	**CI (Kcals)**	**Additional PE's caloric equivalent (Kcals)**
1	1965	0
2	1715	0
3	1965	310
4	1715	310
5	2215	310
6	2215	626

b. Low CD and high PE

CD preference	PE preference
Very Low *or* Low	Normal *or* High
Resulting recommendations ranking	
CI (Kcals)	**Additional PE's caloric equivalent (Kcals)**
2215	626
2215	310
1965	310
1965	0
1715	310
1715	0

Consider the first scenario, where the patient prefers to have a *normal* or *high* CD (e.g., eating significantly less), while having *low* or *very low* PE (e.g., performing very little exercise). Results in Table 12.a show that the top four recommendations introduce CD values of 469 (#1 and 3) and 719 (# 2 and 4) Kcals: which fall in the *normal* and *high* categories respectively based on our CD fuzzy sets (cf. Figure 10.a). The first two recommendations do not add any exercise while the third and fourth recommendations add 316 Kcals worth of PE daily caloric expenditure; i.e., the equivalent of 17% of the patient's BMR, which falls in the *very low* PE fuzzy set category (cf. Figure 10.b). As for the last ranked recommendation, it introduces a minimal CD of 219 Kcals and a daily PE caloric expenditure of 626 Kcals; i.e., the equivalent of 35% of the BMR (which falls in the *low* PE fuzzy set category). Hence, the latter ranking of the results clearly reflects the patient's preferences in terms of *normal/high* CD and *very low*/*low* PE.

Likewise for the second scenario where the patient wishes to keep a *low* CD (e.g., eating regularly) with *high* PE (e.g., performing more exercise). Results in Table 12.b show that the recommendation having the lowest CD and the highest PE is correctly ranked as the first option, while recommendations with larger CD and smaller PE are decrementally ranked accordingly.

5. Experimental Evaluation

We have implemented our *PIN* framework as a web-based application, using methods from the *jFuzzyLogic* open source library (Cingolani P. and Alcalá-Fdez J. 2013, Cingolani P. and Alcala-Fdez J. 2012) in implementing our fuzzy logic agents, to allow easy access for patients and experts using and evaluating the system[30]. We have empirically tested the different components of our system using multiple sets of experiments which we categorize in two main groups: i) *comparative* evaluation: comparing the recommendations of *PIN*'s main agents (i.e. *WAR*, *CIER*, and *PERA*) with those of human nutrition experts, and ii) *correctness* evaluation: allowing human experts to evaluate *PIN*'s recommendations, and rate their level of agreement with the system's outputs. A total of 11 nutrition experts where involved in conducting the experiments, where each experiment was performed by 4 different testers (certain testers participated in multiple experiments). We first start by describing our test data, experimental scenarios and metrics, and then we present our empirical results. The system implementation, experimental datasets, and test results are available online[31].

5.1. Experimental Test Data

We built a test dataset of 50 patient cases, consisting of 25 female and 25 male cases (cf. Table 13). The 25 male cases were selected from the Carleton College public dataset (Johnson R. W. 1996). Yet, due to the lack of published female cases, we collected the latter data from local pharmacies where body composition machines (measuring BFP) were available. The patient profiles were carefully selected to cover different cases ranging from low BFP to overweight patients.

Table 13. Description of experimental test data

a. Male data summary

Input	**Age**	**Weight** (Kg)	**Height** (m)	**BFP**	**BMI**
Avg	33.64	84.52	1.81	18.18	25.89
Min	23.00	56.36	1.72	5.30	18.89
Max	65.00	163.42	1.97	36.30	48.52
STD	10.36	19.96	0.07	8.39	5.93

b. Female data summary

Input	**Age**	**Weight** (Kg)	**Height** (m)	**BFP**	**BMI**
Avg	28.92	62.99	1.65	29.30	23.24
Min	18.00	50.00	1.56	16.10	18.94
Max	59.00	88.40	1.75	46.20	30.23
STD	11.49	8.76	0.05	7.63	2.90

Note that different subsets of the experimental dataset are used in the different experimental phases. All 50 cases are used to evaluate the WAR agent in the first experimental phase, while a subset of 20 cases are used to evaluate CIER in the second

[30] On the server-side, we adopt a three-layer architecture consisting of: i) a *Web API* layer that allows client-side applications to communicate with the server to request data and services; ii) a *Business Logic* layer where *PIN*'s main decision making processes are implemented; and iii) a *Data Access* layer where data storage and retrieval take place. Every layer is internally designed in a modular way to allow for separate testing and evaluation of every module. We used the SPRING framework (VMware Inc. 2021) to build the Web API, the *JFuzzyLogic* open source library (Cingolani P. and Alcalá-Fdez J., 2013, Cingolani P. and Alcalá-Fdez J., 2012) to implement *PIN*'s fuzzy models, and Hibernate (Hibernate ORM 2021) and the Object Relationship Mapper (O'Neil E.J. 2008) to build the data access layer. Angular 6 was used the develop the client-side Web application, where communication between the client-side and server-side applications is established through REST API over HTTP. An early version of the prototype was described in (Salloum G. and Tekli J., 2018).

[31] http://sigappfr.acm.org/Projects/PIN/

experimental phase, and a subset of 10 cases are used to evaluate PERA in the third experimental phase. The reason for not using all 50 cases in all three phases is the sheer number of aggregated recommendations that would need to be evaluated, which is not practically feasible given the number of (11) testers involved in the study. In total, the number of recommendations that are considered in our experimental study comes down to around: 50 WAR + 80 CIER + 80 PERA = 210 recommendations. Given that every recommendation is evaluated by 4 different testers, every nutrition expert evaluated on average 80 different recommendations, requiring around 3.5-to-4 hours of manual effort. Please note that following our review of the related literature and following the confirmation of most nutrition experts involved in our study, this experimental evaluation is the largest and most comprehensive of its kind, and can be considered as its own contribution to the nutrition literature (in addition to the theoretical and computation models in the study).

5.2. Experiments and Metrics

Experiments and metrics were designed with the help of our elect nutrition experts to evaluate each of *PIN*'s three main agents: *WAR*, *CIER*, and *PERA*. We describe them in the below subsections.

5.2.1. WAR Agent Evaluation

***Comparative evaluation*:** In this experiment, we provide the expert testers with input data for all 50 patients, consisting of 25 female and 25 male cases. The input data includes: age, height, weight, and BFP of the patients. For each case, 4 expert testers are requested to provide: i) a goal recommendation (i.e., patient needs to *lose* weight, *gain* weight, or *maintain* current weight), ii) a target BFP, and iii) a target weight. For each of the latter, we evaluate:

i. Average *inter-tester agreement*: computed as the pairwise similarity scores between the recommendations produced by the expert testers, averaged over all test cases.
ii. Average *PIN-tester agreement*: computed as the similarity between system recommendations and those produced by the expert testers, averaged over all test cases.

Here, we compute the similarity between two *goal recommendations* using Formula 12, and the similarity between two target BFPs (likewise for two target weights) using Formula 13:

$$Sim(g_x, g_y) = \begin{pmatrix} 1 & if\ g_x = g_y \\ 0.5 & else\ if\ g_x \lor g_y = maintain \\ 0 & otherwise \end{pmatrix} \in [0, 1] \qquad \textbf{(12)}$$

$$Sim(x, y) = \frac{|x-y|}{Max(x,y)} \in [0, 1] \qquad \textbf{(13)}$$

where g_x and g_y represent two goal recommendations, and x and y represent either two target BFPs or two target weights.

Note that *WAR* can sometimes produce more than one option (following the nature of its *condition-action* rules, cf. Section 4.1), allowing the patient to *maintain* a *good* BFP/weight, or slightly reduce/*loose* BFP/weight to reach a more "perfect" or *excellent* health state. In this experiment, we only consider the *good* state which is recommended for non-athlete patients. We will consider *excellent* BFP/weight recommendations in a future study targeting athletes and patients who regularly exercise.

***Correctness evaluation*:** We provide the experts with *WAR*'s goal, target BFP, and target weight recommendations for each of the 50 patient cases, and ask the experts to evaluate and rate them on an integer scale ranging from 0 (strong disagreement, or "absolutely incorrect") to 4 (strong agreement, or "absolutely correct"). Every case is rated by 4 different experts. We then compute the average ratings and their standard deviations, and evaluate *WAR*'s scores accordingly.

5.2.2. CIER Agent Evaluation

***Comparative evaluation*:** In this experiment, the expert testers are requested to produce *CI* and *PE* recommendations, to be compared with *CIER*'s recommendations. We provide the experts with 20 patient cases organized in three groups: i) 5 cases that require *gaining* weight, ii) 5 cases that require *maintaining* weight, and iii) 10 cases that require *losing* weight. Each case includes the current BFP and weight, the target BFP and target weight, in addition to the exercise preference (i.e. the amount of exercise the patient desires to perform daily, e.g., *low*, *high*), and the caloric deficit preference (i.e. the amount of calories the patient desires to abstain from daily, e.g., *low*, *high*). Each case is evaluated by 4 experts, and every recommendation (by the experts and *CIER*) is represented as a doublet (*CI*, *PE*), where CI represents the recommended caloric intake and PE the percentage of exercise's caloric equivalent. We treat the latter as a single recommendation, and compute the similarity between two recommendations (CI_x, PE_x) and (CI_y, PE_y) as the linear sum of their CI and PE similarities:

$$Sim\left((CI_x, PE_x), (CI_y, PE_y)\right) = \alpha \times \frac{|CI_x - CI_y|}{\max(CI_x, CI_y)} + (1-\alpha) \times \frac{|PE_x - PE_y|}{\max(PE_x, PE_y)} \in [0, 1] \qquad \textbf{(14)}$$

where $\alpha \in [0, 1]$. We initially set $\alpha = 0.5$ to give equal weights to both CI and PE recommendation components. Similarly, to the previous experiment, we first compare the recommendations produced by the expert testers themselves, quantifying *inter-tester agreement*, and then evaluate *PIN-tester agreement* by comparing the recommendations produced by *PIN*'s *CIER* agent with those produced by the experts. Note that each expert can produce multiple possible options (usually 1-to-3 following nutrition recommendation common practice). Similarly, *PIN* can produce multiple options (usually up to 6, following the nature of the *condition-action* rules of the *CIER* fuzzy agent, cf. Section 4.2). Thus, when comparing the recommendations of two agents (i.e., *inter-tester* and *PIN-tester*), we consider all possible combination pairs and apply two types of analyses: i) *maximum analysis*, where we select the combination with the highest similarity, and ii) *average analysis*, where we compute the average similarity of all recommendation combinations. More formally, considering $agent_1$ producing *m* pairs of recommendations (CI_1, PE_1) and $agent_2$ producing *n* pairs (CI_2, PE_2):

$$Sim_{Max}(agent_1, agent_2) = Max_{\text{ for } i=1-\text{to}-m,\ j=1-\text{to}-n}\left(Sim\left((CI_1^i, PE_1^i), (CI_2^j, PE_2^j)\right)\right) \in [0,1] \quad \textbf{(15)}$$

$$Sim_{Avg}(agent_1, agent_2) = Avg_{\text{ for } i=1-\text{to}-m,\ j=1-\text{to}-n}\left(Sim\left((CI_1^i, PE_1^i), (CI_2^j, PE_2^j)\right)\right) \in [0,1] \quad \textbf{(16)}$$

Correctness evaluation: In this experiment, we present the expert testers with the CI and PE recommendations produced by *CIER* for each test case, and then ask the experts to evaluate and rate system recommendations on an integer scale from 0 (absolutely incorrect) to 4 (absolutely correct). When rating *weight loss* cases, we ask the experts to provide their feedback, not only on the *correctness* of the recommendation, but also on recommendation *preference*: evaluating whether the system recommendations meet the *preferences* of the patients (i.e., whether they prefer to reduce their CI, i.e., eat less, or increase their PE, i.e., do more physical exercise). Recall that additional exercise is not necessary for *weight gain* and *weight maintenance* cases, and thus the latter are only evaluated in terms of recommendation *correctness*[32]. Every case is rated by 4 different experts, where both human experts and *PIN* might produce multiple recommendations for every patient case (as described in the previous section). Hence, we apply two types of analyses in evaluating the rating results: i) *maximum analysis* where we consider the maximum rating produced for each case, and ii) *average analysis* where we consider the average rating produced for each case. We finally compute average ratings and the standard deviations, and evaluate *CIER*'s scores accordingly.

5.2.3. PERA Agent Evaluation

***Comparative evaluation*:** In this experiment, we provide the experts with 10 cases, where each case represents i) the profile of a patient, ii) the target BFP and target weight of the patient, and iii) multiple scenarios of different BFP/weight targets that could be reached by the patient (i.e., 20%, 40%, 50% and 75% of the target BFP/weight[33]). Experts are then required to rate the patients' progress as: *slow*, *moderate*, or *good*. Here, we define the similarity between two recommendations as follows:

$$Sim(prog_1, prog_2) = \frac{|prog_1 - prog_2|}{\text{Max}(prog_1, prog_2)} \in [0,1] \quad \text{where} \quad prog = \begin{pmatrix} 1 & \text{if progress is } slow \\ 2 & \text{if progress is } moderate \\ 3 & \text{if progress is } good \end{pmatrix} \quad \textbf{(17)}$$

Similarly to the previous experiments, we first compare the recommendations produced by the expert testers themselves, evaluating *inter-tester agreement*, and then evaluate *PIN-tester agreement* by comparing the recommendations produced by *PIN*'s *PERA* with those produced by the experts.

***Correctness evaluation*:** In this experiment, we ask the experts to rate the recommendations produced by *PERA*, on an integer scale ranging from 0 (absolutely incorrect) to 4 (absolutely correct) for the same cases processed in the previous experiment, where every case is rated by 4 different experts, and then compute average ratings and their standard deviations accordingly.

5.3. Experimental Results

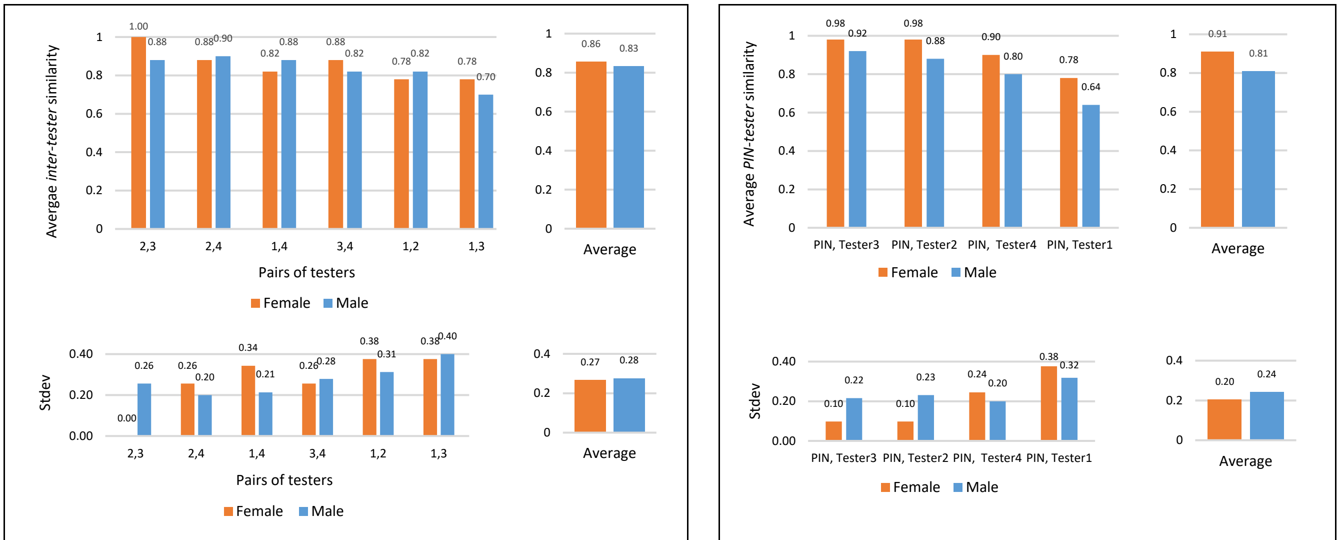
5.3.1. WAR Agent Evaluation

***Comparative evaluation*:** We first evaluate nutrition *goal* agreement (i.e., *lose*, *maintain*, or *gain* weight), comparing the experts' recommendations with those produced by *PIN*'s *WAR* agent. Figure 17.a presents *inter-tester* average similarity results produced for the 25 female and 25 male cases considered in our study, and Figure 17.b provides *PIN-tester* average similarities for the same cases. Two observations can be made here:

- The highest average *inter-tester* similarity is equal to 1 (i.e., 100% since they match exactly) and is obtained between experts 2 and 3, while the lowest average *inter-tester* similarity is 0.6 and is obtained between experts 1 and 3. In the case of *PIN-tester* scores, the highest average similarity is 0.96 for both *PIN* vs expert 1 and *PIN* vs expert 2, while the lowest similarity is 0.64 for *PIN* vs expert 1. Also, *PIN* scores 0.87 and 0.8 similarity on average for female and male cases respectively, which is higher than the average *inter-tester* similarity. This shows that *PIN*'s *WAR* goal recommendations highlight an overall accuracy similar (and even surpassing) those of human experts.

[32] *PIN* does not recommend additional exercise when the goal is to *lose* or *maintain* weight. We report this special case to a dedicated future work specifically focused on fitness and exercise.
[33] The chosen values represent the boundaries of the progress classification and fuzzy memberships presented in Section 4.

- In addition, we notice, that for both *inter-tester* and *PIN-tester* recommendations, *goal* similarity scores are higher on average for female cases, compared with male cases. This means that both human experts and *PIN* tend to agree more when evaluating female cases, compared with male cases. This is probably because males are usually given more options between *maintaining* and *losing* weight (leading to more variation in the recommendation result), whereas fewer options are usually recommended for female patients.



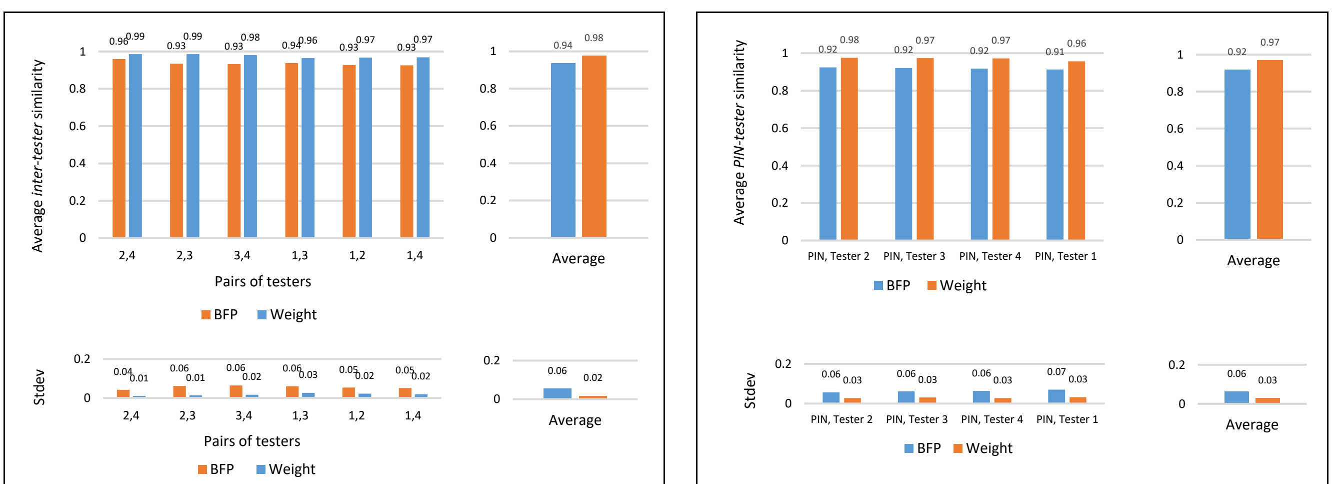
a. *Inter-tester* agreement

b. *PIN-tester* agreement

Figure 17. Nutrition *goal* similarity results: comparing average *inter-tester* and *PIN-tester* agreement levels

In addition to comparing nutrition *goal* agreement, Figure 18 presents *inter-tester* and *PIN-tester* agreement results in terms of average *target BFP* and *target weight* values. Two main observations can be made here:

- By comparing the experts' recommendations for both BFP and weight, we notice very high *inter-tester* similarities, with a slightly higher agreement on weight recommendations versus BFP recommendations. We also notice relatively low standard deviations (of 0.06 and 0.02 for BFP and weight respectively) underlining high *inter-tester* agreement for most cases.
- Also, results clearly show very close agreement between *WAR*'s recommendations and those provided by experts, producing high *PIN-tester* average similarity levels in terms of both BFP (0.94 and 0.92 respectively) and weight (0.98 and 0.97 respectively), coined with relatively low standard deviations. This indicates *PIN*'s ability of producing human-like BFP and weight recommendations.



a. *Inter-tester* agreement

b. *PIN-tester* agreement

Figure 18. *Target BFP* and *target weight* similarity results: comparing average *inter-tester* and *PIN-tester* agreement levels

***Correctness evaluation*:** In this experiment, we evaluate the human experts' ratings of the recommendations produced by *PIN*'s *WAR* agent (provided in the form of integers ∈ [0, 4], ranging from: absolutely incorrect - to - absolutely correct):

- Results in Figure 19 show high overall average correctness ratings of 2.81 and 2.77 (with relatively low standard deviations of 0.3 and 0.2) for female and male cases respectively. Considering all cases combined, we notice that 18% of the ratings are greater than or equal to 3.5, 46% fall between 3.5 and 2.75, 24 % of the ratings fall between 2.5 and 2, and 12% of the ratings fall between 1.75 and 1.25.
- Results also show an almost opposite correlation between average tester rating and standard deviation: i.e., as the average rating decreases, the standard deviation increases. From the latter, we can infer that testers tend to agree more on the cases where they provide high ratings, i.e., cases where they strongly agree with *WAR*'s goal recommendations, while they tend to agree less among themselves on the cases where they provide lower ratings, i.e., cases where they do not strongly agree with *WAR*'s goal recommendations.

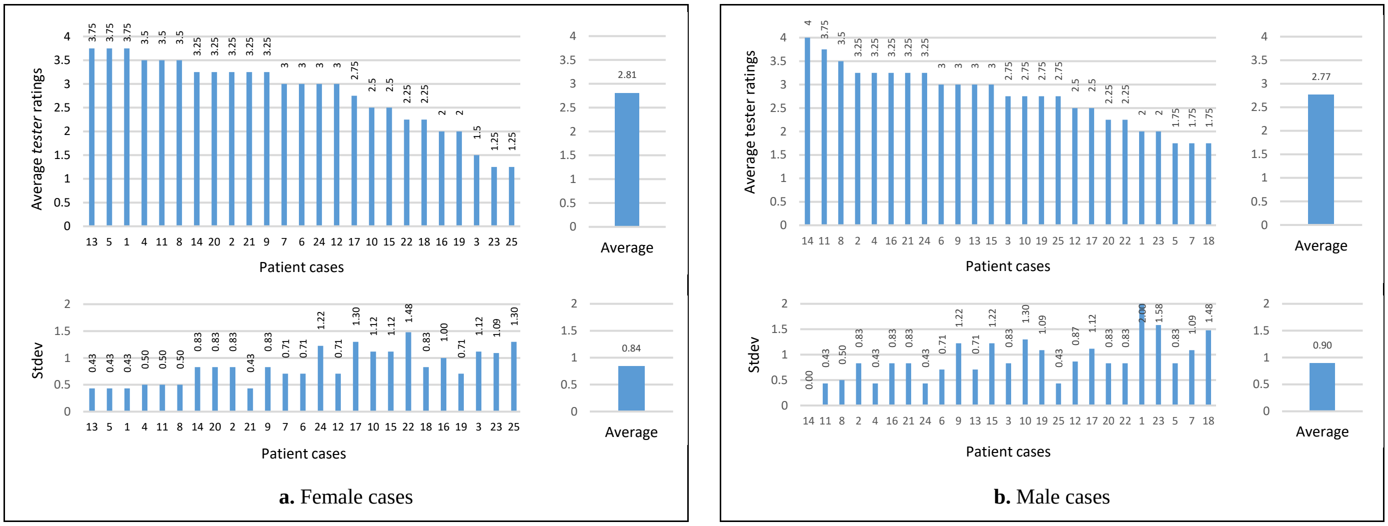


Figure 19. Average expert ratings for *WAR*'s *goal*, *target BFP*, and *target weight* recommendation results

***Discussion*:** Experimental results show high correlation between the nutrition goal, target BFP, and target weight recommendations of *PIN*'s *WAR* agent and those of the nutrition experts. Results also show that average *PIN-tester* similarity scores fall within the same range of *inter-tester* similarity scores obtained when comparing the experts' recommendations with each other. In addition, the high expert correctness ratings of *WAR*'s recommendations demonstrate the system's ability in producing mostly correct nutrition goal, target BFP, and target weight recommendations. To sum up, *PIN* can be considered as "yet another human tester" (as stated by one of the expert nutritionists), producing recommendations which accuracy and correctness are on a par with those of human expert recommendations.

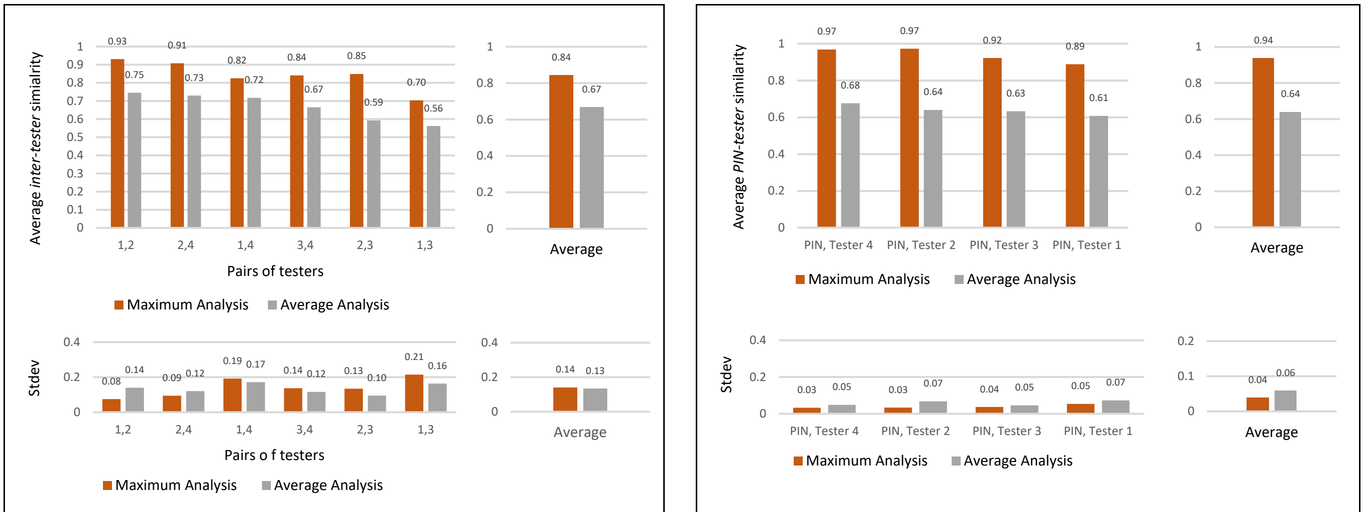
5.3.2. CIER Agent Evaluation

The *CIER* agent generates caloric intake (CI) and percentage of exercise (PE) recommendations based on i) the patient's current weight, ii) target weight, iii) physical activity level, and iv) preferences regarding exercise and caloric deficit.

***Comparative evaluation*:** In this experiment, we evaluate and compare *inter-tester* and *PIN-tester* CI and PE recommendations. As previously described (in Section 4), patient cases can be classified in three categories; i) *weight loss*, ii) *weight gain*, and iii) *weight maintenance* cases, where the experts and *CIER* can produce multiple optional recommendations for every case (e.g., to *lose* weight, a patient can either: decrease CI; or maintain CI and add PE). Results are provided in Figure 20-23 and underline the following observations. Considering *weight loss* cases in Figure 20:

- When applying *maximum analysis* (i.e., selecting the combination with the highest similarity), *CIER*'s recommendations show an average 0.94 overall agreement with the experts' recommendations, compared with a lower average *inter-tester* agreement of 0.84. We also notice a smaller standard deviation of 0.04 on average for *PIN-tester* agreement, compared with a 0.14 standard deviation for *inter-tester* agreement.
- When applying *average analysis* (i.e., computing the average similarity of all recommendation combinations), *CIER*'s recommendations show an average 0.64 overall agreement with the experts' recommendations, compared with an almost equivalent average of 0.67 for *inter-tester* agreement. *PIN-tester* results also show a smaller standard deviation of 0.06 in comparison with 0.13 for *inter-tester* agreement.

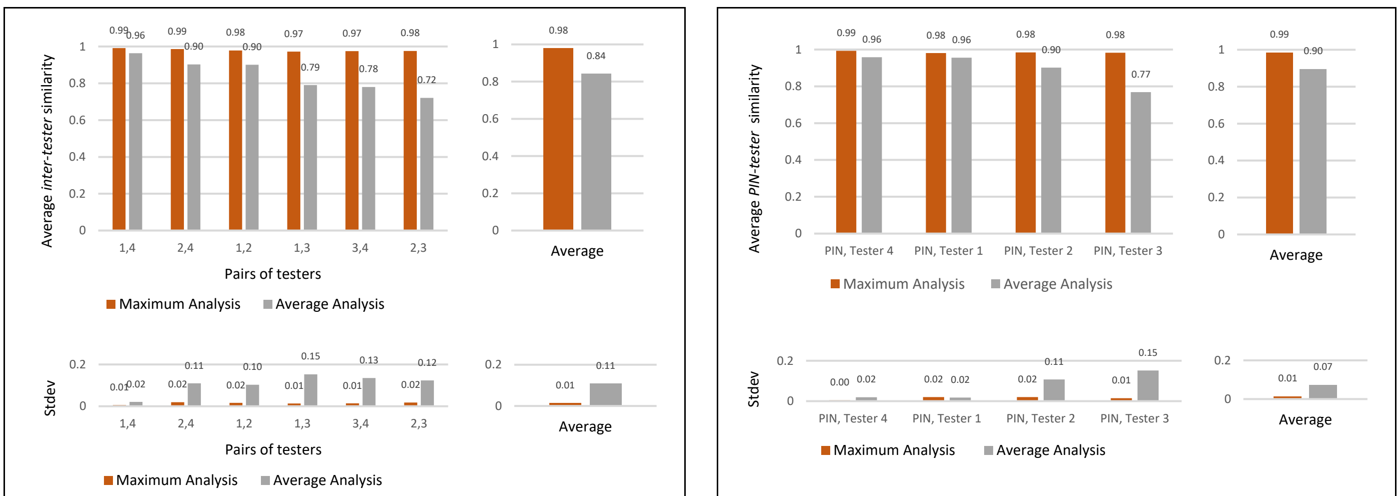
The latter results show that *CIER*'s recommendations are in close agreement with those of human experts when handling *weight loss* cases.



a. *Inter-tester* agreement

b. *PIN-tester* agreement

Figure 20. CI and PE average similarity results: comparing *inter-tester* and *PIN-tester* agreement levels for *weight loss* cases



a. *Inter-tester* agreement

b. *PIN-tester* agreement

Figure 21. CI and PE average similarity results: comparing *inter-tester* and *PIN-tester* agreement levels for *weight gain* cases

Similar results are obtained with *weight gain* cases in Figure 21:

- When applying *maximum analysis*, we obtain very high average agreements of 0.99 (0.01 standard deviation) and 0.99 (0.01 standard deviation) for both *inter-tester* and *PIN-tester* results respectively.
- When applying *average* analysis, we obtain an average agreement score of 0.84 (0.11 standard deviation) for *inter-tester* similarity and a slightly higher average agreement score of 0.90 (0.07 standard deviation) for *PIN-tester* similarity.

The high agreement levels show that *CIER*'s recommendations are in close agreement with those of human experts when handling *weight gain* cases. Different from *weight loss* and *weight gain* cases, a single recommendation is usually needed for *weight maintenance* cases: recommending a CI that fulfills the patient's TEE (Total Energy Expenditure). Similarly to *weight loss* and *weight gain* cases, Figure 22 shows high agreement levels of 0.78 (0.09 standard deviation) and 0.85 (0.15 standard deviation) when comparing both *inter-tester* and *PIN-tester* results respectively.

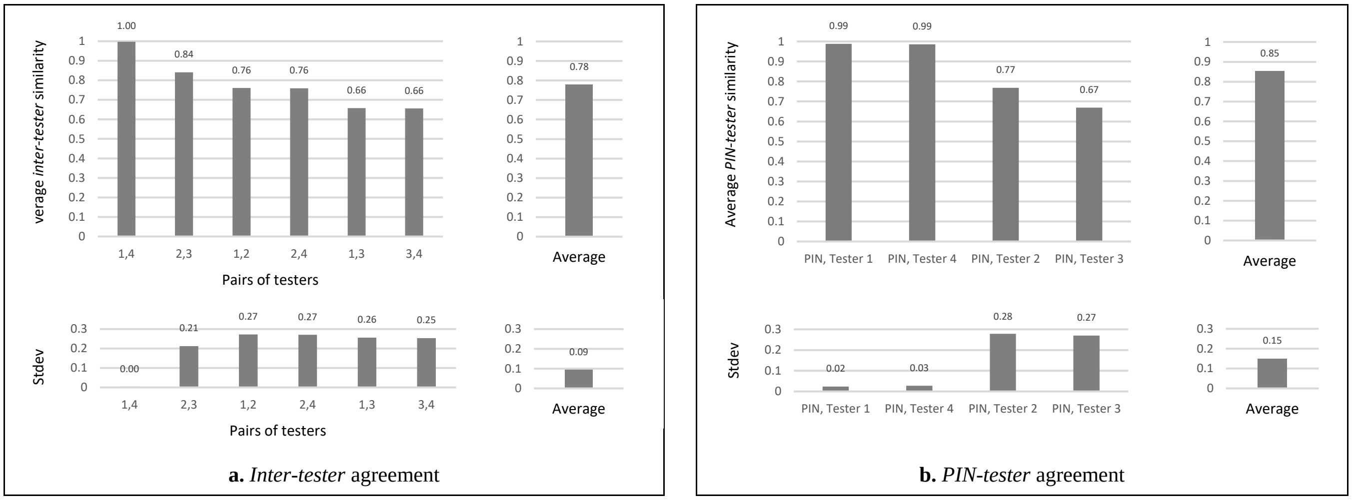


Figure 22. CI and PE average similarity results: comparing *inter-tester* and *PIN-tester* agreement levels for *weight maintenance* cases

***Discussion*:** By comparing the results of the three case categories, we notice higher agreement levels among human experts when dealing with *weight gain* cases (average 0.99 with *maximum analysis*), compared with *weight loss* cases (average 0.84) and *weight maintenance* cases (average 0.78). Following our discussions with the nutrition experts, we realized that *weight gain* is considered as the more straightforward case among the three categories, where nutritionists usually suggest somewhat standardized/homogenous recommendations, in contrast with *weight loss* and *weight maintenance* cases which are considered more delicate and challenging, and where expert recommendations can differ from one expert to the other. We also noticed that *CIER* adheres to this observation and produces higher agreement levels with human experts in *weight gain* cases (average 0.99 with *maximum analysis*) when compared with *weight loss* cases (average 0.94) and *weight maintenance* cases (average 85). The latter observation is mainly due to the different possible PE recommendations that the system suggests for *weight loss* cases, compared with the fewer (and more typical) options that the system produces for the other case categories. Given both *inter-tester* and *PIN-tester* agreement levels, we highlight that *PIN*'s *CIER* recommendations are comparable and on a par with those of human expert recommendations.

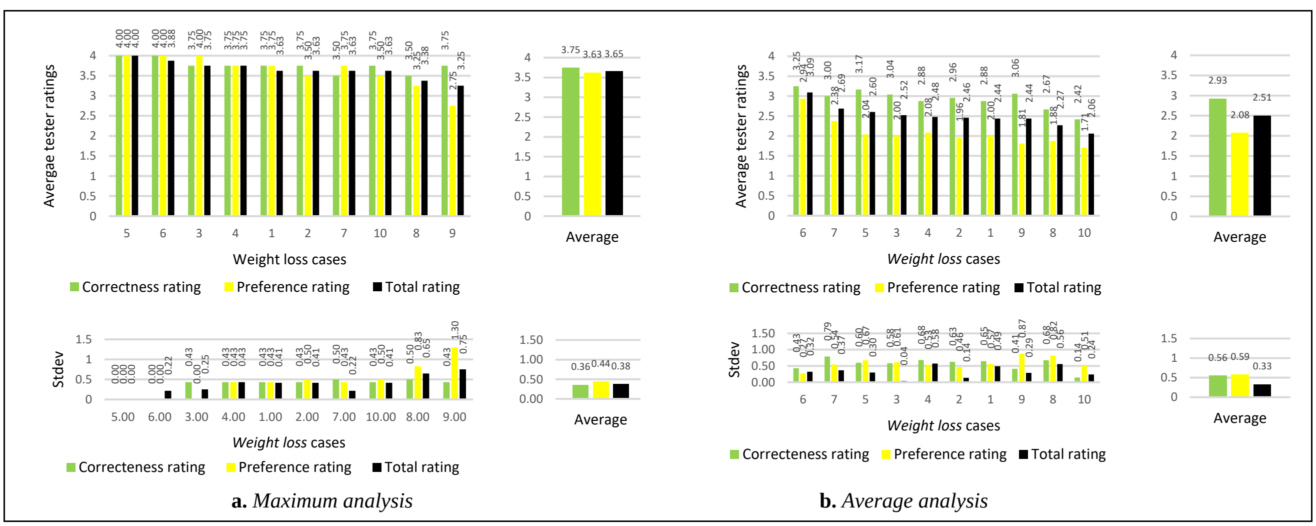
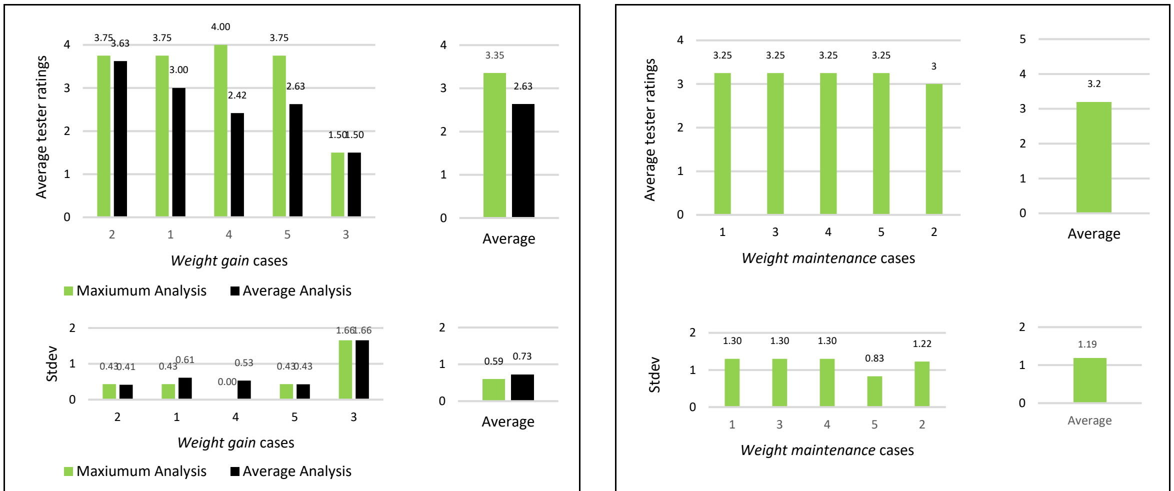


Figure 23. Average expert ratings for CI and PE recommendations for *weight loss* cases

Correctness evaluation: In addition to the above comparative analysis, we evaluate the human experts' ratings of CI and PE recommendations produced by *PIN*'s *CIER* agent (provided in the form of integers $\in$ [0, 4], ranging from: absolutely incorrect - to - absolutely correct). We use two types of ratings to evaluate every recommendation: i) a *correctness* rating and ii) a *preference* rating. We first ask the experts to provide a *correctness* rating for each recommendation, evaluating the expert's level of agreement with the system generated recommendation. We also ask the testers to provide a *preference* rating describing how the recommendation meets the tester's preferences towards the recommended CI and PE levels (whether patients prefer to reduce their CI or increase their PE). In addition, we use two types of analyses to evaluate multiple recommendations per patient case: i) *maximum* analysis and b) *average* analysis. Since multiple recommendations can be provided for one patient case, we perform *maximum* analysis (i.e., identifying the maximum rating score among all provided recommendations) and *average* analysis (i.e., identifying the average rating score among the provided recommendations), in order to produce a single aggregate rating score for every patient case. This results in 4 different rating scores evaluating each patient case: i) *correctness* grade based on *maximum* analysis, ii) *correctness* rating based on *average* analysis, iii) *preference* rating based on *maximum* analysis, and iv) *preference* rating based on *average* analysis. Figure 23 shows the results of *weight loss* cases, and Figure 24 shows the results of both *weight gain* and *weight maintenance* cases[34]. Recall that additional exercise is not necessary for *weight gain* and *weight maintenance* cases, and thus the latter are only evaluated in terms of recommendation *correctness* (cf. Figure 24).



a. *Weight gain* cases

b. *Weight maintenance* cases

Figure 24. Average expert ratings for CI and PE recommendations for *weight gain* and *weight maintenance* cases

Here, we highlight the following observations:

- Regarding *weight loss* cases with *maximum analysis*, Figure 23.a shows high rating scores for CI and PE recommendation *correctness* (average = 3.75) and *preference* (average = 3.63). The lowest score of 2.75 is obtained for the *preference* rating of patient case 9, and is associated with the highest standard deviation (i.e., highest tester disagreement). Regarding *average analysis* results in Figure 23.b, we notice that *preference* scores are generally lower (average = 2.08) than their *correctness* counterparts (average = 2.93). This is due to the fact that *CIER* produces all the possible recommendations and then sorts them based on patient preference without eliminating any recommendation, while all the produced recommendations (those with high and low preference scores) are considered in computing the average ratings.
- Regarding *weight gain* cases, results in Figure 24.b show satisfying human expert ratings for *CIER*'s recommendations, considering both *maximum analysis* (average = 3.35) and *average analysis* (average = 2.63).
- Regarding *weight maintenance* cases, Figure 24.c also shows satisfying human tester ratings (average = 3.20). Recall that there is no need for *maximum* and *average analyses* here since a single recommendation is produced for every patient case (consisting of the CI that fulfills the patient's TEE, cf. Section 4.2).

***Discussion*:** The above results highlight *PIN*'s ability of producing CI and PE recommendations that are in strong agreement with those of human experts. The system recommendations have also been largely approved by the expert testers as reflected by their high correctness rating scores.

5.3.3. PERA Agent Evaluation

PIN's *PERA* agent evaluates patient progress based on their i) current BFP, ii) target BFP, and iii) the expected date to reach the target BFP after running *WAR* and *CIER*'s recommendation processes. First, it classifies progress as *slow*, *moderate*, or *good*. In the case of *slow* or *moderate* progress, it adjusts the CI and PE recommendations accordingly. Otherwise, in the case of *good* progress, it maintains the same CI and PE recommendations without adjustment, since the patient is on the right nutrition track.

***Comparative evaluation*:** In the first part of this experiment, we evaluate *PERA*'s progress classification quality, i.e., its ability to correctly classify progress cases as *slow*, *moderate*, or *good*. Various test cases covering the different progress classes were considered. Figure 25 shows *inter-tester* and *PIN*-tester classification similarity. Results show that *PIN-tester* classification

[34] Figure 23.a shows the *correctness* and *preference* ratings based on *maximum* analysis per case, sorted from highest to lowest scores. In addition, we compute and show a *total rating* score which is the average of both *correctness* and *preference* ratings. Figure 23.b provides *correctness* and *preference* ratings based on *average* analysis. Figure 24.a provides the results for *weight gain* cases considering both *maximum* and *average* analyses. Figure 24.b provides the results for *weight maintenance* cases, where only one recommendation is provided for every patient case. Hence, the latter are rated without the need for *maximum* and *average* analyses.

similarity scores are very close to, and slightly surpass, those of *inter-tester* classification similarities. In other words, *PERA*'s classification results are on a par with (and even slightly surpass) those of human nutrition experts.

In the second part of the experiment, we evaluate *PERA*'s CI and PE recommendation adjustment quality. We consider two classification scenarios: i) *slow* progress and ii) *moderate* progress, disregarding *good* progress where recommendation adjustment is not required. Note that *PERA* provides one single recommendation for *slow* progress cases, while it can generate one or more recommendation options for *moderate* progress cases (based on the fuzzy agents' condition action rules, cf. Section 4.3).

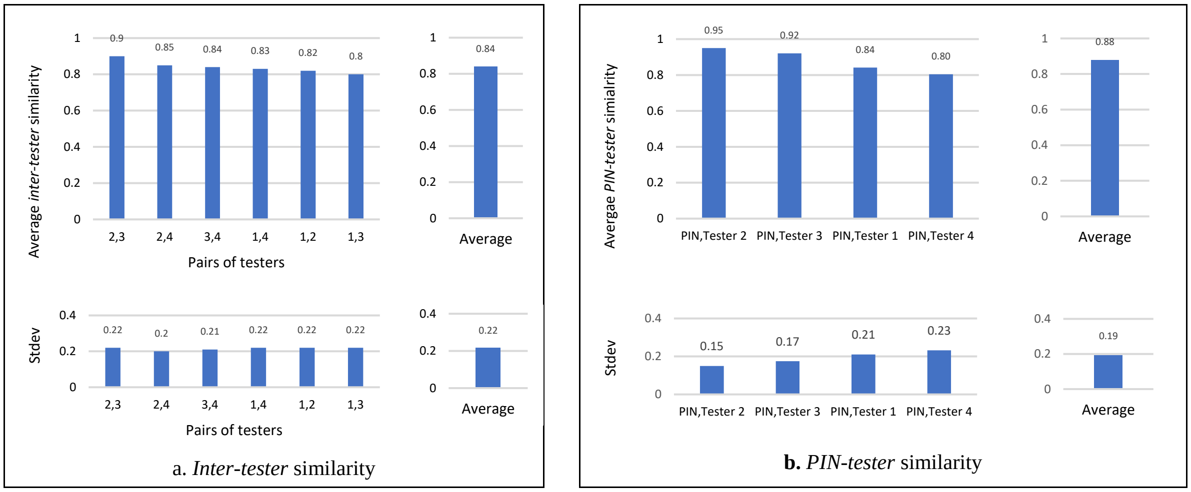


Figure 25. *Progress classification* results: comparing *inter-tester* and *PIN-tester* agreement levels

Results in Figure 26 show average similarity scores considering all generated options, mapping *slow* progress against *moderate* progress cases[35]. One can clearly realize that *PIN-tester* average similarity and standard deviation results are almost identical to those of *inter-tester* results, which means that *PERA*'s adjusted CI and PE recommendations for both *slow* and *moderate* progress cases are very similar to those of human experts.

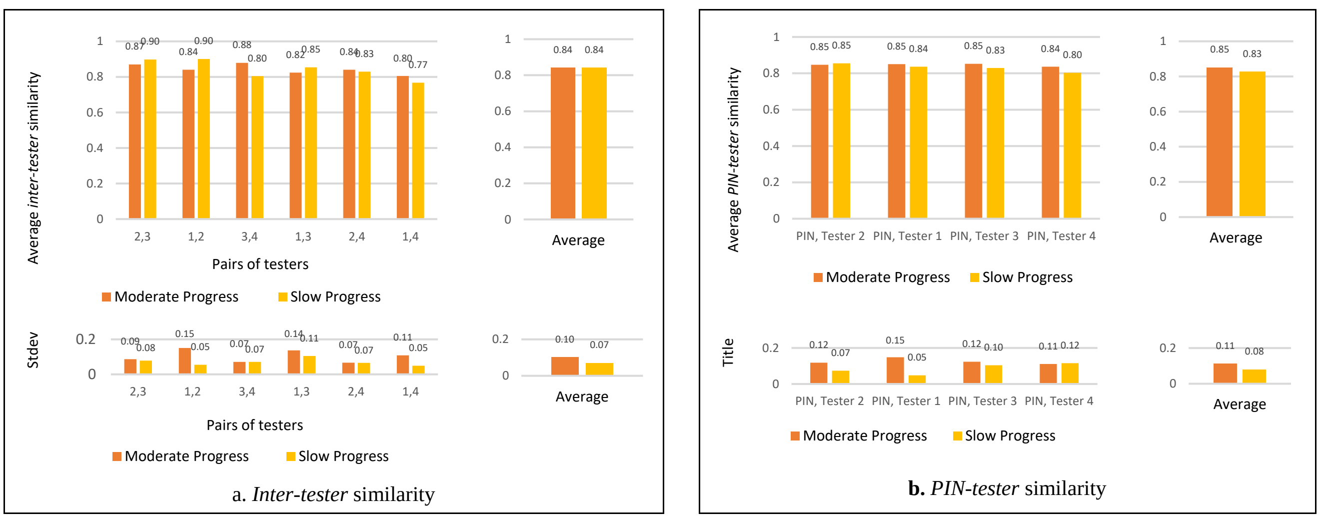
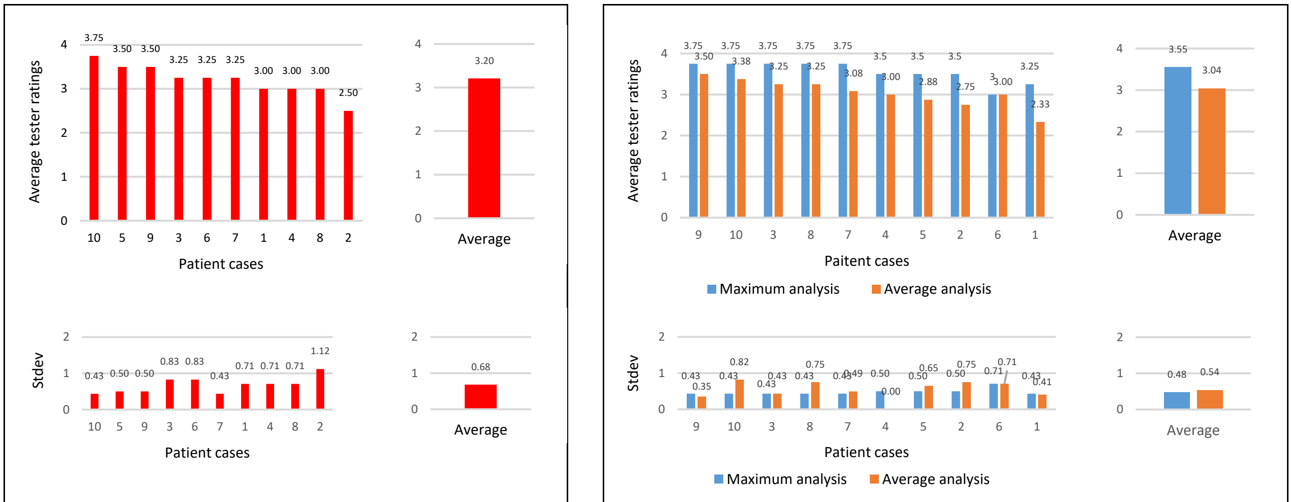


Figure 26. CI and PE progress adjustment results: comparing *inter-tester* and *PIN-tester* agreement levels

***Correctness evaluation*:** In addition to the above results, we asked the expert testers to evaluate the correctness of *PERA*'s recommendations by rating them from 0 (absolutely incorrect) to 4 (absolutely correct). Recall that *PERA* can provide one or more recommendation options for *moderate* progress cases, where we consider both *maximum analysis* and *average analysis* methods in presenting the corresponding results. Results in Figure 27 show satisfying expert ratings, considering both *slow* progress cases (average = 3.20) and *moderate* progress cases (average = 3.5 and 3.04 based on *maximum analysis* and *average analysis* respectively).

[35] *Maximum analysis* results for moderate cases, compared with *average analysis* results, are omitted here for clearness of presentation, and are provided in (Salloum G. and Tekli J, 2020).

Discussion: Experimental results show high correlation between *PIN*'s patient progress classification and its adjusted CI and PE recommendations compared with those provided by nutrition experts. Results clearly show that *PIN-tester* similarity scores are on a par with *inter-tester* similarity scores. In addition, the satisfying ratings provided by the expert testers demonstrate *PIN*'s ability in adjusting CI and PE recommendations for patients struggling to reach their BFP and weight targets. Note that in the case of *good* progress, *PERA* invokes the *WAR* agent to generate new target BFP and weight recommendations, hence re-starting *PIN*'s overall assessment process to allow for continuous patient re-evaluation.



a. *Slow progress* cases

b. *Moderate progress* cases

Figure 27. Average expert ratings for CI and PE recommendation adjustment results

6. Conclusion

In this paper, we introduce a novel framework for Personalized Intelligent Nutrition recommendation titled *PIN*, allowing to automate the health assessment, recommendation, and monitoring services offered by a nutrition expert. It consists of three main agents designed using the fuzzy logic paradigm to simulate the "human common sense" thought process involved in nutrition health assessment and recommendation: i) Weight Assessment and Recommendation (*WAR*) agent, providing an assessment of the patients' nutrition health state and recommending BFP adjustments to *gain*, *lose*, or *maintain* their weight, ii) Caloric Intake and Exercise Recommendation (*CIER*) agent, estimating CI and exercise levels based on the patients' target BFP and weight, and physical activity preferences, and iii) Progress Evaluation and Recommendation Adjustment (*PERA*) agent, monitoring and evaluating the progress of the patients towards their target BFP and weight, and adjusting their CI and exercise recommendations accordingly. Experimental results reflect *PIN*'s effectiveness and quality in producing (BFP, weight, CI, exercise, and adjusted) recommendations which are on a par with (and sometimes surpass those of) human experts.

We are currently completing an extended study, building on *PIN*'s nutrition health assessment and recommendation capabilities to perform automated and personalized meal planning: generating meal plans which fulfill a recommended CI, personalizing the plans following patient preferences, and evaluating the relevance of the produced plans w.r.t. the target patients (Salloum G. and Tekli T. 2021). In the near future, we aim to extend *PIN*'s *CIER* and *PERA* agents to include exercise recommendations even when the patient's goal is to *lose* or *maintain* weight. This is a special case that would be most useful to athletes or patients who regularly exercise. On the long run, we plan to develop a dedicated exercise planning mechanism that incorporates and schedules multiple exercise types (e.g., jogging, swimming) based on the patient's time availability and exercise preferences (Elliott M. *et al.* 2019). Using alternative computation techniques such as non-parametric and lazy machine learners (e.g., fuzzy *k*-nearest neighbors, or fuzzy support vector machines (Abboud R. and Tekli J. 2019, Fahmi A. *et al.* 2019, Abboud R. and Tekli J. 2018)) could be most useful in this context, in order to compensate for the lack of formal rules and lack of sizeable training data linking physical exercise with nutrition recommendations. Another aspect that needs to be considered is the user friendliness of the application interface, allowing the user to easily input the required health data and access the output recommendations. Summarization techniques based on fuzzy logic could be useful in this regard (Kacprzyk J. *et al.* 2006), allowing to present the data as short quantified sentences of natural language (Hudec M. *et al.* 2018). Furthermore, data security and privacy aspects need to be considered in the future, to make sure that the patient's nutrition health data is not compromised and is safely processed online.

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