Automated Knowledge-based Nutrition Health Assessment, Recommendation, Progress Evaluation, and Meal Planning

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Automated Knowledge-based Nutrition Health Assessment, Recommendation, Progress Evaluation, and Meal Planning

George Kamil Salloum

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 nature and quantity of foods being consumed, 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. As a result, people reach out for nutrition experts which entails various obstacles: (i) the cost of seeking an expert’s help which is recurring and non-trivial, (ii) the time commitment required from a person to attend regular meetings with the expert, and (iii) the need for readily accessible health services which might be difficult to provide by a human expert. In this master thesis study, we design, implement, and evaluate a novel framework titled PIN: a computerized solution for Personalized Intelligent Nutrition recommendations. PIN consists of four main modules allowing four essential complementary functionalities: (i) Weight Assessment and Recommendation (WAR), (ii) Caloric Intake and Exercise Recommendation (CIER), (iii) Progress Evaluation and Recommendation Adjustment (PERA), and (iv) personalized Meal Plan Generation (MPG) and adaptation following patient chosen parameters (e.g., food preference, food compatibility, price, etc.). While most existing computerized solutions focus solely on the meal plan generation task, PIN provides the first full-fledged solution for nutrition health assessment, which results are required to run the meal planning task. It relies on the fuzzy logic paradigm to simulate human expert health assessment including weight, caloric intake, and exercise recommendations as well as progress evaluation and recommendation adjustments. PIN also provides a novel contribution in meal planning, introducing an
adaptation of the transportation optimization problem to dynamically generate, change, adapt, and self-evaluate meal plans following the patient’s needs, compared with most existing meal planning solutions which fail to integrate all the different essential factors (meal-food compatibility, inner-food compatibility, preferences, diversity, and variety) while producing meal plans. We have conducted a large battery of experiments involving 50 patient profiles, 11 nutrition expert evaluators, and 5 non-expert testers, to test the performance of PIN, evaluating its health assessment and meal plan generation quality. Results highlight PIN’s assessment and recommendation qualities which are on a par with and sometimes surpass those of human nutrition experts.

Keywords: Fuzzy Logic, Fuzzy Agents, Transportation Problem, Shortest Path Computation, Nutrition Health Assessment, Meal Planning, Food Graph, Caloric Intake, Body Fat Percentage, Exercise Recommendation, Progress Evaluation, Parametric Model.
# Table of Contents

**Introduction** .................................................................................................................................................. 1

**Background on Nutrition Health** .................................................................................................................. 5

2.1. Weight and Body Fat Percentage ............................................................................................................... 5
2.1.1. Weight and Body Fat Percentage Assessment ...................................................................................... 5
2.1.2. Weight and Body Fat Percentage Recommendation .............................................................................. 7

2.2. Caloric Intake, Expenditure and Exercise ................................................................................................... 7
2.2.1. Basic Metabolic Rate and Total Energy Expenditure ........................................................................ 8
2.2.2. Caloric Intake Recommendation ....................................................................................................... 8
2.2.3. Exercise Recommendation ............................................................................................................... 10

2.3. Progress Monitoring and Recommendation Adjustment ............................................................................. 12
2.3.1. Expected Days to Target .................................................................................................................. 12
2.3.2. Progress Evaluation ......................................................................................................................... 12

2.4. Meal Planning ............................................................................................................................................... 13
2.4.1. Calories to Macronutrients .............................................................................................................. 14
2.4.2. The Food Exchange List System and Servings .............................................................................. 14
2.4.3. Food Selection and Assignment ..................................................................................................... 17

**Literature and Related Works** .................................................................................................................... 18

3.1. Optimization Techniques ............................................................................................................................ 18
3.1.1. Linear Programming ........................................................................................................................ 19
3.1.2. Integer Linear Programming .......................................................................................................... 20
3.1.3. Other Optimization Techniques .................................................................................................... 22

3.2. Metaheuristic Approaches ........................................................................................................................ 23
3.2.1. Evolutionary Algorithms ............................................................................................................... 24
3.2.2. Practical Swarm Optimization ....................................................................................................... 27

3.3. Case-Base Reasoning Approaches ........................................................................................................... 28
3.3.1. Case-Based Reasoning with Rule-Based Correction ...................................................................... 29
3.3.2. Case-Based Reasoning with Genetic Algorithms ........................................................................... 30
6.3.4. Running Examples ...................................................................................................................... 96

6.4. Progress Evaluation and Recommendation Adjustment (PERA) Agent ........................................ 99
  6.4.1. Progress Monitoring and Evaluation .......................................................................................... 99
  6.4.2. Caloric Recommendation Adjustment Agent ............................................................................ 103
  6.4.3. Caloric Recommendation Adjustment Fuzzy Agent ................................................................. 105
  6.4.4. Running Examples ...................................................................................................................... 118

6.5. Recommendation Ranking ........................................................................................................... 121
  6.5.1. Fuzzy Scores .............................................................................................................................. 122
  6.5.2. Example .................................................................................................................................. 123

6.6. Meal Plan Generation (MPG) Agent ............................................................................................... 125
  6.6.1. Macro-Nutrient Calculator ........................................................................................................ 126
  6.6.2. Servings Calculator .................................................................................................................... 126
  6.6.3. Servings and Food Assignment ................................................................................................. 127

6.7. Self-Evaluation ............................................................................................................................... 138
  6.7.1. Meal-food compatibility ........................................................................................................... 139
  6.7.2. Preferences ............................................................................................................................... 140
  6.7.3. Inter-Food Compatibility .......................................................................................................... 140
  6.7.4. Economic Cost ......................................................................................................................... 141
  6.7.5. Example .................................................................................................................................. 142

Experimental Evaluation .................................................................................................................... 144

7.1. Prototype Implementation ............................................................................................................. 144

7.2. Evaluation Protocols and Metrics ................................................................................................. 145
  7.2.1. WAR Agent Evaluation ............................................................................................................ 146
  7.2.2. CIER Agent Evaluation ............................................................................................................ 147
  7.2.3. PERA Agent Evaluation ............................................................................................................ 149
  7.2.4. MPG Agent Evaluation ............................................................................................................ 151

7.3. Test Data ....................................................................................................................................... 153
  7.3.1. Empirically Collected Data ....................................................................................................... 153
  7.3.2. System Generated Data ............................................................................................................ 154

7.4. Experimental Results ..................................................................................................................... 154
  7.4.1. WAR Agent Recommendations Evaluations ............................................................................ 154
7.4.2. CIER Agent Recommendations Evaluation .......................................................... 162
7.4.3. PERA Agent Recommendations Evaluation ....................................................... 174
7.4.4. MPG Agent Meal Plans Evaluation ........................................................................ 179
7.4.5. Discussion ............................................................................................................. 185

Conclusion and Future Works ...................................................................................... 186

Bibliography .................................................................................................................. 189

Appendices ..................................................................................................................... 195

    Appendix A Body Fat Percentage Classification ......................................................... 196
    Appendix B Ideal Body Weight Formulas ................................................................. 197
    Appendix C BMI and Body Fat Percentage Fuzzy Sets ............................................. 198
    Appendix D Sample Meal Plan ..................................................................................... 205
    Appendix E Case by Case Similarity of BFP & Weight Recommendations for Males and
    Females ....................................................................................................................... 206
    Appendix F Self-Evaluation Functions Results .......................................................... 209
        Set 1 ......................................................................................................................... 209
        Set 2 ......................................................................................................................... 210
        Set 3 ......................................................................................................................... 211
        Set 4 ......................................................................................................................... 212
        Set 5 ......................................................................................................................... 213
        Set 6 ......................................................................................................................... 214
List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DHL fuzzy sets</td>
<td>36</td>
</tr>
<tr>
<td>2</td>
<td>PCP fuzzy sets before genetic learning</td>
<td>37</td>
</tr>
<tr>
<td>3</td>
<td>PCP fuzzy sets after genetic learning</td>
<td>38</td>
</tr>
<tr>
<td>4</td>
<td>Recommendation type-2 fuzzy membership</td>
<td>41</td>
</tr>
<tr>
<td>5</td>
<td>Temperature fuzzy membership example</td>
<td>48</td>
</tr>
<tr>
<td>6</td>
<td>Fuzzy logic controller</td>
<td>49</td>
</tr>
<tr>
<td>7</td>
<td>Fuzzy inference result</td>
<td>51</td>
</tr>
<tr>
<td>8</td>
<td>Fuzzy aggregation by maximization</td>
<td>52</td>
</tr>
<tr>
<td>9</td>
<td>Transportation problem model</td>
<td>53</td>
</tr>
<tr>
<td>10</td>
<td>Simplified activity diagram describing PIN's overall architecture</td>
<td>57</td>
</tr>
<tr>
<td>11</td>
<td>Activity diagram describing the weight recommendation process</td>
<td>58</td>
</tr>
<tr>
<td>12</td>
<td>Simplified activity diagram describing the BFP recommendation agent’s fuzzy control logic</td>
<td>60</td>
</tr>
<tr>
<td>13</td>
<td>BMI fuzz sets</td>
<td>61</td>
</tr>
<tr>
<td>14</td>
<td>BFP sets for males between 20 and 29</td>
<td>62</td>
</tr>
<tr>
<td>15</td>
<td>BFP fuzzy sets for females between 20 and 29</td>
<td>62</td>
</tr>
<tr>
<td>16</td>
<td>BMI fuzzy memberships</td>
<td>65</td>
</tr>
<tr>
<td>17</td>
<td>BFP fuzzy memberships</td>
<td>66</td>
</tr>
<tr>
<td>18</td>
<td>BFP inference mechanism for output 1</td>
<td>68</td>
</tr>
<tr>
<td>19</td>
<td>BFP aggregation and defuzzification for output 1</td>
<td>68</td>
</tr>
<tr>
<td>20</td>
<td>BFP inference mechanism for output 2</td>
<td>69</td>
</tr>
<tr>
<td>21</td>
<td>BFP inference mechanism for output 4</td>
<td>70</td>
</tr>
<tr>
<td>22</td>
<td>BFP aggregation and defuzzification for output 4</td>
<td>71</td>
</tr>
<tr>
<td>23</td>
<td>Activity diagram describing the CI and exercise recommendation process</td>
<td>74</td>
</tr>
<tr>
<td>24</td>
<td>Simplified activity diagram describing CI recommendation agents fuzzy control logic</td>
<td>77</td>
</tr>
<tr>
<td>25</td>
<td>Female TEE fuzzy sets</td>
<td>79</td>
</tr>
<tr>
<td>26</td>
<td>Male TEE classification</td>
<td>80</td>
</tr>
<tr>
<td>27</td>
<td>Female CI fuzzy sets</td>
<td>80</td>
</tr>
<tr>
<td>28</td>
<td>Male CI fuzzy sets</td>
<td>81</td>
</tr>
<tr>
<td>29</td>
<td>CI fuzzy memberships</td>
<td>84</td>
</tr>
<tr>
<td>30</td>
<td>CI inference mechanism for output 1</td>
<td>86</td>
</tr>
<tr>
<td>31</td>
<td>CI aggregation and defuzzification for output 1</td>
<td>87</td>
</tr>
<tr>
<td>32</td>
<td>CI inference mechanism for output 2</td>
<td>88</td>
</tr>
</tbody>
</table>
Figure 65: Average inter-tester similarity, and standard deviation, of CI and exercise recommendations for weight loss cases ................................................................. 163
Figure 66: Average PIN vs tester similarity, and standard deviation, of CI and exercise recommendations for weight loss cases ................................................................. 163
Figure 67: Average inter tester similarity, and standard deviation, of CI and exercise recommendations for weight gain cases .................................................................................. 165
Figure 68: Average inter-tester similarity, and standard deviation, of CI and exercise recommendations for weight gain cases .................................................................................. 166
Figure 69: Inter tester average similarity, and standard deviation, for weight maintenance cases ........ 168
Figure 70: PIN vs tester average similarity, and standard deviation, for weight maintenance cases .... 168
Figure 71: Average expert ratings, and standard deviation, of CI and exercise recommendations for weight loss cases based on Maximum Analysis ........................................................................ 170
Figure 72: Average grade, and standard deviation, of CI and exercise recommendations for weight loss cases based on average Analysis .................................................................................. 171
Figure 73: Average rating, and standard deviation, of CI and exercise recommendations for weight gain cases ............................................................................................................. 172
Figure 74: Average rating, and standard deviation, of CI and exercise recommendations for weight maintenance cases ....................................................................................................... 173
Figure 75: Inter-tester average similarity, and standard deviation, for progress classification .......... 175
Figure 76: PIN-tester average similarity, and standard deviation for patient progress classification ... 175
Figure 77: Average inter-tester similarity, and standard deviation, for adjust CI recommendations .... 176
Figure 78: Average PIN vs tester similarity, and standard deviation, for adjust CI recommendations .... 177
Figure 79: Average rating per case for CI and exercise readjustment in case of slow progress .......... 178
Figure 80: Average rating per case for CI and exercise readjustment in case of slow progress .......... 178
Figure 81: Average meal plan ratings, and standard deviation, per CI for Set A ................................. 180
Figure 82: Average meal plan ratings, and standard deviation, per CI for Set B ................................. 181
Figure 83: Meal plan non-experts average ratings and standard deviation ........................................ 182
Figure 84: Self-Evaluation average scores ......................................................................................... 184
Figure 85: BMI fuzzy sets ............................................................................................................. 198
Figure 86: BPF fuzzy sets for males between 20 and 29 ................................................................. 198
Figure 87: BPF fuzzy sets for males between 30 and 39 ................................................................. 199
Figure 88: BFP fuzzy sets for males between 40 and 49 ................................................................. 199
Figure 89: BFP fuzzy sets for males between 50 and 59 ................................................................. 200
Figure 90: BFP sets for males between 60 and 69 ......................................................................... 201
Figure 91: BFP sets for males between 70 and 79 ......................................................................... 201
Figure 92: BFP fuzzy sets for females between 20 and 29 ....................................................... 202
Figure 93: BFP fuzzy sets for females between 30 and 39 .......................................................... 202
Figure 94: BFP fuzzy sets for females between 40 and 49 ............................................................. 203
Figure 95: BFP fuzzy sets for females between 50 and 59 ............................................................ 203
Figure 96: BFP fuzzy sets for females between 60 and 69 ............................................................ 204
Figure 97: BFP fuzzy sets for females between 70 and 79 ............................................................ 204
Figure 98: BFP recommendation case by case average similarity for males .................................. 206
Figure 99: BFP recommendation case by case average similarity for females ............................. 207
Figure 100: Weight recommendation case by case average similarity for males .......................... 207
Figure 101: Weight recommendation case by case average similarity for females ....................... 208
List of Tables

Table 1: BMI classification ............................................................................................................ 5
Table 2: BMI case comparison ........................................................................................................ 6
Table 3: PAL factors .......................................................................................................................... 8
Table 4: Female case caloric expenditure ....................................................................................... 10
Table 5: Food exchange categories and their calorific and macronutrient properties per serving .... 15
Table 6: Transportation matrix ....................................................................................................... 54
Table 7: BFP recommendation fuzzy agent condition-action rules ............................................ 63
Table 8: Male case 1 weight input used for BFP recommendation fuzzy agent example ............. 64
Table 9: Male case 1 inputs used for weight assessment ............................................................... 72
Table 10: Male case 1 weight recommendations .......................................................................... 72
Table 11: Female case 1 inputs used for weight assessment ........................................................... 73
Table 12: Female case 1 weight recommendations ..................................................................... 73
Table 13: Male case 2 inputs used for weight assessment ............................................................. 73
Table 14: Male case 2 weight recommendations ......................................................................... 73
Table 15: Exercise recommendation percentages ....................................................................... 76
Table 16: Male CI classification ................................................................................................. 78
Table 17: Female CI classification .............................................................................................. 78
Table 18: Weight loss agent condition-action rules .................................................................... 81
Table 19: Weight gain agent condition-action rules .................................................................... 82
Table 20: Male case 1 weight input used for CI recommendation fuzzy agent example ............ 83
Table 21: Male case 1 target weight input used for CI recommendation fuzzy agent example .... 83
Table 22: Male case 1 resulting BMR and TEE used for CI recommendation fuzzy agent example .. 84
Table 23: Daily caloric deficit classification .................................................................................. 90
Table 24: Exercise recommendation agent condition action rules .............................................. 92
Table 25: Male case 1 input for exercise percentage recommendation fuzzy agent ................... 92
Table 26: Male case 1 used for CI and exercise recommendation ................................................. 96
Table 27: Male case 1 CI and exercise recommendations ............................................................... 97
Table 28: Female case 1 used for CI and exercise recommendation ............................................. 97
Table 29: Female case 1 CI and exercise recommendations ........................................................... 98
Table 30: Male case 2 used for CI and exercise recommendation .................................................. 98
Table 31: Male case 2 CI and exercise recommendations .............................................................. 98
Table 32: Progress percentage classification .............................................................................. 101
Table 33: Additional exercise percentage classification ............................................................. 106
Table 34: Caloric recommendation adjustment fuzzy agent condition-action rules ................................................. 110
Table 35: Male case 1 input used for caloric recommendation adjustment example ............................................. 118
Table 36: Case 1 Scenario A resulting caloric recommendation adjustment .................................................................. 118
Table 37: Case 1 Scenario A resulting caloric recommendation adjustment .............................................................. 119
Table 38: Female case 2 input used for caloric recommendation adjustment example .............................................. 119
Table 39: Case 1 Scenario A resulting caloric recommendation adjustment .............................................................. 120
Table 40: Case 1 Scenario A resulting caloric recommendation adjustment .............................................................. 120
Table 41: Recommendation ranking example for low exercise and high restriction preferences ............................... 123
Table 42: Recommendation ranking example for high exercise and low restriction preference .............................. 124
Table 43: 2000 Kcal CI servings plan ......................................................................................................................... 128
Table 44: 2107 Kcal CI servings plan ......................................................................................................................... 129
Table 45: Food assignment transportation matrix ........................................................................................................ 131
Table 46: Food assignment example .......................................................................................................................... 138
Table 47: Produced self-evaluation score for 2107 Kcal sample meal plan ................................................................. 142
Table 48: Male data summary ......................................................................................................................................... 153
Table 49: Female data summary ..................................................................................................................................... 153
Table 50: Aggregate average rating for CI and exercise recommendations grades for weight loss cases. 171
Table 51: Body fat percentage for males by ACSM ........................................................................................................ 196
Table 52: Body fat percentage for females by ACSM .................................................................................................... 196
Table 53: Ideal body weight formulas ............................................................................................................................ 197
Table 54: Sample meal plan for 2107 CI ........................................................................................................................ 205
Table 55: Set 1 weights combination ............................................................................................................................... 209
Table 56: Set 1 self-evaluation results ............................................................................................................................ 209
Table 57: Set 2 weights combination ............................................................................................................................... 210
Table 58: Set 2 self-evaluation results ............................................................................................................................ 210
Table 59: Set 3 weights combination ............................................................................................................................... 211
Table 60: Set 3 self-evaluation results ............................................................................................................................ 211
Table 61: Set 4 weights combination ............................................................................................................................... 212
Table 62: Set 4 self-evaluation results ............................................................................................................................ 212
Table 63: Set 5 weights combination ............................................................................................................................... 213
Table 64: Set 5 self-evaluation results ............................................................................................................................ 213
Table 65: Set 6 weights combination ............................................................................................................................... 214
Table 66: Set 6 self-evaluation results ............................................................................................................................ 214

xvii
Chapter 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 nature and quantity of foods being consumed, 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. Poor nutrition and a lack of physical activity has been shown to increase the risks of dangerous complications such as obesity, diabetes, and other health issues [1]. 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 time commitment required from a person to attend regular meetings with the expert, and (iii) the need for readily accessible health services which might be difficult to provide by a human expert. An alternative popular approach is the use of electronic solutions, such as mobile applications and websites that are highly available and provide basic health and nutrition services, yet these solutions share some major weakness such as: (i) a lack of a complete automated process requiring either expert intervention ([2] [3] [4]) or the patient (user) to be familiar with or have some knowledge about nutrition health ([5] [6]), in order to utilize (and tune the parameters of) the corresponding e-solution properly, (ii) providing the patient with fixed (predefined) meal plans with limited adaptability to the patient’s needs ([7] [8]), (iii) providing limited health assessment considering one indication of the weight status (e.g.,
BMI\(^1\) only, while disregarding other more informative indicators (e.g., BFP\(^2\)) ([9] [10]) and (iv) performing meal planning or meal plan evaluation based on pre-defined inputs (set by the e-solution designer), without however performing health state assessment or evaluation ([7] [11]). In fact, to our knowledge, there is no existing automated solution to perform nutrition health state assessment.

With the importance of healthy nutrition and the wide access to electronic solutions, the main goal of our research project is to create an intelligent agent that offers the same quality of services offered by a human nutrition expert albeit doing it through a readily available, fully automated, and cheap e-solution. We aim to eliminate the existing hurdles of reaching out to nutrition experts, while countering the limitations of existing solutions by providing patients (users) with quality health services and recommendations.

To solve these issues, we design and develop a framework for Personal Intelligent Nutrition titled PIN that automates the services offered by a nutrition expert, providing the patient seeking nutrition advice with: (i) an assessment regarding her nutrition health state: whether she should gain, lose, or maintain her weight (based on different nutrition-health measurements), (ii) a recommendation to strike a good balance between food intake (how much and what the patient should eat) and physical exercise (how much and how the patient should exercise), (iii) monitoring the progress of the patient’s health state and adjusting the corresponding health recommendations accordingly, (iv) providing the patient with multiple possible plans, while evaluating and ranking them following the patient’s preferences (e.g., recommending bigger meals coupled with longer exercise sessions, or smaller meals with less exercise). To achieve the latter target services, our solution consists of four main components:

i. **Weight Assessment and Recommendation (WAR) agent**: specially designed using the fuzzy logic paradigm to evaluate the weight state of a patient based on various

\[ \text{BMI} = \frac{\text{Weight(Kg)}}{\text{Height}^2(\text{m}^2)} \]

\[ \text{BFP} = \frac{\text{Body Fat Weight}}{\text{Total Body Weight}} \]

---

1 The Body Mass index is evaluated as the user’s weight divided over the user’s height: \( BMI = \frac{\text{Weight(Kg)}}{\text{Height}^2(\text{m}^2)} \)

2 The Body Fat Percentage is computed as the ratio of the patient’s body fat weight over the total body weight.
inputs (age, sex, height, weight, and body fat percentage (BFP)) and then accordingly recommend a target weight and BFP for the patient.

ii. **Caloric Intake and Exercise Recommendation (CIER)** agent: specially designed using the fuzzy logic paradigm to produce Caloric Intake (CI) and exercise recommendations based on the level of activity of the patient and the patient’s target weight produced by the WAR agent.

iii. **Progress Evaluation and Recommendation Adjustment (PERA)** agent: specially designed using the fuzzy logic paradigm to monitor and evaluate the progress of the patient towards her target weight, and adjust the CI and exercise recommendations when required; i.e. when the patient is not making progress.

iv. **Meal Plan Generation (MPG)** agent: designed based on an adaptation of the transportation optimization problem to simulate the “human thought process” involved in generating daily meal plans, based on the patient’s CI requirements determined by WAR or PERA.

The remainder of this report is organized as follows. Chapter 2 presents the nutrition health background related to weight assessment, CI, exercise management, and meal planning. Chapter 3 briefly reviews the related works and existing solutions revolving around automated nutrition health assessment and meal planning. Chapter 4 describes the motivation of this work and the objectives of the research. Chapter 5 presents some preliminary concepts and definitions. Chapter 6 described our proposed solution, including the general architecture of our PIN framework as well as the design and functionality of each of its components. Chapter 7 describes our implementation, experimental protocols, and experimental results. Finally, Chapter 8 concludes with potential improvements and future directions.

**Acronyms**

i. BMI: body mass index

ii. BFP: body fat percentage

iii. BMR: basic metabolic rate
iv. CI: caloric expenditure  
v. TEE: total energy expenditure  
vi. KB: Knowledge-Base  
vii. WAR: weight assessment and recommendation  
viii. CIER: caloric intake and exercise recommendation  
ix. PERA: progress evaluation and recommendation adjustment  
x. MPG: meal plan generation  
xi. ASCM: American College of Sports Medicine
Chapter 2

Background on Nutrition Health

This chapter covers basic concepts in nutrition and health required to perform nutrition health assessment and meal planning. Section 2.1 discusses weight and body fat percentage metrics and evaluation. Section 2.2 discusses CI, caloric expenditure, and exercise. Section 2.3 presents progress monitoring and recommendation adjustment. Section 2.4 discusses meal planning. Health and Nutrition Background

2.1. Weight and Body Fat Percentage

2.1.1. Weight and Body Fat Percentage Assessment

One of the main factors indicating the healthiness of a person is the weight. However, evaluating the weight by itself is not enough. The Center of Disease Control and Prevention presents the body-mass index (BMI) as a tool to evaluate the weight state of a person [1]. The BMI is defined as follows:

\[ BMI = \frac{Weight(Kg)}{Height^2(m^2)} \] \hspace{1cm} (I)

The BMI can be used as an indicating of the weight state of a person while considering the height. Based on the World Health Organization [12] the body mass index is used to classify both male and female weight state as follows:

\emph{Table 1: BMI classification}

<table>
<thead>
<tr>
<th>BMI</th>
<th>Weight Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below 18.5</td>
<td>Underweight</td>
</tr>
<tr>
<td>18.5 – 24.9</td>
<td>Normal or Healthy Weight</td>
</tr>
<tr>
<td>25.0 – 29.9</td>
<td>Overweight</td>
</tr>
<tr>
<td>30.0 and above</td>
<td>Obese</td>
</tr>
</tbody>
</table>
However, the BMI index alone, even though it provides a general indicative of the weight status, ignores an important factor: if the additional weight is an additional muscle mass or fat mass.

As demonstrated by the authors in [13]: “About 39 and 87% of subjects classified as normal and overweight by BMI were obese according to their body fat percentage”. Similarly a study of 13601 subjects (age 20-79.9, 48% men) showed that the performance of BMI diminishes as age increased [14]. In addition we consider two cases extracted from the data set adopted in [15]. The data set provides data of body composition for 252 males; including weight, height, age and body fat percentage. The two following cases are considered:

<table>
<thead>
<tr>
<th>Case</th>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage (p)</th>
<th>Body fat mass (weight × p/100)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>49</td>
<td>1.89 m</td>
<td>97 Kg</td>
<td>27.2</td>
<td>27.2 %</td>
<td>26.4 Kg</td>
</tr>
<tr>
<td>Case 2</td>
<td>39</td>
<td>1.89 m</td>
<td>105 Kg</td>
<td>29.5</td>
<td>16.9 %</td>
<td>17.8 Kg</td>
</tr>
</tbody>
</table>

Both cases have the same height. The second case has a higher weight resulting in a higher BMI. Both cases rank in the overweight classification, however when we consider the BFP (body fat percentage) we notice the in the second case the body fat percentage is lower than the first case. The body fat is the combination of essential (necessary for physiological functioning, usually around 3% for males and 12% for females) and storage fat (the additional energy reserves in triglycerides form) expressed as a percentage of the total body weight [1].

By calculating the body fat mass based on the total weigh and the body fat percentage we notice that even though in the second case the total weight is higher, the body fat contribution to the weight is smaller. This signifies a better body composition in terms of
body fat mass and muscle mass, thus we deduce that the BFP must be considered to perform a valid assessment.

In order to determine the weight state classification based on the BFP we consider the classification suggest by the American College of Sports Medicine guidelines based on a study conducted on 28857 males and 12116 females [16]. Classifications are presented in Appendix A. Based on the BFP classification, in the first case the patient has a very poor BFP while in the second case the patient has a good BFP.

We conclude that combining the BMI with the BFP allows for a better classification.

2.1.2. Weight and Body Fat Percentage Recommendation

Height-Weight tables provided a tool for relating heights for females and males to a recommended weight. Several ideal weight formulas were introduced as well to recommend an ideal weight based on the height of a person [17]. Ideal body weight formulas presented in Appendix B. The Height-Weight tables and ideal body formulas provide a target weight recommendation based on sex and height. Meaning, based on this approach, any two males/females of the same height should weigh the same. These approaches disregard the current weight of the person, the age, and more importantly the body composition.

Even though ideal body weight formulas provide an indicative what the ideal weight should be, similar to BMI classification, the approach is not case specific.

Weight and BFP recommendation is a service mostly provided by a nutrition expert. There are no algorithmic procedures to compute a BFP recommendation. Our literature review and discussions with professional nutritionists indicate this a “fuzzy” task by nature, which usually relies on the experience and expertise of the nutritionist.

2.2. Caloric Intake, Expenditure and Exercise

The standard unit for measuring energy is the calorie. A calorie is the amount of heat energy needed to raise the temperature of 1 ml of water at 15° C by 1° C. Both the caloric intake (CI), i.e. the amount of energy consumed from food, and the caloric expenditure,
i.e. the amount of energy that a person needs to carry a physical function such as breathing, circulating blood or physical activity, are measured in calories. Because of the large amount of energy involved in the metabolism of food the kilocalories (1 kcal = 1000 calories) is used to measure it [1].

2.2.1. Basic Metabolic Rate and Total Energy Expenditure
The basic metabolic rate (BMR) is the energy expenditure of the human body without contribution from physical activity or food digestion. One of the most adopted approaches to determining the BMR is the St. Jeor Mifflin formula [1].

\[
BMR_{\text{male}} = 10 \times \text{weight} + 6.25 \times \text{height} - 5 \times \text{age} + 5
\]

\[
BMR_{\text{female}} = 10 \times \text{weight} + 6.25 \times \text{height} - 5 \times \text{age} - 161
\]

The equation then accounts for the Physical Activity Level (PAL) in order to calculate the Total Energy Expenditure (TEE) defined as follows:

\[
TEE = BMR \times \text{PAL factor}
\]

where:

<table>
<thead>
<tr>
<th>Physical Activity Level</th>
<th>PAL factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sedentary, little to no exercise</td>
<td>1.2</td>
</tr>
<tr>
<td>Lightly active, light exercise 1-3 days a week</td>
<td>1.375</td>
</tr>
<tr>
<td>Moderately active, moderate exercise 3-5 days a week</td>
<td>1.55</td>
</tr>
<tr>
<td>Very active, hard exercise 6-7 days a week</td>
<td>1.725</td>
</tr>
<tr>
<td>Extremely active, hard daily exercise or physical job</td>
<td>1.9</td>
</tr>
</tbody>
</table>

2.2.2. Caloric Intake Recommendation
Weight change is directly related to the daily caloric deficit or surplus. A caloric deficit indicates that the caloric Intake (CI) is smaller than the Total Energy Expenditure (TEE), while a surplus indicates the opposite. A caloric deficit state results on a rely on stored fat for energy and thus weight loss. A caloric surplus state results in storage of excess energy
as fat storage, and thus weight gain. Finally, a caloric balance between the CI and TEE results in weight maintenance [18].

A widely adopted approach in the nutrition literature, and as stated by the National Institute of health and the Academy of Nutrition and Dietetics in the USA, is the 3500 kcals per pound (0.45 kilograms) rule: a cumulative energy deficit of 3500 kcals is the equivalent of the loss of 1 pound per bodyweight [18] [19].

It is also considered that a steady weight loss rate is about 1 pound (0.45 kilograms) per week [18]. This translate into a daily 500 Kcals deficit. Accordingly, 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 at 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.

However, based on the American Office of Disease Prevention and Health Promotion guidelines [20], the CI estimations for adult female and males range from 1600-to-2400 and 2000-to-3000 Kcals respectively based on their level of activity. However, this is case by case dependent. Moreover, females and males are not recommended to consume less than 1200 and 1500 Kcals respectively, those CI values are generally associated with weight loss. In this study, we attempt to provide personalized recommendations on a case by case basis, following standard health guidelines.

Another service provided by a nutrition expert is determining the CI of the patient while considering: (i) the goal weight of the patient, (ii) the TEE of the patient, and (iii) exercise, which is discussed in the upcoming section. When determining the CI, three options arise:

i. If the goal set for the patient is to maintain weight, the CI should be equal to the TEE, no decision making is required.

ii. If the goal is to gain weight, the CI must be greater than the TEE.

iii. Finally, if the goal is to lose weight, the CI must be lower than the TEE.
We consider the following female patient case from our experimental data set, who requires weight loss due to a high BFP. We assume sedentary life style:

![Table 4: Female case caloric expenditure](image)

<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
<th>BMR</th>
<th>TEE</th>
</tr>
</thead>
<tbody>
<tr>
<td>28</td>
<td>1.59 m</td>
<td>57.6 Kg</td>
<td>22.82</td>
<td>34.4</td>
<td>1269 kcals</td>
<td>1523 kcals</td>
</tr>
</tbody>
</table>

Based on the BMI and BFP classification presented in the previous section even though the BMI is in the normal range the body fat percentage is classified as very poor and needs to be reduced.

In such case if the 500 kcals per day rule is applied the CI is reduced to 1023 kcals per day which is well below the recommended minimum intake for females of 1200 kcals. In such case, weight loss must be done at a lower rate by applying a smaller caloric deficit. In addition, daily exercise can contribute in increasing the TEE. Thus being said we draw two main conclusions:

i. The CI deduction process is not a simple mathematical procedure, rather it includes common sense decision making and can be considered as a “fuzzy” process.

ii. For cases where weight loss is required and the TEE is too low, exercise recommendations are required since increasing the level of activity becomes the only alternative.

### 2.2.3. Exercise Recommendation

As demonstrated in the previous section, in some cases, exercise is the only way to lose weight without recommending an excessively low, unhealthy CI. International health organization promote the need for exercise and maintaining a minimum level of physical activity. Based on the physical activity guidelines for Americans [20] adults between the ages of 18 and 64 should do at least 2 hours and 30 minutes of moderate-intensity workout
per week. However, the exercise caloric expenditure is relative to body weight; thus general guidelines are difficult to apply to every case.

The nutrition expert will recommend a personalized amount of exercise for the patient. There are not algorithmic procedures to determine the CI and the exercise amount. Based on the literature and our discussions with nutrition experts, the additional amount of calories that can be consumed through exercise is decided based on (i) the CI, (ii) the TEE, (iii) general exercise guidelines, and often considering (iv) the patient’s preferences towards exercise. With different factors involved, both CI and exercise recommendations are “fuzzy” human though processes that depend on the expertise and decision making logic of the expert, especially since (i) exercise guidelines are general and not case specific and (ii) including the patient preferences increases the fuzziness of the problem at hand.

2.2.3.1. Metabolic Equivalent of a Task

In order to quantify the hours of a task in terms of calories, the Metabolic Equivalent of a Task (MET) can be adopted. The MET is a measure to express the energy cost of an activity based on the weight of the person performing the activity for a duration for 1 hour [21].

\[
MET = 1 \times \frac{Kcal}{Kg \times \text{hour}} \quad (5)
\]

Based on a study conducted by Harvard Medical School, we consider the following options for exercise [22]:

i. Walking briskly at 4.8 Km/hours with MET = 3.3
ii. Casual cycling at 16 Km/hours with MET = 4.0
iii. Crawl style swimming, slow, with MET = 8
iv. Running at 12.9 Km/hour with MET = 13.5

The MET equivalent can be used to calculate the number of hours form an exercise needed per week by knowing the total number of calories needed, and vice-versa.
2.3. Progress Monitoring and Recommendation Adjustment

The aim in nutrition is to meet the needs of the patient, thus monitoring and frequent re-evaluation are required [1]. This ensures that unmet objectives are addressed. Therefore, a monitoring and adjustment system is required to track the progress of the patient and adjust the caloric intake (CI) and the exercise recommendations if required, meaning the case where the patient made small or no progress despite abiding the recommendations.

2.3.1. Expected Days to Target

As previously presented a cumulative energy deficit of 3500 kcals is the equivalent of the loss of 1 pound per bodyweight. The advised rate of weight change (gain or loss) is 1 pounds per week [18] [19] and can be achieved through a 500 kcals surplus or deficit per day. The expected numbers to reach the target weight can be calculated as follows:

\[ n = 7 \times \frac{|W - W'|}{G} \]

where:

i. \( n \) is the days needed to reach the target.
ii. \( W \) is the current weight.
iii. \( W' \) is the target weight.
iv. \( G \) is the caloric gap between the total CI and TEE per day.

We notice that the BMR (eq. (2) (3)) depends on the weight. As the patient’s weight changes the BMR changes, meaning the TEE changes and thus the weight loss rate changes since \( G \) depends on TEE. Based on our discussions with experts, a periodic reassessment in required to monitor the progress of the patient and adjust the caloric recommendations based on the evolving weight and BMR.

2.3.2. Progress Evaluation

Studies show that even a small weight loss between 5 and 10 % of the initial total body weight leads to great benefits, such as improving blood pressure, blood cholesterol, and reducing cardio vascular disease risks [34]. Thus even the smallest weight loss progress
must be accounted for. The nutrition literature lacks a clear classification for progress; there is no clear classification of how much progress is acceptable progress in case the patient did not lose (or gain) all the expected weight. As per our discussion with multiple nutrition experts, the literature does not define a classification for progress and which measures to follow for adjustment when needed. We also notice subjectivity when evaluating progress, and that opinions on progress differs between experts as we demonstrated in one of our experiments (cf. Section 7.4.3.1).

In this study we adopt the following approach for adjustment when a patient is facing difficulty losing weight: reduce the CI and increment the exercise amount in a reasonable amount while abiding by the recommended guidelines [20]. This is under the assumption that the patient is abiding by the meal plan and exercise recommendations, but not reaching the expected results. Similar to the initial CI and exercise recommendations, there are no algorithmic procedures or methods in the literature that define this process. We address these issues later in our design (cf. Chapter 6).

2.4. Meal Planning

Another major service provided by a nutrition expert is translating the daily CI into an actual daily meal plan. The meal plans provided by the expert must meet the caloric requirements of the patient.

When dealing with meal planning we consider two main concepts: (i) macronutrients and (ii) energy density.

Any food is composed of the three main macronutrients: (i) carbohydrate, (ii) protein and (iii) fat. The relationship between macronutrient and energy density can be described as follows 1 gram of fat contains 9 Kcal; 1 gram of protein or carbohydrate contains 4 Kcal [35]. Based on the energy density of macronutrient, the CI can be transformed into grams of macronutrients as we demonstrate in the upcoming sub-section.


2.4.1. Calories to Macronutrients

A normal diet translates the CI into grams of macronutrients as follows: the CI into consists of 45% to 55% of calories from carbohydrates, 15% to 20% of calories from protein and 20% to 30% of calories from fat [1]. In this study we adopt the following percentage classification based on expert recommendations: 50% carbohydrates, 20% protein, 30% fat.

Therefore, the required amount of grams of each macro-nutrient can be computed as follows:

\[
\text{grams}_{\text{carbohydrates}} = \frac{\text{calories} \times 50}{100 \times 4} \\
\text{grams}_{\text{protein}} = \frac{\text{calories} \times 20}{100 \times 4} \\
\text{grams}_{\text{fat}} = \frac{\text{calories} \times 30}{100 \times 9}
\]

(7)

(8)

(9)

2.4.2. The Food Exchange List System and Servings

In this research, we adopt one of the most widely utilized approach by nutrition experts for meal planning: the exchange list system for diabetic meal planning. The approach is suggested by a committee of the American Diabetes Association and American Dietetic Association (known as the Academy of Nutrition and Dietetics as of 2012) [1].

Foods are grouped in categories in this exchange list. Each food category contains foods grouped together because they have similar nutrient contents based on an adjusted serving sizes. Each serving of a food has about the same amount of carbohydrate, protein, fat, and calories as the other foods in the same category. One of the main motivations behind this approach was that by determining the number of servings from a specific category, multiple options can be selected from the list of foods available for this category [36].

In this study we adopt the six following basic food categories:
Table 5: Food exchange categories and their calorific and macronutrient properties per serving

<table>
<thead>
<tr>
<th>Food Categories</th>
<th>Carbohydrates (grams)</th>
<th>Proteins (grams)</th>
<th>Fats (grams)</th>
<th>Calories (Kcal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>cat₁  Starch (Bread, cereals, starchy vegetables, crackers, beans, and peas)</td>
<td>15</td>
<td>0-3</td>
<td>0-1</td>
<td>80</td>
</tr>
<tr>
<td>cat₂  Fruits</td>
<td>15</td>
<td>-</td>
<td>-</td>
<td>60</td>
</tr>
<tr>
<td>cat₃  Milk (low-fat)</td>
<td>12</td>
<td>8</td>
<td>0-3</td>
<td>100</td>
</tr>
<tr>
<td>cat₄  Non-starchy Vegetables</td>
<td>5</td>
<td>2</td>
<td>-</td>
<td>25</td>
</tr>
<tr>
<td>cat₅  Meat (lean)</td>
<td>-</td>
<td>7</td>
<td>0-3</td>
<td>45</td>
</tr>
<tr>
<td>cat₆  Fats</td>
<td>-</td>
<td>-</td>
<td>5</td>
<td>45</td>
</tr>
</tbody>
</table>

In addition, we consider combination foods. Combination foods are dishes that are defined as a combination of different servings from different categories. For example, a grilled chicken sandwich is the equivalent of 3 servings of carbohydrates (starch) and 4 servings of lean meat.

The second step of the meal planning process consists in converting the grams of macronutrients into servings from each category. The amount of servings required can be computed through a mathematical process commonly adopted by nutrition experts when using the exchange list system.

i. Select one serving of milk

ii. For CI below 2200 Kcals select three 3 servings of fruits and 3 servings of vegetables. For CI above 2200 Kcals the servings of fruit are increased to 4 and the servings of vegetable are increased to 5.
iii. Calculate the number of starch servings by subtracting the amount of carbohydrates from milk, vegetable and fruit servings from the total required amount of carbohydrates. The amount of carbohydrates calculated is divided by 15 since each serving of starch contains 15 grams of carbohydrates.

\[
s_{\text{starch}} = \frac{g_{\text{carbohydrates}} - (12s_{\text{milk}} + 5s_{\text{vegetable}} + 15s_{\text{fruit}})}{15}
\]

(10)

where:
- \(g\) is the amount of grams of a macronutrient
- \(s\) is the number of servings of a good category

iv. Calculate the number of meat servings by subtracting the amount of proteins from milk, vegetable, fruit and starch servings from the total required amount of protein. Note that fruits contain 0 grams of protein. The amount of protein calculated is divided by 7 since each serving of meat contains 7 grams of protein:

\[
s_{\text{meat}} = \frac{g_{\text{protein}} - (8s_{\text{milk}} + 5s_{\text{vegetable}} + 3s_{\text{starch}})}{7}
\]

(11)

v. Finally, calculate the number of fat servings in the same fashion; based on the number of grams of fat in the pre-selected servings. Note that fruits and vegetables contain zero servings of fat. The amount of fat calculated is divided by 5 since each serving of fat contains 5 grams of fat:

\[
s_{\text{fat}} = \frac{g_{\text{fat}} - (1s_{\text{milk}} + 2s_{\text{meat}} + 2s_{\text{starch}})}{5}
\]

(12)
2.4.3. Food Selection and Assignment

The final step in meal planning is to transform the number of servings from each category into an actual meal plan. By supplying the pre-calculated amount of servings form each category correctly, the expert insures the healthiness of the meal plan in terms of providing the correct amount of calories and macronutrients. In this research we consider a five meal approach: breakfast, lunch, dinner and two snacks in between each of two of the three main meals.

Meal planning however goes beyond providing the numbers correctly. Important “logical” factors are to be considered, namely:

i. The compatibility between the meal and the food. Example: Eggs are compatible with breakfast, milk is compatible with breakfast, meat is compatible with lunch, etc. We refer to this compatibility as the meal-food compatibility.

ii. The food preferences of the patient.

iii. The variety of the foods from day to day.

iv. The inter compatibility between foods being assigned to the same meal, to make sure the foods go well together.

This multi-factor process is rather simple for human experts who apply common sense and expertise to assign the necessary amount of servings of foods form the available resources in the exchange list over the five meals, while keeping in mind and respecting the factors mentioned above.

Unlike the previous two steps, this process cannot be performed based on a defined mathematical model. In the upcoming sections, we described how we attempt to translate “human-like” though process into a step by step approach in aims of producing quality meal plans.
Chapter 3

Literature and Related Works

This chapter summarizes the literature and existing works in the field of nutrition recommendations and meal planning. Section 3.1 describes optimization techniques. Section 3.2 describes metaheuristic approaches. Section 3.3 presents case-based reasoning approaches. Section 3.4 presents knowledge-based approaches. Section 3.5 presents learning-based approach, and Section 3.7 sums up the chapter with a discussion of the properties of the different existing approaches.

3.1. Optimization Techniques

One of the earliest approaches to solving the meal planning problem came in 1945 in an attempt to find the least cost meal by modeling the problem as a mathematical model and adopting a trial-and-error based approach [31]. The approach produced a list of unstructured foods that meet standard nutrition requirements while optimizing the economic cost. The designed model: The Stigler model, was later adopted and extended in multiple optimization approaches, e.g., [23] [37] [24] [38] [25] [26] [27], that aim to solve the diet problem. As shown by the authors in [39], the Stigler diet problem model can be mathematically represented as follows:

\[
\text{Minimize } \sum_{j=1}^{J} c_j x_j \text{ subject to } \sum_{j=1}^{J} n_{ij} x_j \geq b_i \text{ for } i = 1, 2, \ldots, n, x_j \geq 0 \text{ for all } j
\]

where:

i. \( c_j \) is the cost of the j-th food.
ii. \( x_j \) is the quantity of the j-th food.
iii. \( n_{ij} \) is the i-th nutrient content of the j-th food.
iv. \( b_i \) is the i-th nutrient requirement.
Since the past two decades, optimization techniques have been widely used in the meal planning problem. Different techniques have been adopted including: (i) linear programming, (ii) integer programming, (iii) mixed integer programming, and (iv) goal programming under multi-criteria optimization, which we briefly describe in the following sub-sections.

3.1.1. Linear Programming

Some of the early approaches adopt linear programming (LP) with emphasis on cost optimization, e.g., [23] [24] [25] [26] [27]. Linear programming is a technique that aims to optimize a linear objective function subject to linear equality constraints of decision variables. Both the objective function to be optimized and the constraints are linear in terms of decision variables. Danzig’s simplex method, introduced in 1948, is usually used to solve LP problems [28]. The linear programming formulation of the diet problem was first introduced through the Stigler model in 1945 [29]. In general, the linear programming diet problem can be modeled as follows [30]:

Minimize the cost \( z = c^T x \) subject to \( Ax = b, \ x \geq 0 \)

where:

i. \( A \ (m \times n) \) is the nutrient requirements vector for foods. With \( m \) nutrients and \( n \) foods.
ii. \( c \) is the cost vector for \( n \) foods.
iii. \( b \) is the vector for \( m \) nutrient requirements.
iv. \( x \ (x_1, x_2, \ldots \ x_n) \) is the vector of variables to be solved, representing the amount of each items to be selected.

The model designed in [25] aimed to minimize the cost of a list of unstructured foods while meeting recommended nutrition requirements. In this approach, the authors extend the diet model presented in [31] to account for: (i) the varying prices of food, (ii) the introduction of additional nutrition requirements in the nutrition literature (such as: Magnesium, Vitamin E, Vitamin B₆, etc.). The new costs where reflected in the Stigler
model. The additional nutrient requirements where reflected in the constraints. Yet the approach ignored factors such as preferences and it ignored the nature of the food (e.g., including non-palatable foods such as flour) while focusing on solving the model mathematically. Similarly, the model developed in [26] does not provide fully structured daily meal plans and lacked food variety and user preference consideration. Similarly, the other early liner models focused on cost optimization while meeting nutrition requirements, disregarding user preferences, food variety, and inter-food compatibility.

Another study using linear programming, aimed to prioritize user preferences that previous works adopting linear programming tended to ignore [32]. The aim was to develop a children’s diet for breakfast, lunch snack, and dinner that complied with their preferences. The problem is modeled into a mathematical linear programming model considering constraints such as: caloric requirements, macro-nutrient requirements and limits, as well as six micro-nutrient requirements and limits (including sodium, potassium, calcium, etc.). Yet the economic cost constraint was ignored; in contrast to previous works, instead of optimizing the economic cost of the generated meal plan the aim of the study was to solve the diet problem based on a score provided by experts (pediatrician) for each food based on nutritional value: the experts’ preferences regarding the foods. The tool produced a set of meals that were re-distributed over the meals by human intervention. A similar approach was developed in [33], focusing on user preferences rather than meal economic cost. The linear programming model in [33] was solved using the simplex method to generate healthy meal recommendations considering both user preferences and nutrition requirements. However, the model did not produce structured meals based on inter-food compatibility and food variety, rather the produced result was a sheer list of several foods rather than a properly structured meal plan.

3.1.2. **Integer Linear Programming**

Another optimization technique adopted in meal planning is integer programming. Integer linear programming (ILP) is a variation of linear programming, where the problem is
modeled similarly but the difference being that all the variables and solutions are restricted to be integers [40].

One of the earliest approaches to develop computer assisted meal planning systems using integer programming came in 1964 [37]. The aim of the study was to find the best combination of menu items that satisfy nutritional requirement for multiple days at a minimum cost. In addition, structural requirements were considered by grouping foods into categories such as: appetizers, entrée, bread, etc. Foods were pre-classified as breakfast, dinner or supper and meal planning was done accordingly. The problem was mathematically modeled using integer programming and integer approximation was adopted to approximate the optimal solution. The model developed in [37] served as a computer assisted meal planning system that can be used by domain experts, to help them produce meal plans. At that point, human intervention was still required. One of the main additions to the diet problem model was the addition of the course-based meal structure constraints (e.g., appetizers, entrée, etc.). As per [39], the problem in [37] modeled as follows:

Minimize $\sum_{k=1}^{K} \sum_{j \in N_k} c_{kj} x_{kj}(t)$ subject to the following constraints:

i. $\sum_{k=1}^{K} \sum_{j \in N_k} a_{ikj} x_{kj}(t) \geq (\leq) b_i$ for $i = 1, 2, \ldots, I$

ii. $\sum_{j \in N_k} x_{kj}(t) = 1$ for $k = 1, 2, \ldots, K$

iii. $x_{kj}(t) = 0$ if $S_{kj}(t) > 0$

iv. $x_{kj}(t) = 0$ or $1$ for $j \in N_k$, $k = 1, 2, \ldots, K$

where:

i. $c_{kj}$ is the cost of the $j$-th menu item in the $k$-th course.

ii. $a_{ikj}$ is the $i$-th nutrient value of the $j$-th menu item in the $k$-th course.

iii. $s_{kj}$ is the separation rating for the $j$-th item in the $k$-th course.

iv. $N_k$ is the index set for in course $k$.

v. $x_{ij}$ is the $j$-th menu item in the $k$-th course.

vi. $t$ is the time scale in terms of inter-meal time periods.
Constraint (i) specifies the nutrient constraints. Constraints (ii)-to-(iv) are course structure constraints and menu item separation constraints which create multiple programming problems solved sequentially by integer programming for each time period.

The author then improved his computer assisted meal planning system by applying a multiple-choice programming algorithm for food management application [38]. The objective was to develop a computer assisted program for meal planning that can be adopted in institutions such as schools and hospitals.

A common problem often faced in linear optimization approaches when modeling the problem mathematically is that adding restrictions reduces the feasibility of the problem. This makes considering different factors (nutrition requirements, preferences, cost, compatibility, etc.) rather difficult.

### 3.1.3. Other Optimization Techniques

This section introduces other approaches that adopt different other optimization techniques, namely: (i) mixed integer linear programming, (ii) goal programing.

Mixed integer programming (MIP) is an optimization problem where a subset of variables is an integer subset (represented by a space of n-dimensional non-negative integer vectors) and a subset of variables is a real-valued (continuous) subset (represented by a space of p-dimensional nonnegative real vectors). The optimization function and constraints are linear similarly to LP and ILP [41]. If the size of the integer vectors space is zero, the problem is a ILP problem. If the size of the real vectors space is zero, the problem is a LP problem.

Goal programming is a branch of multi-criteria decision optimization. It is an extension of linear programming to handle multiple objective measures. Each of the measures is given a value to be achieved [42].

Other approaches under the category of optimization techniques adopt mixed integer linear programming [36] and goal programming [43] for meal planning. The study in [36] applies the exchange system for menu planning in the context of non-clinical adults, given
that the diet exchange systems offers the option of serving food substitutions from the same food group (e.g., for instance substituting 1/2 a cup of pasta with 1/3 cup of white rice, since they both represent a serving of the starch category). The problem is modeled using mixed integer programming with focus on preference maximization. A classifier was developed to classify foods as part of one of the groups of the exchange system based on caloric and macro-nutrient composition. User preferences were collected on a scale from 1 to 10 for items included in meal planning. The mathematical model was solved to produce daily structured meal plans, yet meal plans obtained using this approach resulted in incompatibilities between foods as well as between foods and meals in addition to the issue of too small portion sizes. Similarly, the study in [43] placed emphasis on user preferences while considering nutrition requirements (calories, protein, fat, calcium, iron, vitamin C, vitamin Be, Vitamin E, magnesium and zinc.) and disregarding other factors. The designed model did not produce fully structured meals. Similarly, the second study did not categorize the selected foods into meals structure, rather they were presented as an unstructured list of foods.

Other studies also adopt integer programming and bi-criteria mathematical programming in aims of producing meal plan recommendations, yet these early studies focused on optimizing only one or two factors such as economic cost, preparation time [29], and healthy nutrition [44].

3.2. Metaheuristic Approaches

Metaheuristic approaches have been integrated with several techniques in aims of produce producing personalized meal plans based on different factors. Similar to optimization techniques, metaheuristic approaches are utilized to solve optimization problems. Compared to mathematical optimization algorithms, metaheuristics do not guarantee a globally optimal solution. The goal of metaheuristic approaches is to provide a sufficiently good solution to an optimization problem [45] [46]. Techniques such as genetic algorithms and practical swarm optimization are utilized to provide near optimal solutions for the Stigler diet problem previously presented in Section 3.1.
3.2.1. Evolutionary Algorithms

3.2.1.1. Genetic Algorithms

A self-adaptive hybrid genetic algorithm (SHGA) was developed in [11] to perform menu planning for Malaysian adolescents aged between 13 and 18 in schools. This approach aims to optimize meal budget and food variety and to meet the standard recommended nutrient intake requirements. The study considers 409 types of both Malaysian and western menu items grouped in 10 food categories. The approach also aims to consider general student preferences and the availability of raw food material, by allowing changing the meals used by the genetic algorithm. Integer encoding is used to map the foods, from each of ten food categories (e.g., cereal, meat, vegetable, fruit, etc.), associated with one of six meals to a chromosome. The fitness function is evaluated as a mathematical model defined to meet the budget constraint; the total cost of the candidate solutions in the meal should not surpass the budget, and the recommended nutrient intake; the total amount of each nutrient in the candidate solution should be bound by the recommended upper and lower limit. The initial population and the budget constraint are to be defined by the carters. Next the feasibility is evaluated such as if an individual does not meet the defined mathematical constraints is considered non-feasible. The non-feasible solutions are repaired at the next step through a novel local search method combining two local search techniques; insertion search combined with delete-and-create to avoid local optima. Roulette wheel selection is chosen for the selection process; the selected individuals are used in a 4-point crossover selection with a 0.6 crossover probability based on empirical results. The final step of the genetic process is mutation. A self-adaptive probability approach was implemented where random mutation probabilities are assigned to each individual such that fitter individuals have higher probabilities of mutating. Experimental results showed that the adaptation of insertion search requires at least a population size of 30 individuals to produce a feasible solution with an average time of 53.1 seconds while insertion search with delete-and-create requires only a population size of ten to produce a feasible solution with an average time of 119.6 seconds and 270.6 seconds with a population size of 30. The larger the set of menu items selected,
the larger the search space becomes making converting to an optimal solution more
difficult. Experimental results also show that the proposed self-adaptive probability for
mutation directs the search towards fittest individuals in a less computational time. The
proposed approach produces daily structured meal plans that meet caloric and nutrient
requirements based on general guideline recommendations rather than personalized
adaptive participant requirements. Even though the proposed approach aims to optimize
meal budget, food variety and meeting nutrient requirements, important factors are left
out such as, user food preferences and more importantly inter-food compatibility and
meal-food compatibility. In addition, no domain experts were involved in assessing the
produced meal plans.

3.2.1.2. Multi-Level Genetic Algorithms
A study adopts a multi-level genetic algorithm, with rule-based post processing, in the
aims of healthy personalized weekly meal planning [47]. The designed agents
(MenuGene) aims to satisfy macro-nutrient, user preferences and food compatibility
constraints at the meal, day and week level. To do so a divide and conquer multi-level
genetic algorithm is designed to meet the constraints by sub-dividing the problem from
the weekly level down to the daily and meal level. An initial database of meal plans is
used to set up an initial population of 20 to 400 individuals. The database contains
information about 569 dishes with information regarding, macro-nutrients, macro-
nutrients and calories. The agent is integrated with the Cordelia project [48] that provides
personalized advice to promote healthy life style and healthy nutrition. The authors
adopted is a multi-level genetic algorithm: (i) at the weekly level, the weekly meal plans
are the individuals and the meals within are the attributes; (ii) at the daily meal plan level,
the individuals are the daily meal plans and the attributes are the meals, and (iii) at the
meal level, the actual dishes are the attributes to be evaluated. An abstract genetic process
is defined to be adopted at each level. The fitness function assesses the individual based
on goodness, which itself is defined as the sum of fitness functions as a negative curve
with the optimum being zero. For each criterion (protein, carbohydrates, calories, micro-
nutrients, etc.) a numerical fitness function is defined based on the lower limit, upper limit
and the actual value of the individual. Next rule-base processing is applied on the fitness function of the individual to adjust the fitness value based on a set of defined food harmony rules both on a daily and weekly level. Initial results showed that items associated with good solutions were frequently selected, thus a similar rule base approach is utilized to avoid repetitiveness. Results showed that the agent is able to produce near-optimal solution after 1000 iterations when the mutation rate is set to 10% with the desirable rate generally being 0.5%. After the 1000th iteration no more significant improvements appear. MenuGene is capable of producing personalized complex meal plans and it offers intelligent features such as re-using produced fit meal plans as part of future initial populations, yet the genetic process requires between 10 and 15 minutes of processing in order to produce a weekly meal plan.

A research motivated by increasing chronic diseases that require special types of diets, and the shortcomings of classical deterministic optimization method to find an optimal multiple trade-off solution led to the development a n-days meal planner in [49], based on the integration of optimization techniques with evolutionary techniques in order to meet these shortcomings. The problem is formulated as a multi-dimensional Knapsack problem with the values being defined with respect to a food based on the: quality, economic cost, and aesthetic parameters (taste, color, temperature and preparation method). The volumes are defined based on the dietary recommendation and guidelines regarding the macro-nutrient and caloric composition of the foods. A multi-level evolutionary algorithm: NSGA-II is applied to solve the multi-dimensional Knapsack problem. At the n-days level, the attributes are defined as the daily meals, at the daily level the attributes are defined as the meals, and at the meal level the attributes are defined as a pair of the food composition and quantity. The evolutionary process begins with a set of 100 random or pre-determined solutions consisting of multiple individuals. The fitness of the individuals is evaluated using a numerical representation based on the defined value (quality, cost, and aesthetic parameters), while factors such as preferences of the patient is disregarded. The next step consists of evaluating the feasibility of the individuals based on the compliance with the caloric, macro-nutrient and micro-nutrient requirements. A repair process is applied
before the selection process; a deterministic optimization procedure based on the simplex method is adopted to refine the quantity of solutions by replacing individuals that do not satisfy constraints by more appropriate ones. Selection is based on a combination of non-dominant sorting, where solutions that are dominated by an individual in the population are disregarded temporarily and crowded-distance sorting, where the cost is formulated based on the distance from neighbor solutions. The aim is to produce non-dominate, and less-crowded solutions. A Two-point/Simulated binary crossover is applied followed by a linear descending mutation with probabilities of 0.14-0.01, 0.2-0.01, 0.1-0.01 at the n-day, daily and meal level respectively. Finally, a best among parents and offspring replacement is adopted to produce the next generation. 250 iterations are applied to produce feasible solutions. Due to the time complexity of the algorithm, governed mainly by the dominate-sorting part, the process takes between several minutes and a couple of hours to generate a 21-day meal plans for the evolutionary algorithm to converge. The human factor is still needed at the last level in order to select a meal plan from the set of meal plans produced as a result of the genetic process.

A similar study in [50] aims to adopt multi-objective genetic algorithms to solve the diet problem by optimizing: micro-nutrition fulfillment, user preferences, and food price in the context of non-clinical cases. User preferences are collected for the involved food on a scale from 1 to 10. Dietary reference intakes and recommended dietary allowance general guidelines are adopted based on the U.S. Food and Nutrition Board of the National Academy of Sciences to estimate the energy and nutrient requirements of the meal plan, rather than personalized caloric and nutrient recommendations. The NSGA-II algorithm is adopted. The final result produced is limited to a list of foods rather than a structured (set of) meal(s).

### 3.2.2. Practical Swarm Optimization

Particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality [21].
A recent study that aims to optimize athlete nutrition adopts the particle swarm optimization technique in an attempt to produce structured meal plans that enhance athlete performance according to the athlete’s exercise [51]. During endurance training, the body requires a balance of fat and carbohydrates while during high intensity training the athlete’s body requires a higher percentage of carbohydrates in comparison with fat. The inputs of the meal planning process are represented by the list of three-day exercises summary of the athlete represented by the average heart rate and the duration of each exercise, which can be converted into calories burned, as well the potential foods that can be assigned at each meal represented by the name, the amount, and the calories in the particular food. The fitness function for each meal is represented as a mathematical function in terms of the calories burned by training and the calories contained by the meal. Initial experiments showed successful meal plan generation approved by a sports trainer specialist. However, caloric requirements are the only factor included in decision making with factors such as macro-nutrients, athlete preferences, and food variety stated as future directions.

### 3.3. Case-Base Reasoning Approaches

Other studies aim to develop intelligent computer-assisted meal planning frameworks and tools to aid humans in meal planning by automating the process as much as possible. These studies aim to build meal plans by identifying the best fit meal plan from a set of existing ones using case-based reasoning and including additional modifications by integrating an adaptation mechanism which usually involves rule-based reasoning.

Case-based reasoning is the process of solving a new problem based on the solutions of past similar problems. Generally, case-based reasoning can be formalized as a four step process: (i) retrieve similar cases to the problem at hand, (ii) adapt the solutions of previous cases to the target problem, (iii) revise the solution at hand and perform the required adjustments, and (iv) retain the revised solution, which is added to the existing set of cases for handling upcoming similar cases [52].
3.3.1. Case-Based Reasoning with Rule-Based Correction

One study uses case-based reasoning to produce personalized meal plans based on previous similar cases while adopting rule-based reasoning for correction and regulation [8]. The system is designed to generate meal plans for healthy adults while considering minimum and maximum nutrient constraints as well as user food preferences. The main premise behind the approach is to build meal plans based on existing meal plans for similar cases. Once the nutrition and caloric requirements of the user are identified with the help of the expert, the menu that fits best the nutrition constraints is selected. A refinement mechanism is implemented to refine the selected meal if it does not properly fit the requirements through a rule-based pattern regulator. Even though meal planning is implemented by refining existing meal plans, as per the authors, some of the challenges faced are that the meal plans generated produce odd food combinations and lacks the human common sense factor.

A similar approach adopts case base reasoning integrated with a feedback mechanism to produce a tool that aims to generate meal plans without expert intervention [3] [2]. The study was motivated by the fact that existing solutions at the time did not include a feedback mechanism and adaptive patterns. The authors aimed to develop a case base reasoning system capable of developing patient tailored meal plans with learning capabilities from new cases. The aim was achieved by developing a case-based knowledge representation combined with knowledge acquisition using ripple down rules (RDR). As per the authors, RDR is a technique that complements case-based reasoning that allows incremental acquisition of knowledge from experts without the intervention of knowledge engineers. The rules added by the expert follows a human readable if-else structure. A mechanism, defined initially by a knowledge engineer, converts the rules introduced by the experts into knowledge without further intervention from the knowledge engineer.

In this study, the problem specification is defined as a set of requirements (patient information, nutrient requirements, special medical cases such as: liver mal function, constipation, etc.) and possible solutions (possible meal plans). A trapezoid-shaped fuzzy
scoring mechanism is used to score meal plans based on the nutrient requirements of the patient. The fuzzy scoring mechanism is applied to rank all the cases of the case base. The existing previous cases describe: (i) the problem specification previously described, (ii) the nutrient requirements of the patient, and (iii) the menus previously selected for this patient. The best case solution is determined by the domain expert capable of modifying the meal plan to adapt to the patient’s special needs in terms of micro-nutrients as well as special medical conditions. This is where ripple down rules are used as follows: when the expert adapts a meal, the expert must provide the system with an explanation of why a decision is made through a designed framework. The decisions of the expert are mapped into rules used to increment the knowledge of the system. The acquired knowledge is utilized to generate meal plans for future cases. The study evaluated factors such as the number of actions needed and the number of rules needed to produce improved meal plans as well as the correctness of the modifications made by the system after learning as per the domain expert through statistical analysis. One domain expert was involved in the tool’s evaluation. Results showed that the expert judged 95% correctness of system adaptation after learning. 330 rules were added by the domain expert before the tool was able to produce its own adaptation for generated meals without further intervention when considering only two types of patients. The designed system introduced at the time two new contributions: (i) meal planning for specific medical cases, as well as (ii) incremental acquisition of knowledge through RDR as previously described. However due to the complexity of dealing with medical cases, considering different medical cases requires a lot of expert intervention and a large number of rule addition to the knowledge base. Furthermore, the expert’s intervention was required to determine the nutrient goals of the patient as well.

3.3.2. Case-Based Reasoning with Genetic Algorithms
A similar approach, motivated to provide assistance to cancer patients through dietary recommendations, aims to develop a personalized diet system by adopting case base reasoning, rule base reasoning as well as a genetic algorithm [53]. A user management model is used to input the information the user’s personal information. A diet planning
module is defined to identify the nutrient requirements of the patients by adopting both case base and rule base reasoning. The nutrient requirements of the patient are deduced by finding the best similar match to the input among the existing knowledge of previous cases. A menu constructor mechanism is built using a genetic algorithm, crossover is applied on the meal plans. Selection is done based on the meals that fit best the user’s requirements computed in the previous step. Mutation is utilized as a repair mechanism that keeps mutating a diet by altering dishes until it meets the desired requirements levels. The user can either chose to accept or alter the suggested diet. A menu adaptation module allows manual dish substitution. Initial experiments show that the produced meal plan does not meet all required nutritional constraints since genetic algorithms might not find a perfectly fit solution and rather converge to a near optimal solution. Increasing the database size increases probability of converging to better solutions. In addition, the genetic algorithm dish replacement mechanism and fitness evaluation function do not seem to consider inter-food compatibility within the meal.

3.4. Knowledge-based Approaches

Knowledge based approaches have been also adopted in meal plan recommendation. One study develops a knowledge-based framework for food recommendation based on a Taiwanese food ontology [4]. The knowledge based constructed consists of two forms of knowledge: an ontology and a set of rules defined with the help of experts based on the Taiwanese clinical practice guidelines. The personalized food ontology presents two main concepts: (i) “person” under which information such as weight, height, age, BMI, diet goal, health status and food preferences are defined. (ii) “food” under which concepts such as food type, food group, nutrition level, etc. are defined. A rule-based knowledge base is defined based on some recommendations from a clinical practice guideline document issued by the Taiwanese Ministry of public health. The developed framework recommends potential meals for the patient based on the rule base developed.

The approach requires domain expert intervention to determine the required CI for each participant. Furthermore, the framework does not provide a fully structured meal plan
recommendation, but rather provides a list of recommended healthy foods for the patient to choose from.

3.4.1. Fuzzy-Logic Knowledge-Based Approaches

Fuzzy systems have been adopted, in combination with knowledge based representations, aiming to simulate human thought decision making in meal plan assessment and meal plan recommendation. Fuzzy logic systems are adopted for their ability to design robust systems that deal with uncertainties in real-life applications. As a result, FLSs have been used in a wide range of applications including fuzzy decision making and fuzzy ontologies [54].

Different approaches are available. Some address (i) meal plan assessment of existing manually generated meal plans, while others perform (ii) meal plan recommendation.

3.4.1.1. Meal Plan Assessment

Some approaches were developed to infer the healthiness of meals and meal plans by combining a fuzzy mechanism with food and patient profile ontologies.

An Intelligent healthy diet planning multi-agent (IHDPMA) was developed to provide semantic diet health state analysis, in an attempt to promote nutrition awareness and healthy eating habits [55]. The agent receives as input meals consumed by the patient and provides the probability of the meals being healthy based on the patient profile and a food ontology, containing nutrition information regarding Taiwanese foods. The food ontology is defined in three separate and interconnected layers:

i. The upper layer is labelled as the “domain layer” and defined the “meal”. This layer simply defines the “meal” concept.

ii. The middle layer is labelled the “category layer”, and describes meal course categories such as: “main courses”, “side dishes”, etc.

iii. The lowest layer is labeled the “concept layer” is split into two sub-categories: describing the meal items and their nutrition facts:
a. The “item sub-layer”. In this layer foods items, such as “garlic bread” and “grapes toast” are aggregated and belong to the corresponding meal course category in the category layer, e.g., in this example: “side dishes”.

b. The “nutrition facts sub-layer” defines the calories and macro-nutrient for every food defined in the “item sub-layer”.

The food ontology is constructed by domain experts, using a fuzzy logic inference mechanism for decision making. The agent was evaluated by comparing the agent’s evaluation and experts’ evaluations of 20 recorded meals for each of 20 participants. The assessment resulted in an accuracy of 90% when the membership degree threshold of healthy diet state is set between 0.55 and 0.7. However, the agent required domain expert intervention to determine the caloric and nutrient requirements of each patient before the fuzzy decision making process is applied.

The approach was extended towards a type-2 fuzzy system (T2FDAA) in a subsequent study, yet it did not show any major improvement over the type-1 fuzzy system approach, as stated by the authors in [56].

A similar study aimed to adopt a type-2 fuzzy ontology and type-2 fuzzy markup language (FML), to design an agent (FML2DAA) to promote awareness on healthy eating for people suffering diseases such as diabetes [54]. Similar to the work in [55][56], the agent provides a probability score associated to a linguistic variable (e.g., “healthy”, “very healthy”, “not healthy”, etc.) to assess the healthiness of the meal. Domain experts constructed a type-2 fuzzy Ontology containing Taiwanese food information and provided the caloric and macro-nutrient requirements for the patients. The concepts and relationships of the type-2 fuzzy ontology are constructed by fuzzy variables, fuzzy sets and type-2 fuzzy sets. The ontology is defined as follows:

i. The upper layer is labelled as the “domain layer” and defined the “Type-2 fuzzy food” concept.

ii. Similar to [55], courses categories are defined at the “category layer”, such as “main course”.
iii. At the “fuzzy concept layer” the items are defined, similar to the “item-sub layer” in the previous work.

iv. Below the “fuzzy concept layer”, a layer labelled as “fuzzy variable layer” is defined. At this layer concepts such as “percentage of calories from carbohydrate(PCC)” and “percentage of calories from protein(PCP)” are defined. Each item defined in the “fuzzy concept layer” is related to concepts in the “fuzzy variable layer”. This relationship represents the percentage of macronutrients in the food.

v. Beneath the “fuzzy variable layer”, the “fuzzy set layer” is defined, including fuzzy concepts for the variables in the layer above. For example: “PCC” at the “fuzzy variable layer” is associated with the fuzzy sets “low”, “balanced” and “high” in the “fuzzy set layer”.

vi. At the lowest layer labelled “type-2 fuzzy set layer”, the fuzzy sets of the “Healthy Diet State” are defined based on the variables defined in the upper layer.

Participants would input the consumed food, and then the semantic analysis is provided accordingly. The evaluation process consisted of a domain expert, the agent developed in this research, and the two agents from two previous studies IHDPMA [55] and T2FDAA [56] evaluating the healthiness of 20 meals for each of multiple participants. The mean squared error of the assessment of each agent, for each subject’s meal record, was computed agent against the assessment of the expert. Even though one expert participated in the assessment process, results showed that the type-2 fuzzy System adaptation did not always result in more accurate meal assessments (similarly to [56]).

Another study aiming to promote healthy nutrition for Japanese foods develops a Fuzzy Markup Language (FML) based ontology to evaluate a diet health level as a score between 1 and 10 [57]. FML is a language used to define fuzzy variables, fuzzy sets, and fuzzy inference rules. The aim is to provide the diet health level considering factors such as the participant caloric requirements and her level of activity, which was not considered in prior similar studies [56] [58]. Dietitians first construct a food ontology based on the
Japanese diabetes society food exchange list [59], similar the one presented in the previous paragraph.

The authors also construct FML-based personal profile ontologies, representing information about user health profiles, such as: gender, age, weight, hours of sleeping, hours of taking-up stable activity, and hours of doing light/medium/heavy exercise. The personal profile ontology defines concepts as fuzzy sets and fuzzy variables.

This ontology is used to infer the daily level of activity of the participant and to calculate her caloric requirements based on the information contained in the ontology described above.

Finally, a FML-based dietary assessment ontology is defined based on both the food ontology and the personal profile ontology. The ontology defines the fuzzy sets and the fuzzy rules necessary to deduce the “dietary health level (DHL)” of the meal of the patient. The fuzzy sets for the “DHL” is shown in Figure 1 below. Based on caloric and macro-nutrient information about the foods consumed, which are deduced from the FML-based food ontology, and caloric and macro-nutrient requirements deduced from the FML-based personal profile ontology, the agent infers the healthiness of the daily meals consumed, rather than individual meals. The agent was evaluated based on 60 recorded meals by a single participant. The mean squared error was computed versus the evaluation of a single domain expert, the results showed an error of 1.73. Even though the agent infers the energy requirements of the patient, it does not provide any decision making regarding the ideal energy requirements that promote weight loss, or weight gain if the participant requires so.
Genetic approaches have also been integrated with Fuzzy Markup Language (FML) based ontologies. These studies attempt to adopt genetic learning to improve the results of the diet healthiness assessment by training the agent. In aims to promote healthy, balanced, and enjoyable diets, a Genetic Fuzzy Markup Language (GFML) based agent has been developed to provide diet health state assessment based on Taiwanese foods [58]. The agent consists of a fuzzy profile ontology defined as follows:

i. "Fuzzy profile" is defined at the “domain layer”

ii. At the “category layer” categories such as “Africa”, “Asia”, “Europe”, etc. are defined. These concepts are linked with a Generalization (is-kind-of) relationship.

iii. At the “fuzzy concept layer” fuzzy concepts such as “people”, “size”, “behavior”, are defined. The concepts are linked with the categories in the layer above through an aggregation (is-part-of) relationship.

iv. At the “fuzzy variable layer” variables aggregated with concepts from the upper layer are defined. Such as “age” and “gender” aggregated with the fuzzy concept “people”

v. Finally, at the lowest layer: “fuzzy set layer”, fuzzy sets are defined and associated with each fuzzy variable, such as “small”, “medium”, and “big” associated with the fuzzy concepts “height” and “weight” defined in the “fuzzy concept” layer.

Similarly, a multi-level fuzzy food ontology is defined, having the same five layers as the fuzzy profile ontology. At the “category layer” the six food categories adopted are defined, then at the “fuzzy concept layer” concepts such as “serving of food groups”,

![Figure 1: DHL fuzzy sets](image-url)
“nutrition fact of each portion”, “contained calories of each serving of food groups”, etc. are defined. At the “fuzzy variable layer” variables such as sets of different food categories and grams of different macro-nutrients are defined. Finally, at the bottom level, the “fuzzy set layer”, fuzzy sets are defined for each variable in the “fuzzy variable layer”. Figure 2 below shows the fuzzy sets for the “percentage of calories from protein” (PCP) before training.

![Figure 2: PCP fuzzy sets before genetic learning](image)

Subsequently, a fuzzy personal food ontology is defined by combining the two previously designed ontologies. The ontology defines two top layer categories: a “planned healthy diet goal” category based on the personal profile ontology and an “actual diet” category based on the fuzzy food ontology. The first, defines the personal information of the patient and the required amount of calories and nutrients following the nutrition expert’s input, while the latter defines the information about the actual foods consumed. At the “fuzzy concept layer”, concepts such as planned calories for meals and planned servings per food category are defined. The fuzzy concept layer also defines actual eaten items per category concepts. Similar to the previous ontologies, at the “fuzzy variable layer” fuzzy variables are defined and linked to the concepts from the upper layer. At the “fuzzy set layer” the fuzzy sets for the fuzzy variables are defined. This ontology is used to infer the health state of a meal similar to previous studies. However, in this study the ontology is subject to genetic learning where the knowledge base, meaning the fuzzy sets, and the rule base, meaning the inference rules defined in FML, are subject to training. The rule base and the knowledge base are mapped into a chromosome representation and genetic
evolution is applied with domain expert involvement to determine the desired output for each case. The rules and fuzzy sets are modified accordingly. Figure 3 below shows the fuzzy sets for the “percentage of calories from protein” (PCP) after training. The domain experts are involved as well in determining the caloric and nutrient requirements of the participants. Seven participants that record their meals over 20 days were involved. The 20 records of the first student were used for genetic training while the other 120 records were adopted for testing. Similar to previous works, mean squared error was utilized to evaluate the performance of the agent versus the evaluations of the domain expert, performing evaluation before the genetic learning and after learning. Results show that 52% training data performs better after training while 70% of the testing data performs better after the genetic learning. Results also show that the optimal GFML is generated over 1000 generations. However, transformation the Fuzzy Markup Language (FML) representing the knowledge and the rule base to a chromosome to apply the genetic process and back to FML at each iteration slows down the execution of the genetic process, as stated by the authors.

A similar study motivated by the increase of chronic diseases, aims to develop an agent that provides adaptive personalized linguistic recommendations regarding the healthiness level of a meal consumed by the participant, as a score between 1 and 10, based on an extended version of the GFML agent by adopting type-2 fuzzy system based genetic learning mechanism [60]. A knowledge base and food database is constructed by domain experts. Ontology experts construct the adaptive personal diet assessment & recommendation ontology from the food database and the collected meal records. The
agent provides CI recommendations based on FDA standards, rather than providing a decision making process that determines a CI to help the participant reach an ideal healthy weight. Similar to the previous work in [58], the type-2 GFML is mapped to a chromosome and genetic evaluation is applied to modify the inference rules and the type-2 fuzzy sets. To evaluate the work, the linguistic evolution of the agent is compared with those of the domain expert. In addition, the type-2 fuzzy agent is compared against itself before and after training as well as the type-1 fuzzy agent developed in the previous study. A record of 20 meals were collected for each of the 8 participants involved. The 160 records were fivefold crossed for training and testing. Mean squared error was computed versus the domain expert recommendations. One-to-one accuracy was computed as well for each recommendation. Results show that training reduces the mean squared error and increases accuracy from 55% to 76%. Results in [60] show that introducing type-2 fuzzy systems improved accuracy as well versus type-1 fuzzy systems, by 6.5% for training data and by 8.7% for testing data.

Discussion
All mentioned studies in this sub-section tackle meal assessment rather than recommendation. Furthermore, the approaches require expert intervention to either determine the caloric needs of the patient, or to supervise the training where genetic learning is involved.

3.4.1.2. Meal Plan Recommendation
Fuzzy logic has also been integrated with knowledge-based representations in aims to develop meal plan recommendation agents.

One study that aims to do so develops a personal food recommendation agent (PFRA) to provide dinner recommendations that insure a wide variety of healthy foods for diabetes patients in the context of Taiwanese Food [61]. A Taiwanese food ontology is built based on common Taiwanese food. The “category layer” presents the six food categories adapted: “grains & starch”, “vegetables”, “fruits”, “milk”, “meats & proteins”, and “fat”. At the layer beneath; the “instance layer”, instances of foods from each category
are defined where the *calories, macro-nutrient composition*, and the *membership in each food category* are defined. A “personal food ontology” is built as well to represent the personal profile of each participant (*gender, age, height, weight*), her *favorite foods* and her *daily CI goal*, that is determined by the intervention of the human expert.

The agent receives the breakfast and lunch consumed by the participant. Fuzzy inference is applied to infer the remaining caloric dinner allowance and the needed servings from each food category. Based on the servings inferred, multiple dinner menus that fit the requirement are suggested for dinner. For each category multiple options are suggested, however no decision is made on a complete meal where the combination between the foods from the different categories is considered. Experts are involved in evaluating the produced output.

The authors extend their work in another study to develop an intelligent diet recommendation agent (IDRA) by integrating type-2 fuzzy food ontology (type-2 FFO) and a type-2 fuzzy personal profile ontology (type-2 FPPO), in order to improve the quality of the menu recommendation [62]. Subsequently a type-2 fuzzy personal profile food ontology (type-2 FPPFO) is defined based on the two described ontologies. This study adopts the some ontologies previously introduced in [58] and described in the Meal Plan Assessment section. The multi-layer type-2 FPPFO is adopted to infer the dinner recommendation for the patients.

Similar to PFRA, IDRA produces dinner recommendations based on the consumed meals for breakfast and lunch, by inferring the dinner caloric allowance and the number of servings allowance for the food categories. Several meal options are suggested. In addition, a semantic description mechanism was introduced to provide the patient with semantic recommendations. Such as the calories eaten are *Little*. And a recommendation to have for dinner *Much (Little or Balanced) Meats and Proteins*. The fuzzy membership for the recommendation is shown in Figure 4 below. Similar to the previous study, no decision is made on a complete meal, and food combinations are not considered: different food options from different food categories are suggested and it is up to the patient to
select a food from each category. Eight volunteers participated in a five-month experiment where IDRA was evaluated versus PFRA. Both agents were evaluated based on both volunteer satisfaction and domain expert satisfaction. The extended agent IDRA showed better satisfaction rates.

Figure 4: Recommendation type-2 fuzzy membership

Discussion
Although the previously mentioned approaches aim to integrate intelligent engineering algorithms with meal plan recommendation and generation, these approaches determine the caloric requirements of the participants through the intervention of human experts, or based on CI guidelines, rather than an automated process where an intelligent component: (i) provides health state assessment for the patient, (ii) determines a target CI for the user and (iii) provide complete daily meal plans to achieve the required CI and guide the user to a healthy state.

3.5. Learning-based Approach
A learning approach has also been adopted to developed personalized meal recommendation systems, based on image analysis [63]. The designed system consists of an image analysis model and an online learning framework that learns food preferences
based on image comparison using deep convolutional networks and multi-task learning. The designed system learns the user preferences by allowing the user to select his favorite foods through images. Then, image recommendations are made based on image analysis of similar foods, with aims to meet general user set goals such as increase or decrease in calories or in a specific macronutrient. An evaluation with 227 anonymous users showed the system’s high accuracy of predicting foods based on user preferences. When evaluating the users’ acceptance of the provided meals, experiments also showed that the proposed solution improves the meal acceptance rate by 42.63% compared with traditional survey based recommendation systems. The aim of the study is to improve the recommendations of survey based systems where preferences are learned through surveys by using image analysis based preference learning. The study does not aim to produce target weight or intake recommendations, nor does it produce meal plans that meet the nutrition requirements of a patient.

3.6. Mobile and Web Applications

Various nutrition and health related mobile and Web applications have been developed recently and are becoming increasingly available online. They fall into two main categories: (i) Calorie Tracking applications, and (ii) Meal Planning applications.

3.6.1. Calorie Tracking Applications

Calorie Tracking applications ([5] [6] [9] [10]) help patients (users) monitor their daily CI and consumed macro-nutrients by accepting as input the patient’s consumed foods, and producing/calculating as output the amount of calories and macro-nutrients contained in the consumed foods. One of the widely used mobile applications for calorie tracking is MyFitnessPal [5]. The tool accepts as input the patient’s consumed foods selected from a database of available food items, and then calculates and keeps track of the CI and macro-nutrient grams consumed by the patient based on her/his provided inputs. The application requires the patient to provide information such as age, weight, height, and level of activity. Nonetheless, the patient is also required to determine more technical inputs such as (i) target weight, (ii) daily CI and (iii) macro-nutrient distribution, which would be
difficult to produce by non-expert users. Another similar tool is MyPlate [6], a mobile application that allows CI and macro-nutrient tracking. Similarly, to MyFitnessPal, the tool collects the patient’s information and requires the patient to determine her own target weight. The tool then estimates CI levels based on the calculated TEE and the manually provided target goal by the patient. No exercise recommendations are suggested in the case of low TEE to compensate for the recommended low CI. Other similar tools such as MyNetDiary [9] and SparkPeople [10] are also available on the Web. Even-though the tools mentioned above and their counterparts online provide target weight recommendations, nonetheless most of them suffer from the following major limitations:

(i) they require technical inputs which might be difficult to provide by non-expert users/patients (e.g., target weight and macro-nutrient distribution),
(ii) the BFP levels of patients are not collected and processed, such that the recommendations are based solely on the weight and height which are not always accurate due to a lack of distinction between fat mass and muscle mass (Section 2.1).

3.6.2. Meal Planning Applications

Meal Planning applications ([7] [64] [65]) generate daily meal plans based on patient (user) provided CI requirements. MakeMyPlate [7], is a mobile application that provides patients with daily pre-defined meal plans fulfilling user specified CI levels (limited to 1200, 1500, and 1800 Kcals in the free version of the application). It allows the patient to replace a meal with an existing meal stored in a meal database, yet without verifying whether the replacement meal is calorically equivalent to the original one. Thus, replacing meals might result in surpassing or dropping below the recommended CI and macro-nutrient amounts. Moreover, the tool does not provide the patient with the capability of defining personal food preferences. Similarly, Eat This Much [64] and Fitness Meal Planner [65] are mobile applications that provide daily meal plans. Yet, they share some limitations, namely: (i) requiring the patient to set the target weight herself, which in turn requires knowledge and expertise in nutrition and might not be feasible with non-expert users, (ii) not considering the actual amount of each food available in the user’s stock, and (iii) allowing the patient to choose her preferred foods in an include/exclude (binary)
fashion, rather than providing her with the capability of determining different levels of preference toward different foods (on a scale or range of preference values, e.g., love, like, neutral, etc.).

3.7. Discussion

Although many different approaches have integrated different computing techniques (linear and integer programming, metaheuristics, knowledge-based, and learning-based approaches) to perform meal plan recommendation and generation, yet most existing solutions require domain expert intervention at different stages of the recommendation process and suffer from different limitations:

a. Early linear optimization approaches add restrictions which reduce the feasibility of the problem ([31]-[27], [32]-[40]), which makes it difficult to consider different factors (nutrition requirements, preferences, cost, compatibility, etc.). Rather these approaches focus on optimizing one or two factors only.

b. Most knowledge-based approaches tackle meal plan assessment ([4], [54]-[60]) rather than meal plan recommendation. Many approaches do not produce a complete meal plan, but rather generate dinner recommendations based on the breakfast and lunch consumed by the user ([61], [62]).

c. Even though metaheuristic approaches produce complete meal plans, they suffer from some limitations, such as disregarding the factors of inter-food and meal-food compatibility ([11]), and heavy computational complexity ([47],[49]), in addition to the need for human intervention in some cases to select the final meal plan from a set of fit solutions.

Most importantly, none of the existing approaches address case-specific weight assessment and recommendation based on body fat percentage. Similarly, no existing approaches address case-specific CI and exercise recommendation.
Chapter 4

Motivation, Goal, and Objectives

This Chapter presents the motivations behind this work in Section 4.1, the main goal of the research in Section 4.2, and the objectives we aim to accomplish in Section 4.3.

4.1. Motivation

Following an extensive review of the nutrition literature and many discussions with nutrition experts and researchers, we realized that health assessment and recommendation is highly dependent on human expertise and requires so-called “common-sense” decision making based on the experience of the experts, where few mathematical formulas or algorithmic processes exist to automate the process. For instance:

i. The nutrition literature lacks a mathematical or algorithmic approach to determine the target BFP (body fat percentage) of the patient based on height, age gender, current weight and current body fat percentage. Rather, this widely considered as a “fuzzy” task by nature that depends on the expertise of the expert.

ii. Similarly, caloric intake (CI) recommendations and exercise recommendations are considered as “fuzzy” tasks, that depend on multiple varying factors, such as (i) the goal weight, (ii) the Total Energy Expenditure (TEE), and (iii) the exercise preferences of the patient.

iii. When adopting the Food Exchange System [1] for meal planning, the final step of assigning foods to meals is highly dependent on common-sense decision making considering multiple factors such as: the compatibility between the food and the meal, the compatibility between foods, preferences, etc. (cf. Section 2.4.3). The process of manually considering all the latter factors is time consuming for experts.
4.2. **Goal**
Given the motivating problems mentioned above, and our review of existing electronic solutions in the literature, our goal is to design an original algorithmic framework that automates the complete nutrition process, ranging over: (i) weight assessment and recommendation based on BFP, (ii) CI and exercise recommendation, (iii) progress monitoring and recommendation adjustment, and (iv) patient-tailored meal planning considering all categories of required nutrients and personal patient preferences. This will be achieved using a novel approach based on a collection of software agents integrating knowledge representation, fuzzy reasoning, and an adaptation of the transportation problem optimization technique to handle the different phases of the nutrition process.

4.3. **Objectives**
In order to achieve our goal, we aim to:

i. Design a *Weight Assessment and Recommendation* agent, using a specially designed agent using the fuzzy logic paradigm, that recommends a healthy target weight and BFP for a patient.

ii. Design a *Caloric Intake and Exercise Recommendation* agent, using a specially designed agent using the fuzzy logic paradigm, that recommends daily CI alongside personalized exercise recommendations.

iii. Design a *Progress Evaluation and Recommendation Adjustment* agent, using a specially designed agent using the fuzzy logic paradigm, the evaluates the progress of a patient and adjusts the recommendations if she is not achieving the expected progress.

iv. Design a personalized *Meal Plan Generation* agent, that generates meal plans that fulfill the patient’s nutrition requirements while meeting her preferences.

v. Integrate all agents together in a working framework: *PIN*.

vi. Implement a testing prototype system as a simple web application.

vii. Run multiple sets of experiments, with the help of nutrition experts, to evaluate each designed agents, as well as the integrated system. We aim to compare and
correlate the results of our system recommendations with those of human experts in order to evaluate the quality of our system, and highlight potential improvements.
Chapter 5

Preliminaries

This chapter presents preliminary notions and definitions related to fuzzy logic in Section 5.1, and the transportation optimization problem in Section 5.2, which will be utilized in designing our nutrition health assessment and recommendation solution.

5.1. Fuzzy Logic

Fuzzy logic is useful in creating control system based on “*human common sense*”, in aims of creating intelligent agents simulating human reasoning using linguistic variables rather than numerical ones [66]. This section presents some of the main concepts and building blocks required to build a fuzzy logic agent, including fuzzy sets and memberships, fuzzy logic controller, condition-action rules, fuzzification, inference, aggregation, and defuzzification functions which are described in the following sub-sections.

5.1.1. Fuzzy Sets and Membership

Membership functions relate the degree of membership $\mu$ between 0 (no membership) and 1 (absolute membership) for a linguistic term.

![Temperature fuzzy membership example](Figure 5: Temperature fuzzy membership example)

A value of a variable can have more than membership value. For example, in the temperature fuzzy memberships provided in Figure 5, a temperate of 5 °C has a
membership value of 0.5 in both sets Cold and Mod (moderate), whereas a temperature of 9 °C has a membership of \(\approx 0.1\) in Cold and \(\approx 0.9\) in Mod.

Membership functions can be of different shapes: trapezoid, triangle, Gaussian, etc.

5.1.2. Fuzzy Logic Controller

Scalar inputs go through fuzzification: based on the defined fuzzy sets and corresponding membership functions, the membership values of each scalar input are deduced. Inference and aggregation are then applied based on a set of defined condition-action rules to produce a fuzzy output, which is then deffuzified to obtain a scalar output.

5.1.3. Condition-Action Rules (Fuzzy Inference Rules)

The condition-action rules determine the actions of the fuzzy agent. The rules are expressed through an if-then representation: **If** \(<\text{Condition}>\) **Then** \(<\text{Action}>\)

A multi-variable condition-action rule can be represented linguistically as follows:

\[
\text{If} \{\text{variable}\#1 \text{ is } \text{fuzzy term}\} \\
\text{and}\{\text{variable}\#2 \text{ is } \text{fuzzy term}\} \\
\text{and}\{\text{variable}\#3 \text{ is } \text{fuzzy term}\} \\
\text{and} ... \\
\text{Then}\{\text{fuzzy output}\#1 \text{ is } \text{fuzzy term}\} \\
\text{or}\{\text{fuzzy output}\#1 \text{ is } \text{fuzzy term}\}
\]
A condition-action rule can lead to multiple scenarios for outputs. And since a variable can have different memberships in different sets, multiple condition-action rules can be invoked simultaneously.

A rule is translated from a linguistic representation to Boolean logic as follows:

$$fuzzy\ term(V1) \land fuzzy\ term(V2) \Rightarrow fuzzy\ term(V3)$$  \hspace{1cm} (13)

Next, inference is applied. In this study we adopted Mamdani’s approach [66], due to the fact that it reduces computation time while showing acceptable performance based on empirical results. Other approaches such as implication or product, etc. could have been used.

$$P1 \land P2 \Rightarrow P3 = (P1 \land P2) \land P3$$  \hspace{1cm} (14)

Considering scalar inputs $x_1$ and $x_2$ for fuzzy variable inputs $v_1$ and $v_2$ respectively, and fuzzy variable output $v_3$:

$$\left( f(x_1)^V_{fuzzy\ term\ #i} \land f(x_2)^V_{fuzzy\ term\ #i} \right) \land f(x)^V_{fuzzy\ term\ #i}$$  \hspace{1cm} (15)

where:

i. $f(x_1)^V_{fuzzy\ term\ #i}$ represents the membership degree of $x_1$ in fuzzy term $i$ of $v_1$. We refer to the membership value as $\mu_1$.

ii. $f(x_2)^V_{fuzzy\ term\ #i}$ represents the membership degree of $x_2$ in fuzzy term $i$ of $v_2$. We refer to this membership value as $\mu_2$.

iii. $f(x)^V_{fuzzy\ term\ #i}$ represents the graphical membership function of fuzzy term $i$ of $v_3$.

Graphically, this approach translates into the minimum.

$$\min(\min(\mu, \mu'), f(x)^V_{fuzzy\ term\ #1}) = f_i$$  \hspace{1cm} (16)

Where $f_i$ represents the fuzzy graphical output.
5.1.4. Aggregation

Having produces multiple fuzzy outputs through the inference component, aggregation is applied to produce a single fuzzy output. Multiple approaches exist for fuzzy aggregation; such as minimization, bounded sum, etc. In our study we adopt the maximization approach since it empirically produced higher quality results (Section 7.4).

Given i condition-action rules, producing multiple fuzzy results: \( f_1, f_2, \ldots, f_i \):

\[
 f = \max( f_1, f_2, \ldots, f_i )
\]  

(17)

Considering two fuzzy outputs for maximization aggregation:
5.1.5. Defuzzification
Defuzzification is utilized to transform the aggregated fuzzy output into scalar output. Multiple approaches exist for defuzzification. In this study we adopt three different defuzzification mechanism in different fuzzy agents, namely:

i. Center of gravity \( x = \frac{\int x \times f(x) \times dx}{\int f(x) \times dx} \)  

\[ (18) \]

ii. Maximum to the left

iii. Maximum to the right

In Sections 6.2 to 6.4, we describe our designed fuzzy agents and how the different concepts explored in this section were adopted to fit our problem requirements.

5.2. Transportation Problem
The transportation problem is concerned with finding the minimum cost of transporting a single commodity from a given number of sources to a given number of destinations. The data of the model include: (i) The amount of supply at each source and the amount of demand at each destination, as well as (ii) the unit transportation cost of the commodity from each source to each destination [67].

Figure 8: Fuzzy aggregation by maximization
As per [68]:

i. Considering \( m \) different supply centers (source) labeled with \( i = 1, \ldots, m \), the supply of the \( i \)-th center is noted \( S_i \).

ii. Considering \( n \) different demand centers (destination) labeled with \( j = 1, \ldots, n \), the demand of the \( j \)-th center is \( D_j \).

iii. \( X_{i,j} \) is the number of units supplied from supply center \( i \) to demand center \( j \).

iv. \( C_{i,j} \) is the cost associated with \( X_{i,j} \).

Solving the problem at hand comes down to finding the number of supply units to be transported from source \( i \) to destination \( j \) so that the total transportation cost is minimum:

\[
\min \sum_{i=1}^{m} \sum_{j=1}^{n} X_{i,j} C_{i,j}
\]

(19)

While satisfying the constraints that the total amount supplied from a supply center must not exceed the predefined supply amount, and the total amount supplied to a demand center must not exceed the predefined demand required. These two requirements are respectively modeled by the two following equations:

\[
\sum_{j=1}^{n} X_{i,j} = S_i \text{ for all } i = 1, \ldots, m.
\]

(20)
\[ \sum_{i=1}^{m} X_{i,j} = D_j \text{ for all } i = 1, ..., n. \]  

(21)

The transportation problem can then be modeled through a matrix as follows:

Table 6: Transportation matrix

<table>
<thead>
<tr>
<th>Source</th>
<th>Cost per Unit Distributed</th>
<th>Supply</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>C_{11} C_{12} ... C_{1m}</td>
<td>S_1</td>
</tr>
<tr>
<td>2</td>
<td>C_{21} C_{22} ... C_{2m}</td>
<td>S_2</td>
</tr>
<tr>
<td>...</td>
<td>... ... ... ... ... ...</td>
<td>...</td>
</tr>
<tr>
<td>n</td>
<td>C_{n1} ... C_{nm}</td>
<td>S_m</td>
</tr>
</tbody>
</table>

As per [67], when the total demand is equal to the total supply, the transportation problem is said to be a balanced transportation problem. If the demand exceeds the supply, then the problem cannot be solved. If the supply exceeds the demand the problem can be solved by adding a dummy demand center where the demand of this center is equal to the total excess supply, thus making the transportation problem balanced. The costs associated with the dummy demand center are set to be higher than all other demand center cell costs.

Many methods exist for solving the transportation problem. In our design, we adopted the **Minimum (Least) Cost Method**. This approach can be described as follows [67]

i. Assign as much as possible to the cell with the smallest unit cost in the entire matrix.

ii. Cross out the row where the supply center has supplied all available supply.

iii. Cross out the column where the demand center’s demands were satisfied.

iv. Adjust the supply and demand for those rows and columns which are not crossed based on the amount of units supplied.
v. When exactly one row or column is left, all the remaining unit are basic and are assigned the only feasible allocation. In the case of an unbalanced problem, the only feasible allocation is the dummy variable.

We present in Section 6.6.3.3 a modified version of the transportation matrix problem tailored to fit the food to meal assignment process.
Chapter 6
Proposal

This Chapter presents the design of our PIN framework. Section 6.1 presents the overall general architecture of the framework, Sections 6.2 to 6.6 present the design PIN’s components. While Section 6.7 presents our designed evaluation metrics.

6.1. General Architecture
In order to address the issues at hand, we propose a framework titled Personal Intelligent Nutritionist (or PIN), composed of four main components, each covering one of the four main services provided by a human expert:

i. Weight Assessment and Recommendation agent (WAR)
ii. Caloric Intake and Exercise Recommendation agent (CIER)
iii. Progress Evaluation and Recommendation Adjustment agent (PERA)
iv. Meal Plan Recommendation agent (MPG)

The four agents combine into our designed framework: titled PIN the, short for Personal Intelligent Nutritionist.
First the weight assessment and recommendation (WAR) agent is used to suggest weight and body fat percentage (BFP) recommendations for the patient. More than one “healthy” recommendation is provided in some cases, for example: the patient has a weight that is healthy to maintain, but losing weight to reach an ideal BFP is also a possible and healthy option. The patient selects one of the preferred options: the option is stored in the database, and is fed as input to the caloric intake and exercise recommendation (CIER) agent to determine the appropriate CI and amount of exercise. The recommendation chosen by the patient is stored in the database and fed as input to the meal plan generation (MPG) agent to produce appropriate meal plans. Meal plan generation is processed based on the patient’s preferences stored in the database. The progress evaluation and recommendation (PERA) agent allows to assess the progress of the patient and adjust the recommendation if needed. We describe each agent in details in the upcoming sections.
6.2. Weight Assessment and Recommendation (WAR) Agent

As demonstrated in Section 2.1, the combination of the body mass index (BMI) and body fat percentage (BFP) allows for a more accurate assessment of the patient’s weight state, versus only considering the BMI. We also discussed the gap in the literature for an algorithmic procedure that allows determining a target weight while considering the starting weight and BFP. This section presents a **weight assessment and recommendation** WAR agent which accepts as input the patient’s BMI and BFP, and provides as output: (i) the target BFP, (ii) the target weight, and the (iii) the recommendation goal (i.e., loose, gain, or maintain weight).

WAR is designed based on the fuzzy logic paradigm, in order to automate the “human common sense” thought process involved in weight recommendation.

We design a set of fuzzy agents to perform BFP recommendation. A BFP recommender agent receives as input the current BMI and BFP and produces a set of target BFPs. Multiple agents were developed due to the fact that the BFP classification suggested by ACSM³ is gender and age category specific, and thus the fuzzy membership functions were adapted accordingly. The appropriate agent is selected based on the patient’s age and

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³ American College of Sports Medicine
gender following the ACSM classification, and then run on the input BMI and BFP of the patient to produce the recommended BFP as output.

After the target BFP is computed, we deduce the target weight accordingly. Following our extensive review of the nutrition literature, we realized that there is no agreed upon mathematical procedure to determine the percentage of fat lost out of the weight loss. In addition, the literature lacks a clear definition on how much of the weight that is lost is attributed to fat loss. Hence, after many discussions with nutrition experts, we adopt the following simplification: *the 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). Thus, the target weight can be computed as following:

\[ w' = w - (w \times \frac{p}{100} - w' \times \frac{p'}{100}) \]

where:

i. w and w’ are the current and target weights respectively.

ii. p and p’ are the current and target BFP respectively.

The current body weight (w) and current BFP (p) are acquired inputs. The target BFP (p’) is deduced by the fuzzy BFP recommendation agent. Consequently, the target weight (w’) can be deduced as follows:

\[ w' = w - (w \times \frac{p}{100} - w' \times \frac{p'}{100}) \]

\[ w' = w \left( 1 - \frac{p}{100} \right) + w' \times \frac{p'}{100} \]

\[ w' - w' \times \frac{p'}{100} = w \left( 1 - \frac{p}{100} \right) \]

\[ w' \left( 1 - \frac{p'}{100} \right) = w \left( 1 - \frac{p}{100} \right) \]
\[ w' = w \times \left( \frac{1 - \frac{p}{100}}{1 - \frac{p'}{100}} \right) \] (22)

The patient will be provided with multiple “healthy” options. The framework provides the patient with the ability to select one of the available options.

Finally, the recommendation goal is determined: (i) if the target weight is larger than the current weight, the goal is to gain weight, (ii) in the opposite case, the goal is to lose weight, (iii) if the difference between the current and target weight is within 0.5 kilograms, the goal is to maintain the current weight. The above goals were defined following nutrition guidelines following our discussion with nutrition experts.

6.2.1. Body Fat Percentage Recommendation Fuzzy Agent

6.2.1.1. Inputs and Outputs

The weight recommendation decision is based on the (i) BMI and (ii) the BFP. The output of the fuzzy agent is the target BFP that is recommended to the patient.

For the BMI, we adopt the classification suggested by the World Health Organization [12] as presented in Table 1: BMI classification (cf. Section 2.1.1).

For the BFP, both input and (target) output, we adopt the classification suggested by the ACSM [16]. In contrast to the BMI classification that applies for both adult females and males, the BFP classification is both age and gender specific, and consists of 6 different male age categories, as well as 6 different females age categories (cf. Appendix A).
6.2.1.2. **Defining Multiple Fuzzy Agents**

Due to the age and gender specific classification of BPF, we define 12 agents:

i. A male BFP recommendation agent for each age category

ii. A female BFP recommendation agent for each age category

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, i.e., in the fuzzy membership functions. Some sample fuzzy sets are presented in Figure 14, Figure 15, and Figure 16.

The complete fuzzy sets are presented in Appendix C.

6.2.1.3. **Fuzzy Sets**

*Figure 13: BMI fuzz sets*
Figure 14: BFP sets for males between 20 and 29

Figure 15: BFP fuzzy sets for females between 20 and 29
6.2.1.4. **Condition-Action Rules**

The condition-action rules, reflect the common sense logic applied by a nutrition expert to determine a target BFP based on the BMI and current BFP. To overcome the gap in the literature, we have defined as set of condition-actions rules in collaboration with nutrition experts. We present the set of condition action rules in tabular form as follows:

*Table 7: BFP recommendation fuzzy agent condition-action rules*

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

The condition-action rules can be reduced to the following:

- **R₄**: Very Lean(BFP) ⇒ Excellent (BFP) summing up rules R1, R7, R13, and R19
- **R₅**: Excellent(BFP) ∨ Good(BFP) ⇒ Good (BFP) summing up rules R2, R3, R8, R9, R14, R15, R20 and R21
- **R₄**: Underweight(BMI) ∧ Fair(BFP) ⇒ Fair(BFP) ∨ Good(BFP)
- **R₁₀**: Normal(BMI) ∧ Fair(BFP) ⇒ Fair(BFP) ∨ Good(BFP)
R₁₆: Overweight(BMI) ∧ Fair(BFP) ⇒ Good(BFP)
R₂₂: Obese(BMI) ∧ Fair(BFP) ⇒ Good(BFP)
R₆: Poor(BFP) ⇒ Fair (BFP) summing up rules R5, R11, R17, R23
R₇: Very Poor(BFP) ⇒ Poor (BFP) summing up rules R6, R12, R18 and R24

6.2.1.5. Aggregation and De-Fuzzification
We adopt maximization as an aggregation function, given its intuitiveness and empirical performance (it produced better results compared with alternative aggregation functions such as bounded sum and minimization). For defuzzification, we adopt center of gravity (eq.(18)) that showed the optimal results in producing body fat percentage recommendations.

6.2.1.6. Example
We consider the following male patient case from our experimental data set:

Table 8: Male case 1 weight input used for BFP recommendation fuzzy agent example

<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>1.77 m</td>
<td>66.94 Kg</td>
<td>21.2</td>
<td>17.7 %</td>
</tr>
</tbody>
</table>

Fuzzy Input Memberships
We compute the memberships in the inputs’ fuzzy sets based on the BMI fuzzy sets and the BFP fuzzy sets for males between 30 and 39 (cf. Appendix C).

i. BMI
   a. \( f_{\text{normal}}(21.2) = 0.87 \)
   b. \( f_{\text{underweight}}(21.2) = 0.13 \)
   c. Membership in all other sets is equal to 0
Figure 16: BMI fuzzy memberships

ii. BFP

a. $f_{fair} = 0.05$

b. $f_{good} = 0.95$

c. Membership in all other set is equal to 0
Condition-Action Rules, Inference, Aggregation and Defuzzification

Based on the memberships of the inputs the following condition-action rules are invoked:

R_8: Excellent(BFP) \lor Good(BFP) \Rightarrow Good (BFP)

R_4: Underweight(BMI) \land Fair(BFP) \Rightarrow Fair(BFP) \lor Good(BFP)

R_{10}: Normal(BMI) \land Fair(BFP) \Rightarrow Fair(BFP) \lor Good(BFP)

The output functions include different OR combinations. The condition-action rules will result in four different outputs:

i. Output 1

R_8: Excellent(BFP) \lor Good(BFP) \Rightarrow Good (BFP)

R_4: Underweight(BMI) \land Fair(BFP) \Rightarrow Fair(BFP)

R_{10}: Normal(BMI) \land Fair(BFP) \Rightarrow Fair(BFP)
ii. Output 2

\( R_6: \text{Excellent(BFP)} \lor \text{Good(BFP)} \Rightarrow \text{Good (BFP)} \)

\( R_4: \text{Underweight(BMI)} \land \text{Fair(BFP)} \Rightarrow \text{Good(BFP)} \)

\( R_{10}: \text{Normal(BMI)} \land \text{Fair(BFP)} \Rightarrow \text{Fair(BFP)} \)

iii. Output 3

\( R_6: \text{Excellent(BFP)} \lor \text{Good(BFP)} \Rightarrow \text{Good (BFP)} \)

\( R_4: \text{Underweight(BMI)} \land \text{Fair(BFP)} \Rightarrow \text{Fair(BFP)} \)

\( R_{10}: \text{Normal(BMI)} \land \text{Fair(BFP)} \Rightarrow \text{Good(BFP)} \)

iv. Output 4

\( R_6: \text{Excellent(BFP)} \lor \text{Good(BFP)} \Rightarrow \text{Good (BFP)} \)

\( R_4: \text{Underweight(BMI)} \land \text{Fair(BFP)} \Rightarrow \text{Good(BFP)} \)

\( R_{10}: \text{Normal(BMI)} \land \text{Fair(BFP)} \Rightarrow \text{Good(BFP)} \)

**Output 1: Inference Mechanism**

By applying Mamdani’s inference mechanism:

\[
R_b: f_1 = \min(0.95, f(x)_{\text{BFP out}}^{\text{good}})
\]

\[
R_4: f_2 = \min(\min(0.15, 0.05), f(x)_{\text{BFP out}}^{\text{BFP out}}^{\text{fair}}) = \min(0.05, f(x)_{\text{BFP out}}^{\text{BFP out}}^{\text{fair}})
\]

\[
R_{10}: f_3 = \min(\min(0.87, 0.05), f(x)_{\text{BFP out}}^{\text{BFP out}}^{\text{fair}}) = \min(0.05, f(x)_{\text{BFP out}}^{\text{BFP out}}^{\text{fair}})
\]
Output 1: Aggregation and Defuzzification

By applying maximization aggregation function and center of gravity defuzzification function, the output BFP is equal to: 17.14.

The same inference, aggregation, and defuzzification processes are applied to the other three outputs.
Output 2: Inference Mechanism

By applying Mamdani’s inference:

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

Output 2: Aggregation and Defuzzification

By applying maximization aggregation and center of gravity defuzzification function the output BFP is equal to: 17.14. The aggregation function will produce the same aggregate output as output 1. Resulting in the same defuzzification result.

Similarly, in the case of output 3, the same aggregated output will be produced and the same scalar output will result from defuzzification.

Output 4: Inference Mechanism

By applying Mamdani’s inference:

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

**Output 4: Aggregation and Defuzzification**

By applying maximization aggregation and center of gravity defuzzification function the output BFP is equal to: 16.90
Discussion

The agent produces four final outputs, three of which are identical (i.e., BFP = 17.14) and one is very close to the latter (i.e., BFP = 16.90). The latter two target BFP values are used to compute the target weight.

6.2.2. Running Examples

This section presents the results of the weight assessment and recommendation agent produced for three different patient cases extracted from our experimental data set, among which: (i) the first case presents a male with a good weight state, that can afford to lose a little bit of extra weight, (ii) a female with a high BFP that requires losing weight and (iii) a male with a very low BFP that requires gaining weight.
Case 1

Table 9: Male case 1 inputs used for weight assessment

<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>1.77 m</td>
<td>66.94 Kg</td>
<td>21.2</td>
<td>17.7 %</td>
</tr>
</tbody>
</table>

Resulting Recommendations:

Table 10: Male case 1 weight recommendations

<table>
<thead>
<tr>
<th>Goal</th>
<th>Target BFP</th>
<th>Target Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maintain</td>
<td>17.14 %</td>
<td>66.49</td>
</tr>
<tr>
<td>Lose</td>
<td>16.90 %</td>
<td>66.28</td>
</tr>
</tbody>
</table>

As demonstrated in Section 6.2.1.6, the computed BFP outputs are \( \text{BFP}_1 = 17.14 \) and \( \text{BFP}_2 = 16.90 \). The weight is computed using equation (22). For example, for \( \text{BFP}_1 \) the target weight is computed as follows:

\[
w' = 66.94 \times \frac{\left(1 - \frac{17.7}{100}\right)}{\left(1 - \frac{17.14}{100}\right)} \approx 66.487
\]

For this case, two options were provided, to maintain the current weight or to lose 2/3 of a kilogram. Since the patient’s BFP is considered good based on the age and gender, the two options provided allow the patient either to lose some extra weight to reach a lower BPF in the good BFP state or maintain the current BFP.

Case 2

We consider the following female patient case from our experimental data set:
Table 11: Female case 1 inputs used for weight assessment

<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>28</td>
<td>1.59 m</td>
<td>57.6 Kg</td>
<td>22.82</td>
<td>34.4 %</td>
</tr>
</tbody>
</table>

Resulting Recommendations:

Table 12: Female case 1 weight recommendations

<table>
<thead>
<tr>
<th>Goal</th>
<th>Target BFP</th>
<th>Target Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lose</td>
<td>28.07 %</td>
<td>52.53</td>
</tr>
</tbody>
</table>

Since based on the age and gender of the patient, the BFP is considered to be *Very Poor* the resulting recommendation is to drop the BFP and weight as a first step to reach *Poor* BFP classification, since the agent aims to reach the patient to a *good* or *excellent* BFP state in a step-by-step process.

Case 3

Table 13: Male case 2 inputs used for weight assessment

<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>23</td>
<td>1.83</td>
<td>71.88</td>
<td>21.34</td>
<td>9.4 %</td>
</tr>
</tbody>
</table>

Resulting Recommendations:

Table 14: Male case 2 weight recommendations

<table>
<thead>
<tr>
<th>Goal</th>
<th>Target BFP</th>
<th>Target Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gain</td>
<td>13.32 %</td>
<td>75.13</td>
</tr>
</tbody>
</table>
Based on the age and gender of the patient, the BFP classification falls under the *excellent* category. In our research, since the context is non-athletes this patient is required is to gain some additional weight to increase the BFP to fall in the *good* BFP classification.

### 6.3. Caloric Intake and Exercise Recommendation (CIER) Agent

![Activity diagram describing the CI and exercise recommendation process](image)

Figure 23: Activity diagram describing the CI and exercise recommendation process

While the WAR agent computes the target BFP, target weight, and the goal (lose, gain, or maintain weight) of the patient, the **caloric intake and exercise recommendation** (CIER) computes both the caloric intake (CI) and the amount of exercise (or exercise recommendation, ER) that the patient should perform to reach the patient’s weight goal recommended by WAR.

As discussed in Section 2.2.1, the first step in a caloric assessment is determining the basic metabolic rate (or BMR) of a patient, based on (i) gender, (ii) age, (iii) height, and (iv) weight (eq. (2) and (3)). Then the total energy expenditure (TEE) is determined based on (i) the BMR and (ii) the level of activity of the patient (eq. (4)).

Caloric intake (CI) is determined based on two main factors (cf. Background in Section 2.2.2): (i) the weight goal of the patient (lose, gain, or maintain the current weight) and (ii) the TEE. Three main possibilities arise:
i. If the goal set for the patient is to maintain weight, the CI should be equal to the TEE, and hence no decision making is required in this case.

ii. If the goal is to gain weight, the CI must be greater than the TEE.

iii. Finally, if the goal is to lose weight, the CI must be lower than the TEE.

Also, exercise recommendations needed, in addition to CI recommendations, for the patient to remain in a healthy state (cf. Background in Section 2.2.2). Yet, CI and ER are by nature fuzzy processes that involve “common sense” human reasoning considering multiple factors such as, patient preferences, general guidelines, the expertise of the expert, etc. In order to automate these processes, we design two dedicated fuzzy agents: a (i) caloric intake (CI) recommendation fuzzy agent and an (ii) exercise recommendation fuzzy agent. The first agent is responsible for producing CI recommendations based on the TEE of the patient. Then, the later agent is utilized to add exercise recommendations based on the caloric gap: i.e. the difference between the TEE and the recommended CI.

Based on the American Office of Disease Prevention and Health Promotion guidelines [20], different CI recommendation guidelines are provided for males and females. In addition, the decision making process concerning the CI differs if the goal is to lose, gain, or maintain weight, meaning when modeling the problem as a fuzzy model, different sets of condition-action rules need to be defined. Thus we introduce the four following fuzzy agents for CI recommendation:

i. Male weight gain CI and exercise recommendation agent.
ii. Male weight loss CI and exercise recommendation agent.
iii. Female weight gain CI and exercise recommendation agent.
iv. Female weight loss CI and exercise recommendation agent.

The appropriate agent is selected and run based on the patient’s gender and weight goal. In addition, as previously described, if the weight goal of the patient is to maintain the current weight, the CI must be set equal to the total caloric expenditure (CE), and thus no
additional exercise recommendations are required. We do not apply fuzzy processing in such case.

In addition, when the goal is to lose weight, exercise recommendations need to be considered. The exercise percentage recommendation fuzzy agent is designed to meet this purpose. The fuzzy agent receives as input the caloric deficit: i.e., the difference between the TEE and the recommended CI. The exercise recommendation is determined based on the deficit: i.e., if the deficit is small, exercise must be added to achieve a large difference between the total energy consumed and the total CI. On the other hand, if the deficit is large the exercise percentage recommended can be minimal.

We define the exercise percentage, as a percentage of the BMR presented in Section 2.2.1. The additional, exercise recommendation is determined as a percentage of the BMR. For example: if a patient’ BMR is 1500 Kcals and has a sedentary level of activity, referring to Table 3, the TEE would be equal to 1800. In addition, if we assume a 20% exercise recommendation, then the daily exercise amount expected is the equivalent of 300 Kcals per day. The hours equivalent can be calculated through the metabolic equivalent of a task (MET) presented in Section 2.2.3.1.

We adopt a classification for the exercise percentage based on Mifflin St. Jeor BMR and PAL’s classification [1] presented in Table 3. Each PAL factor is translated into an exercise category.

<table>
<thead>
<tr>
<th>Category</th>
<th>Exercise recommended percentage of the BMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low</td>
<td>0 – 20 %</td>
</tr>
<tr>
<td>Low</td>
<td>20 – 37.5 %</td>
</tr>
<tr>
<td>Normal</td>
<td>37.5 – 55 %</td>
</tr>
<tr>
<td>High</td>
<td>55 – 72.5 %</td>
</tr>
<tr>
<td>Very High</td>
<td>55 – 90 %</td>
</tr>
</tbody>
</table>
Both agents produce multiple possible recommendations. The patient is not restricted to a single possible recommendation. Once the recommendations have been produced, the patient is presented with the resulting set of combinations of CI and exercise recommendation values.

In addition, the expected values for the patient to reach the target goal is calculated and presented for the patient based on eq. (6).

We present in the upcoming section an approach to rank the recommendations based on the collected preferences of the patient considering: (i) the amount of exercise the patient wishes to undertake, and (ii) the amount of caloric deficit the patient wished to adhere to. Even though all possible healthy recommendations will be presented to the patient, the recommendation shall be ranked based on relevance to the preferences.

### 6.3.1. Caloric Intake Recommendation Fuzzy Agent

![Figure 24: Simplified activity diagram describing CI recommendation agents fuzzy control logic](image)

#### 6.3.1.1. Inputs and Outputs

The input of the agent is the total energy expenditure (TEE). The agent produces as output a set of possible CI recommendations.

Based on the American Office of Disease Prevention and Health Promotion guidelines [20], the CI estimations for adult males and females range between 2000-to-3000 and 1600-to-2400 Kcals respectively. In addition, the minimum recommended healthy intakes for females and males are 1200 Kcals and 1500 Kcals accordingly. Based on this data, and in collaboration with domain experts, we define the following classifications for CI values:
Table 16: Male CI classification

<table>
<thead>
<tr>
<th>Category</th>
<th>Range (Kcals)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Low</td>
<td>1250-1500</td>
</tr>
<tr>
<td>Very Low</td>
<td>1500-1750</td>
</tr>
<tr>
<td>Low</td>
<td>1750-2000</td>
</tr>
<tr>
<td>Normal</td>
<td>2000-2250</td>
</tr>
<tr>
<td>High</td>
<td>2250-2500</td>
</tr>
<tr>
<td>Very High</td>
<td>2500-2750</td>
</tr>
<tr>
<td>Extremely High</td>
<td>2750+</td>
</tr>
</tbody>
</table>

Table 17: Female CI classification

<table>
<thead>
<tr>
<th>Category</th>
<th>Range (Kcals)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Low</td>
<td>950-1200</td>
</tr>
<tr>
<td>Very Low</td>
<td>1200-1450</td>
</tr>
<tr>
<td>Low</td>
<td>1450-1700</td>
</tr>
<tr>
<td>Normal</td>
<td>1700-1950</td>
</tr>
<tr>
<td>High</td>
<td>1950-2200</td>
</tr>
<tr>
<td>Very High</td>
<td>2200-2450</td>
</tr>
<tr>
<td>Extremely High</td>
<td>2450+</td>
</tr>
</tbody>
</table>

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 the TEE.
6.3.1.2. **Defining Multiple Fuzzy Agents**

As previously described, the CI classification is gender specific. In addition, the condition-action rules required to perform recommendation are weight goal specific. Also, following many empirical simulations, experiments showed that different defuzzification functions could produce optimal results for weight gain and weight loss differently. For all the reasons mentioned above, we define four fuzzy agents for CI recommendation:

i. Male weight gain CI and exercise recommendation agent.
ii. Male weight loss CI and exercise recommendation agent.
iii. Female weight gain CI and exercise recommendation agent.
iv. Female weight loss CI and exercise recommendation agent.

On the one hand, both *loss* agents share the same condition-action rules, but adopt gender specific input and output classifications, resulting in different fuzzy sets. On the other hand, both *gain* agents share the same-condition-action rules different from those of the *loss* agents, while adopting gender specific input and output classifications.

6.3.1.3. **Fuzzy Sets**

We present our fuzzy sets defined based on the classifications presented in Section 6.3.1.1.

*Figure 25: Female TEE fuzzy sets*
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.
6.3.1.4. Condition-Action Rules

Similar to the way a human nutritionist would make recommendations, the agent provides the patient with one or more “healthy” option to choose from based on her preferences. Different deficits/surpluses lead to different weight loss/gain rates, and this is optional for the patient to select the ideal rate at which she wishes to lose or gain weight. The rules are provided in Table 18 and Table 19.

Table 18: Weight loss agent condition-action rules

<table>
<thead>
<tr>
<th>TEE</th>
<th>Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Low</td>
<td>R1: CI is Extremely Low</td>
</tr>
<tr>
<td>Very Low</td>
<td>R2: CI is Very Low OR Extremely Low</td>
</tr>
<tr>
<td>Low</td>
<td>R3: CI is Very Low OR Extremely Low</td>
</tr>
<tr>
<td>Normal</td>
<td>R4: CI is Low OR Very Low OR Extremely Low</td>
</tr>
<tr>
<td>High</td>
<td>R5: CI is Normal OR Low OR Very Low</td>
</tr>
<tr>
<td>Very High</td>
<td>R6: CI is High OR Normal OR Low</td>
</tr>
<tr>
<td>Extremely High</td>
<td>R7: CI is Very High OR High OR Normal</td>
</tr>
</tbody>
</table>
Table 19: Weight gain agent condition-action rules

<table>
<thead>
<tr>
<th>TEE</th>
<th>Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Low</td>
<td>R1: CI is Very Low OR Low OR Normal</td>
</tr>
<tr>
<td>Very Low</td>
<td>R2: CI Low OR Normal OR High</td>
</tr>
<tr>
<td>Low</td>
<td>R3: CI is Normal OR High OR Very High</td>
</tr>
<tr>
<td>Normal</td>
<td>R4: CI is High OR Very High OR Extremely High</td>
</tr>
<tr>
<td>High</td>
<td>R5: CI is Very High OR Extremely High</td>
</tr>
<tr>
<td>Very High</td>
<td>R6: CI is Extremely High</td>
</tr>
<tr>
<td>Extremely High</td>
<td>R7: CI is Extremely High</td>
</tr>
</tbody>
</table>

The weight loss condition-action rules are designed to respect the nutrition guidelines discussed in Section 2.2.2. The recommended CI value will always be comprised within the suggested thresholds. Nonetheless, when the TEE is extremely low or very low, one of the output options is to have the CI equal to the TEE, since very low CI values are not recommended. The issue of extremely high/low TEE will be later tackled with the **exercise percentage recommendation fuzzy agent** introduced in the upcoming section.

### 6.3.1.5. Aggregation and Defuzzification

We adopt for all agent maximization for aggregation for simplicity while producing good results.

The **right most** defuzzification function is adopted with the weight loss agent, while the **center of gravity** defuzzification function is used with the weight gain agents. The latter functions were adopted following a battery of empirical results.

First in case of weight loss, preliminary results show that **right most** defuzzification insures reducing CI in a reasonable fashion, while providing a reasonable number of output recommendations. 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 are not a significant difference, thus selecting either one of these two approaches should not make a great difference. We adopt with right most defuzzification. Finally, (iii) center of gravity provides a total of nine different recommendations which were considered redundant by the experts. The following outputs were produced for the 2531 Kcals intake: 1791, 1841, 1847, 1895, 1999, 2041, 2097, 2249 and 2280 Kcals.

Second, in the case of weight gain agents, the rules are defined to increase the intake. (i) Adopting the right most defuzzification produces very large intake recommendations. For instance, considering a male patient with 2600 Kcals expenditure and who needs to gain weight, a 4000 Kcal intake is computed by the agent. A caloric surplus of 1400 is a very large caloric suppress that defies the maximum recommended surplus of 1000 Kcals presented in section 2.2.2. (ii) Left most defuzzification produced minimal increments resulting in a recommendation of around 2800 Kcals. Hence, after various experiments and empirical tests, we realized that the center of gravity defuzzification function seems to produce better results: increasing the intake in a reasonable fashion. For the presented example recommendation of 3300 Kcals and 3400 Kcals where presented.

6.3.1.6. Example

We consider the following patient case from our experimental data set:

<p>| Table 20: Male case 1 weight input used for CI recommendation fuzzy agent example |
|---------------------------------|---------|--------|---|-------|</p>
<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>1.77 m</td>
<td>66.94 Kg</td>
<td>21.2</td>
<td>17.7 %</td>
</tr>
</tbody>
</table>

Consider the following weight recommendation:

<p>| Table 21: Male case 1 target weight input used for CI recommendation fuzzy agent example |
|---------------------------------|---------|---------|</p>
<table>
<thead>
<tr>
<th>Goal</th>
<th>Target BFP</th>
<th>Target Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lose</td>
<td>16.90 %</td>
<td>66.28</td>
</tr>
</tbody>
</table>
Based on the patient profile the **male weight loss fuzzy agent** is adopted for this case. We assume a *sedentary* level of activity. The resulting BMR and TEE computed based on the equations presented in Section 2.2.1 are provided below:

*Table 22: Male case 1 resulting BMR and TEE used for CI recommendation fuzzy agent example*

<table>
<thead>
<tr>
<th>BMR</th>
<th>TEE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1620.65 Kcals</td>
<td>1944.78 Kcals</td>
</tr>
</tbody>
</table>

**Fuzzy Input Memberships**

TEE fuzzy memberships are computed as shown in Figure 29:

\[
f_{\text{Very Low}}(1994.78) = 0.22
\]

\[
f_{\text{Low}}(1994.78) = 0.78
\]

*Figure 29: CI fuzzy memberships*

**Condition-Action Rules, Inference, Aggregation and defuzzification**

Based on the membership values of the inputs considered in the above example the following condition-action rules are invoked:
The output functions include different OR combinations. The condition-action rules will result in four different outputs.

All cases will not necessarily result distinct outputs. The same logic demonstrated in this example applies regardless the number of cases.

i. Output 1

\[ R_2: \text{Very Low}(\text{TEE}) \Rightarrow \text{Very Low (CI)} \]

\[ R_3: \text{Low}(\text{TEE}) \Rightarrow \text{Very Low (CI)} \]

ii. Output 2

\[ R_2: \text{Very Low}(\text{TEE}) \Rightarrow \text{Very Low (CI)} \]

\[ R_3: \text{Low}(\text{TEE}) \Rightarrow \text{Extremely Low (CI)} \]

iii. Output 3

\[ R_2: \text{Very Low}(\text{TEE}) \Rightarrow \text{Extremely Low (CI)} \]

\[ R_3: \text{Low}(\text{TEE}) \Rightarrow \text{Very Low (CI)} \]

iv. Output 4

\[ R_2: \text{Very Low}(\text{TEE}) \Rightarrow \text{Extremely Low (CI)} \]

\[ R_3: \text{Low}(\text{TEE}) \Rightarrow \text{Extremely Low (CI)} \]

**Output 1: Inference Mechanism**

By applying Mamdani’s inference:

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

\[ R_3: f_3 = \min(0.78, f(x)^{\text{cal intake}_{\text{very low}}}) \]
Output 1: Aggregation and Defuzzification

By applying the maximization aggregation and right most defuzzification functions, the agent computes CI = 1805 kcals.
Output 2: Inference Mechanism

By applying Mamdani’s inference:

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

\[ R_3: f_3 = \min(0.78, f(x)^{\text{cal intake}}_{\text{Extremely Low}}) \]
Output 2: Aggregation and Defuzzification

By applying the maximization aggregation and right most defuzzification functions, the agent computed CI = 1555 Kcals.
Discussion

The two other cases will result in different inference and aggregation results. However due to maximization aggregation and right most defuzzification, the latter produce two results identical to the ones produced by the former cases described above: 1804 and 1555 Kcals.

6.3.2. Exercise Amount Recommendation Fuzzy Agent

Figure 34: Simplified activity diagram describing the exercise recommendation agent’s fuzzy control logic

6.3.2.1. Inputs and Outputs

The agent receives as input the daily caloric deficit, i.e., the difference between the TEE and the recommended daily CI produced by the caloric intake (CI) recommendation fuzzy agent. The agent produces as output an exercise recommendation value representing the percentage of the BMR to be added as physical exercise.

The classification for exercise percentage was defined and presented in the introduction of Section 6.3 in Table 15. Based on the range recommendations for caloric deficits presented in Section 2.2.2, we define the following classification for the caloric deficit categories:
Based on the previously defined CI recommendation fuzzy agent, the maximum possible healthy deficit to be recommended is 750 Kcals, yet in some rare cases, an expert might recommend a 1000 Kcals deficit, thus it was included in the classification. All possible recommendations will fall in one of the categories defined.

The agent is only utilized in weight loss cases. The same classifications apply for both male and female patients since the output is a percentage of the BMR, i.e., the produces recommendations are personalized and case specific. Thus, in contrast to the CI recommendation fuzzy agent, a single fuzzy agent is defined for the exercise recommendation agent.
6.3.2.2. Fuzzy Sets

Figure 35: Caloric deficit fuzzy sets

Figure 36: Exercise percentage fuzzy sets

6.3.2.3. Condition-Action Rules

The rules are defined to supply small deficits with a high amount of exercise in order to compensate the small deficit with exercise alternatives. While on the other hand, very high deficits are supplied with either no or small amounts of exercise. Similar to the previous agent, the defined rules are not restricted to one option, but rather allow multiple optional
exercise amounts, from which the patient can choose the one most adapted to her needs, based on the desired rate at which she wishes to lose weight. The rules are presented in Table 24.

Table 24: Exercise recommendation agent condition action rules

<table>
<thead>
<tr>
<th>Deficit</th>
<th>Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low</td>
<td>R1: Exercise percentage is High OR Normal</td>
</tr>
<tr>
<td>Low</td>
<td>R2: Exercise percentage is Normal OR Low</td>
</tr>
<tr>
<td>Normal</td>
<td>R3: Exercise percentage is Low OR Very Low</td>
</tr>
<tr>
<td>High</td>
<td>R4: Exercise percentage is Low OR Very Low</td>
</tr>
<tr>
<td>Very High</td>
<td>R5: Exercise percentage is Low OR Very Low</td>
</tr>
</tbody>
</table>

6.3.2.4. Aggregation and Defuzzification

We adopt maximization for aggregation for its simplicity while producing good results. We adopt the left most defuzzification that proved optimal in terms of output based on empirical results.

6.3.2.5. Example

We consider the same example case presented in 0. We consider the following TEE and CI values:

Table 25: Male case 1 input for exercise percentage recommendation fuzzy agent

<table>
<thead>
<tr>
<th>BMR</th>
<th>TEE</th>
<th>CI</th>
<th>Caloric deficit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1620.75</td>
<td>1944.78 Kcals</td>
<td>1805 Kcals</td>
<td>140 Kcals</td>
</tr>
</tbody>
</table>

6.3.2.5.1. Fuzzy Input Memberships

As shown in Figure 37, TEE fuzzy membership values obtained are:

\[ f_\text{Very Low}(140.78) = 0.44 \]
\[ f_\text{Low}(140.78) = 0.56 \]
6.3.2.5.2. Condition-Action Rules, Inference, Aggregation and Defuzzification

Based on the membership values of the inputs considered above, the following condition-action rules are invoked:

\[ R_1: \text{Very Low(Deficit)} \Rightarrow \text{High (Exercise %)} \lor \text{Normal (Exercise %)} \]

\[ R_2: \text{Low(Deficit)} \Rightarrow \text{Normal (Exercise %)} \lor \text{Low (Exercise %)} \]

The output functions include different OR combinations. Hence, the condition-action rules will result in four different outputs.

i. Output 1

\[ R_1: \text{Very Low(Deficit)} \Rightarrow \text{High (Exercise %)} \]

\[ R_2: \text{Low(Deficit)} \Rightarrow \text{Normal (Exercise %)} \]

ii. Output 2

\[ R_1: \text{Very Low(Deficit)} \Rightarrow \text{High (Exercise %)} \]

\[ R_2: \text{Low(Deficit)} \Rightarrow \text{Low (Exercise %)} \]
iii. Output 3

R₁: Very Low(Deficit) ⇒ Normal (Exercise %)

R₂: Low(Deficit) ⇒ Normal (Exercise %)

iv. Output 4

R₁: Very Low(Deficit) ⇒ Normal (Exercise %)

R₂: Low(Deficit) ⇒ Low (Exercise %)

**Output 1: Inference Mechanism**

By applying Mamdani’s inference:

\[
R₂: f₂ = \min(0.44, f(x)^{exercise\%}_\text{high})
\]

\[
R₃: f₃ = \min(0.56, f(x)^{exercise\%}_\text{normal})
\]

**Figure 38: Exercise percentage inference mechanism for output 1**

**Output 1: Aggregation and Defuzzification**

By applying the maximization aggregation and the right most defuzzification functions, the agent computed exercise percentage = 29.79 %. Expressed in calories, the exercise
recommendation amounts to 29.79% of the BMR, which is the equivalent of 484 Kcals per day.

![Figure 39: CI aggregation and defuzzification for output 1](image)

**Output 4: Inference Mechanism**

By applying Mamdani’s inference:

\[
R_2: f_2 = \min(0.44, f(x)^{\text{exercise}}_{\text{normal}}) \\
R_3: f_3 = \min(0.56, f(x)^{\text{exercise}}_{\text{low}})
\]

**Output 4: Aggregation and Defuzzification**

By applying maximization aggregation and right most defuzzification, the agent computed exercise percentage = 11.25 %. Expressed in calories, the exercise recommendation amounts to 11.25% of the BMR, which is equivalent to 184 Kcals per day.

**Discussion**

The two other outputs will result in different aggregation results. However due to maximization aggregation and left most defuzzification, the latter will produce two results identical to the ones produced by the former outputs described above: 29.88 % and 11.34%.
6.3.3. Expected Date to Reach Target and Next Assessment Date

Once the CI and exercise amount are known, deducing the expected number of days for the patient to reach the target weight can be calculated through eq. (6) as presented in Section 2.3.1. In the mentioned section, we also discuss the dependency of TEE on the weight showing that the 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. Based on our review of the nutrition literature and various discussions with nutrition experts, we adopt a three-week timeframe for progress monitoring. If the patient is expected to reach her goal in more than three-weeks, an evaluation occurs at the three-week mark to evaluate the progress of the patient and adjust the recommendations accordingly. We present in the upcoming section our mechanism for monitoring, progress evaluation and recommendation adjustment.

6.3.4. Running Examples

We revisit the same cases presented in Section 6.2.2, where the target weight and BFP were produced. We go through the next step of the assessment process: recommending a CI and exercise recommendation.

6.3.4.1. Case 1

Table 26: Male case 1 used for CI and exercise recommendation

<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
<th>Goal</th>
<th>Target BFP</th>
<th>Target Weight</th>
<th>Level of activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>1.77 m</td>
<td>66.94 Kg</td>
<td>21.2</td>
<td>17.7 %</td>
<td>Lose</td>
<td>16.90 %</td>
<td>66.28 Kg</td>
<td>Sedentary</td>
</tr>
</tbody>
</table>
The output recommendations, include different CI, exercise recommendations that lead to patient to the target weight in different number of days. Low CI recommendations, such as the first and second recommendations, include small or no exercise recommendation amounts, while large CI recommendations, such as the third and fourth recommendations include small or large exercise amount recommendations.

Notice that the minimum CI recommendation is 1555 Kcals and does not drop below the minimum 1500 Kcals CI recommendation for males.

6.3.4.2. Case 2

Table 28: Female case 1 used for CI and exercise recommendation

<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
<th>Goal</th>
<th>Target BFP</th>
<th>Target Weight</th>
<th>Level of activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>28</td>
<td>1.59 m</td>
<td>57.6 Kg</td>
<td>22.8</td>
<td>34.4 %</td>
<td>Lose</td>
<td>28.07 %</td>
<td>52.53</td>
<td>Light activity</td>
</tr>
</tbody>
</table>
Table 29: Female case 1 CI and exercise recommendations

<table>
<thead>
<tr>
<th>BMR</th>
<th>TEE</th>
<th>CI Recommendation</th>
<th>Exercise Recommendation</th>
<th>Days to Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>1268.75 Kcals</td>
<td>1744.53 Kcals</td>
<td>1244</td>
<td>0</td>
<td>78</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1244</td>
<td>253</td>
<td>52</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1495</td>
<td>253</td>
<td>78</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1495</td>
<td>476</td>
<td>54</td>
</tr>
</tbody>
</table>

Note that the recommendations for females do not drop below the 1200 Kcal minimum recommendation. Also, the agent provides multiple recommendations to reach the same target in different combinations of exercise and caloric deficits.

6.3.4.3. Case 3

Table 30: Male case 2 used for CI and exercise recommendation

<table>
<thead>
<tr>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>BMI</th>
<th>Body fat percentage</th>
<th>Goal</th>
<th>Target BFP</th>
<th>Target Weight</th>
<th>Level of activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>23</td>
<td>1.83</td>
<td>71.88</td>
<td>21.34</td>
<td>9.4 %</td>
<td>Gain</td>
<td>13.32 %</td>
<td>75.13</td>
<td>Light activity</td>
</tr>
</tbody>
</table>

Table 31: Male case 2 CI and exercise recommendations

<table>
<thead>
<tr>
<th>BMR</th>
<th>TEE</th>
<th>CI Recommendation</th>
<th>Exercise Recommendation</th>
<th>Days to Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>1752.55</td>
<td>2409.75</td>
<td>2653</td>
<td>0</td>
<td>102</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2750</td>
<td>0</td>
<td>73</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3211</td>
<td>0</td>
<td>31</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3413</td>
<td>0</td>
<td>24</td>
</tr>
</tbody>
</table>
In the case of weight gain, no additional exercise recommendations are provided. Different CI recommendations are provided; each increases the CI in an amount that lead to reaching the target weight in a different amount of days. Notice that the largest difference between the TEE and CI recommendation is equal to 1004 Kcals (Case 4). 1000 Kcals is the largest recommended caloric surplus, which PIN abides by.

### 6.4. Progress Evaluation and Recommendation Adjustment (PERA) Agent

#### 6.4.1. Progress Monitoring and Evaluation

As presented in Section 2.3, patient progress monitoring and evaluation are essential parts of the nutrition care cycle. In our study, we adopt a three-week monitoring time frame (which is considered as a good time laps in nutrition literature, cf. Section 2.3). If the patient requires more than three weeks to reach the expected target, a progress evaluation is applied in three weeks.

Weight change depends on energy expenditure, which itself depends on the changing body weight (Section 2.2.1). Even though weight loss is not linear over a long period of time, yet we assume that it is linear within the early three-week time frame (which is an acceptable assumption following our discussion with nutrition experts). At each three-week mark, the CI is adjusted to account for the non-linear nature of weight loss. In addition, the patient might be abiding by the recommendation but not making the expected process. Hence, by adopting a three-week intervention process, the recommendations can be adjusted accordingly.

In this section, we discuss monitoring and adjustment in the case of weight loss objectives. As per our discussion with nutrition experts, a patient should not face weight gain issues if abiding by the recommended meal plan and CI. The CI is increased during weight gain phases to adjust for the increasing TEE of the patient as weight is gained.
We distinguish between two stages of evaluation:

i. Evaluating if the final target goal is reached based on the expected date determined at the caloric assessment stage.

ii. Evaluating the progress after three weeks since the last assessment.

6.4.1.1. Final Goal Evaluation

In Section 2.3.2, we discuss the lack of a clear methodology that nutrition experts adopt to adjust recommendations based on the patient’s progress. In fact, progress evaluation involves “common sense” decision making, where multiple experts usually have 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. As previously mentioned in our study, we adopt the following approach when a patient is having difficulty losing weight: (i) reduce the CI, and (ii) increment the amount of exercise in a reasonable fashion, while abiding by standardized recommended guidelines. This is performed under the assumption that the patient is abiding by the meal plan and exercise recommendations, but not reaching the expected results.

We consider the following factors when evaluating the progress of a patient:
i. The progress percentage defined in terms of:
   a. The expected BFP and expected weight of the patient, i.e. the state the patient should have reached if she had abided by the recommendation.
   b. The actual BFP and actual weight.
ii. The currently recommended daily CI.
iii. The currently recommended daily exercise caloric expenditure.

The WAR agent recommends a target BFP and a target weight. The objective is to monitor the patient’s progress in terms of reaching the target body fat percentage. We define the progress as follows:

\[
P(\%) = \frac{p_o - p_c}{p_o - p_t} \times 100
\]  

(23)

Where:

i. \(p_o\) is the old BFP provided in the previous assessment.
ii. \(p_c\) is the current BFP provided in the current evaluation.
iii. \(p_t\) is the target BFP expected to be reached at the current evaluation.

As previously discussed, even the slightest progress in weight loss introduces health benefits, yet the nutrition literature does not provide a clear classification on progress levels. As a result, in this research, we define the following classification for progress with the help of nutrition experts:

*Table 32: Progress percentage classification*

<table>
<thead>
<tr>
<th>Category</th>
<th>Range (%)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow</td>
<td>[0 – 40]</td>
<td>No significant progress</td>
</tr>
<tr>
<td>Moderate</td>
<td>[40 – 70]</td>
<td>Progress amount good enough to be considered but still far off from target</td>
</tr>
<tr>
<td>Good</td>
<td>[70 – 100]</td>
<td>The progress is significantly close to the expected progress</td>
</tr>
</tbody>
</table>
As shown in Figure 40, the following scenarios might occur:

i. If the patient progress qualifies good, the next step is to re-evaluated the weight state of a person 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.

ii. On the other hand, if the progress is slow or moderate the CRA (caloric recommendation) agent, which we present in an upcoming Section, is utilized to adjust the CI and exercise recommendations. This agent is designed based on the fuzzy paradigm.

A negative progress means that the patient is not abiding by the recommendations. In this case, the process is restarted at the weight assessment and recommendation (WAR) process to set a new target weight and BFP for the patient.

6.4.1.2. Progress Evaluation

Since regular monitoring is required, we re-assess the patient’s progress every three weeks based on expert recommendations. This is due to the fact that the patient might not be making progress and the recommendations, and early intervention is thus required. In addition to the fact that fat loss is not a linear process, as a patient’s weight changes his BMR and caloric expenditure, meaning his intake requires readjustment even if good progress is being made. To deal with this simplification, we apply regular re-evaluations.

Once a patient is evaluated, the target BFP is determined by the WAR (weight assessment and recommendation) agent. Then, the CIER (caloric intake (CI) and exercise recommendation) agent determines the expected number of days, noted n, for the patient to reach the target BFP (eq. (6)).

We also defined progress percentage as the percentage of the BFP lost out of the expected percentage to be lost after the n days through eq. (23).

We define the expected progress at the three-week mark as follows:
\[ p_{3\text{-week}} = \frac{(p_o - p_c)}{(p_o - p_t) \times \frac{\alpha}{n}} \times 100 \]  

Here:

i. \( \alpha (\alpha = 21 \text{ in this case}) \), represents the number of days between the initial assessment and the subsequent assessment when \( n > \alpha \).

The expected progress \((p_o - p_t)\) is scaled by the number of days from the last assessment over the expected number of days to reach the final target. This gives an approximation of the difference in BFP to be achieved after \( \alpha \) days. Then the actual difference in BFP is divided over the expected value to assess the progress percentage.

As shown in Figure 40, at the progress evaluation level, two scenarios might occur:

i. If the patient progress is good, the patient is on track. Even if the final target is not reached yet, Nonetheless, the CI and exercise recommendations do not require adjustment (by the CIER agent) since the progress is good. However, since the TEE (Total Energy Expenditure) is dependent of the changed weight of the patient (Section 2.2.1), the CI and exercise recommendations are updated through the CIER agent, based on the updated input, i.e. the updated TEE.

ii. On the other hand, if the progress is slow or moderate, then the CRA (caloric recommendation adjustment) agent is run to adjust the CI and exercise recommendations.

6.4.2. **Caloric Recommendation Adjustment Agent**

Similar to the initial recommendation process described in Section 6.3, the adjustment of the CI and exercise recommendation is a process that requires human-like decision making. Thus, the agent is designed using the fuzzy logic paradigm.
The agent receives two inputs:

i. The current CI.
ii. The progress percentage.

And produces two outputs:

i. The adjusted CI.
ii. The additional exercise percentage (to be calculated out of the BMR) to be added to the current exercise recommendation.

The new total exercise amount is then calculated and the recommendations are presented to the patient.

Similar to the CIER agent (cf. Section 06.3.1), the CI classifications differ based on gender, thus we define two fuzzy agents:

i. Male caloric recommendation adjustment (MCRA) fuzzy agent.
ii. Female caloric recommendation adjustment (FCRA) fuzzy agent.
6.4.3. Caloric Recommendation Adjustment Fuzzy Agent

6.4.3.1. Inputs and Outputs

The inputs and outputs are defined as (i) the progress percentage and the (ii) current CI. The outputs of the agent are (i) the adjusted CI and (ii) the additional exercise percentage.

For both input and output, we adopt the same CI classification used in the CIR (CI recommendation) agent presented in Section 06.3.1 (cf. The input of the agent is the total energy expenditure (TEE). The agent produces as output a set of possible CI recommendations.

Based on the American Office of Disease Prevention and Health Promotion guidelines [20], the CI estimations for adult males and females range between 2000-to-3000 and 1600-to-2400 Kcals respectively. In addition, the minimum recommended healthy intakes for females and males are 1200 Kcals and 1500 Kcals accordingly. Based on this data, and in collaboration with domain experts, we define the following classifications for CI values:

Table 16, and Table 17).

The progress percentage classification is presented in Section 6.4.1 (cf. Table 32).

Finally, we define a classification for the additional exercise percentage. The initial exercise percentage recommendation classification provides exercise recommendations as a percentage from the BMR between 0 and 90%. This is based on the physical activity level factors [1] presented in Section 2.2.1.
We consider the case of a male with a BMR of 1600 Kcals and a previous exercise percentage recommendation of 50%, which amounts to a daily exercise expenditure of 800 Kcals. If the exercise recommendation is to be increased by another 50%, the total amount of daily exercise expenditure rises to 1600 Kcals, which requires a large amount of intense daily exercise. To avoid excessively large additional exercise recommendations, we define the range of the additional exercise percentage as the very low category in the exercise percentage classification (cf. Table 32).

The very low category exercise percentage lies between 0 and 20%. Since original exercise recommendations have been assigned in the initial assessment, additional exercise must be increased in a minor fashion. For example, consider the 1600 Kcal BMR example presented above, the maximum possible addition is 20% out of the BMR, which is the equivalent of a reasonable additional daily exercise expenditure of 320 Kcals.

<table>
<thead>
<tr>
<th>Category</th>
<th>Range (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>[0 - 7 [</td>
</tr>
<tr>
<td>Moderate</td>
<td>[7 – 14 [</td>
</tr>
<tr>
<td>Good</td>
<td>[14 – 20 [</td>
</tr>
</tbody>
</table>

6.4.3.2. Defining Multiple Fuzz Agents

As previously described, the CI classification is gender specific. Thus, we define two fuzzy agents:

i. Male caloric recommendation adjustment (MCRA) agent.

ii. Female caloric recommendation adjustment (FCRA) agent.

Both agents adopt the same fuzzy inference mechanism, as well as the same aggregation and defuzzification functions. The same condition-action rules are adopted for both agents as well. In addition, the progress and exercise percentage classification are common. The difference between the two agents is the CI classification, which is gender specific.
6.4.3.3. **Fuzzy Sets**

For the input CI, we adopt the fuzzy set presented in Figure 43 and Figure 44 for females and males respectively.

**Figure 43: Female input CI fuzzy sets**

**Figure 44: Male input CI classification**

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 by
excluding values lower than the minimum recommendations. This insures that the agent produces healthy recommendations.

The fuzzy sets for progress percentage and exercise percentage are presented in Figure 47 and Figure 48 respectively.
6.4.3.4. Condition-Action Rules

The condition-action rules are carefully designed to make CI recommendations within the healthy boundaries. The objective is to reduce the CI based on the progress made if required. If the intake is too low to be reduced, or can be reduced by a small amount,
additional exercise is recommended to compensate accordingly. Similar to previous fuzzy agents, multiple options might be available for the patient to choose from.

*Table 34: Caloric recommendation adjustment fuzzy agent condition-action rules*

<table>
<thead>
<tr>
<th>CI</th>
<th>Progress</th>
<th>Slow</th>
<th>Moderate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Low</td>
<td>R1: Adjusted Intake is Extremely Low AND exercise is High</td>
<td>R8: Adjusted Intake is Extremely Low AND exercise is Moderate</td>
<td></td>
</tr>
<tr>
<td>Very Low</td>
<td>R2: Adjusted Intake is Extremely Low AND exercise is Moderate</td>
<td>R9: (Adjusted Intake is Very Low AND exercise is Moderate) OR (Adjusted Intake is Extremely Low AND exercise is Low)</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>R3: Adjusted Intake Very Low AND exercise is Moderate</td>
<td>R10: (Adjusted Intake is Low AND exercise is Moderate) OR (Adjusted Intake is Very Low AND exercise is Low)</td>
<td></td>
</tr>
<tr>
<td>Normal</td>
<td>R4: Adjusted Intake is Low AND exercise is Moderate</td>
<td>R11: (Adjusted Intake is Normal AND exercise is Moderate) OR (Adjusted Intake is Low AND exercise is Low)</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>R5: Adjusted Intake is Normal AND exercise is Moderate</td>
<td>R12: (Adjusted Intake is High AND exercise is Moderate) OR (Adjusted Intake is Normal AND exercise is Low)</td>
<td></td>
</tr>
<tr>
<td>Very High</td>
<td>R6: Adjusted Intake is High AND exercise is Moderate</td>
<td>R13: Adjusted Intake is High AND exercise is Low</td>
<td></td>
</tr>
<tr>
<td>Extremely High</td>
<td>R7: Adjusted Intake is Very High AND exercise is Moderate</td>
<td>R14: Adjusted Intake is Very High AND exercise is Low</td>
<td></td>
</tr>
</tbody>
</table>
The rules are defined with the help of nutrition experts based on the following premises:

i. If the patient is making slow progress, the CI must be reduced and the amount of exercise must be added. In the case where the CI is around the minimum recommended intake, the only “healthy” option is to increases physical activity by increasing the exercise amount.

ii. If the patient is making moderate progress, two options arise:
   a. The CI is reduced and the exercise amount remains the same.
   b. The CI is not reduced, but additional exercise is recommended. The patient can choose based on his personal preferences.

6.4.3.5. Aggregation and Defuzzification

For CI, we adopt the maximization aggregation function and the left most defuzzification function due to their good performance bases on preliminary empirical results. Right most and center of gravity defuzzification increase the CI in certain cases which is not always a “healthy” option. Left most defuzzification insures the reduction of the CI remains within the healthy ranges determined by the designed fuzzy sets.

Similarly, we adopt maximization for aggregation and left most defuzzification for exercise percentage recommendation.

6.4.3.6. Example

We revisit the case presented Table 25: Male case 1 input for exercise percentage recommendation fuzzy agent The input (current) CI adopted is 1805 Kcals and the input (current) exercise amount is 140 Kcals. The BFP reached in 15 days is 17.5 % and the weight is equal to 66.45, resulting in a progress percentage of 25%.

Fuzzy Input Memberships

i. Progress percentage:
   a. $f_{\text{slow}} = 0.75$
   b. $f_{\text{moderate}} = 0.249$
ii. CI
   a. $f_{very\ low} = 0.78$
   b. $f_{low} = 0.22$
**Condition-Action Rules, Inference, Aggregation and Defuzzification**

Based on the membership values of the inputs considered above, the following condition-action rules are invoked:

R₂: Very Low(Intake) ∧ Slow (Progress %) ⇒ Extremely Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₃: Low(Intake) ∧ Slow (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₉: Very Low(Intake) ∧ Moderate (Progress %) ⇒ (Very Low (Adjusted Intake) ∧ Moderate (Exercise %)) ∨ (Extremely Low (Adjusted Intake) ∧ Low (Exercise %))

R₁₀: Low(Intake) ∧ Moderate (Progress %) ⇒ (Low (Adjusted Intake) ∧ Moderate (Exercise %)) ∨ (Very Low (Adjusted Intake) ∧ Low (Exercise %))

The output functions include ‘OR’ and ‘AND’ combinations. The condition-action rules will result in different output combinations. Yet, all combination will not necessarily produce unique outputs.

i. Output 1:

R₂: Very Low(Intake) ∧ Slow (Progress %) ⇒ Extremely Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₃: Low(Intake) ∧ Slow (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₉: Very Low(Intake) ∧ Moderate (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₁₀: Low(Intake) ∧ Moderate (Progress %) ⇒ Low (Adjusted Intake) ∧ Moderate (Exercise %)

ii. Output 2:
R₂: Very Low(Intake) ∧ Slow (Progress %) ⇒ Extremely Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₃: Low(Intake) ∧ Slow (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₉: Very Low(Intake) ∧ Moderate (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₁₀: Low(Intake) ∧ Moderate (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Low (Exercise %)

iii. Output 3:

R₂: Very Low(Intake) ∧ Slow (Progress %) ⇒ Extremely Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₃: Low(Intake) ∧ Slow (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₉: Very Low(Intake) ∧ Moderate (Progress %) ⇒ Extremely Low (Adjusted Intake) ∧ Low (Exercise %)

R₁₀: Low(Intake) ∧ Moderate (Progress %) ⇒ Low (Adjusted Intake) ∧ Moderate (Exercise %)

iv. Output 4:

R₂: Very Low(Intake) ∧ Slow (Progress %) ⇒ Extremely Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₃: Low(Intake) ∧ Slow (Progress %) ⇒ Very Low (Adjusted Intake) ∧ Moderate (Exercise %)

R₉: Very Low(Intake) ∧ Moderate (Progress %) ⇒ Extremely Low (Adjusted Intake) ∧ Low (Exercise %)
Output I: Inference Mechanism

\[ R_2: f_1 = \min(\min(0.75, 0.784), \min(f(x)_{\text{Adjusted Intake} \atop \text{Extremely Low}}, f(x)_{\text{Exercise} \atop \text{Moderate}})) \]
\[ R_3: f_2 = \min(\min(0.216, 0.75), \min(f(x)_{\text{Adjusted Intake} \atop \text{Very Low}}, f(x)_{\text{Exercise} \atop \text{Moderate}})) \]
\[ R_9: f_3 = \min(\min(0.249, 0.784), \min(f(x)_{\text{Adjusted Intake} \atop \text{Very Low}}, f(x)_{\text{Exercise} \atop \text{Moderate}})) \]
\[ R_{10}: f_4 = \min(\min(0.249, 0.216), \min(f(x)_{\text{Adjusted Intake} \atop \text{Low}}, f(x)_{\text{Exercise} \atop \text{Moderate}})) \]

Since fuzzy operation cannot be applied when selecting the minimum between two unknown values, we separate the equations in two different sets; one for the *adjusted intake* and one for the *exercise percentage*. This is possible since the two variables are independent.

- CI

- Exercise Percentage
Figure 52: Exercise percentage inference mechanism for output 1

Output 1: Aggregation and Defuzzification

- CI

By applying maximization aggregation and right most defuzzification, the output CI is determined as 1561 Kcals.

Figure 53: Modified CI aggregation and Defuzzification for output 1

- Exercise Percentage
By applying maximization aggregation and center of gravity defuzzification, the output additional exercise percentage is determined as 8.76 %

![Graph: Exercise percentage aggregation and Defuzzification for output 1](image)

**Figure 54:** Exercise percentage aggregation and Defuzzification for output 1

**Discussion**

The agent produces four output combinations, yet all four produce equal values, amounting to one single recommendation in this case. This is due to adopting maximization aggregation and the left most defuzzification approach. Adopting the center of gravity approach for example, would have resulted in three different (yet very similar) outputs: 9.31, 9.47 and 10.5%.
6.4.4. Running Examples
We revisit the cases presented throughout Sections 6.2.2 and 6.4.4.

6.4.4.1. Case 1
Table 35: Male case 1 input used for caloric recommendation adjustment example

<table>
<thead>
<tr>
<th>Gender</th>
<th>Current CI</th>
<th>Current Exercise amount per day</th>
<th>Current BFP</th>
<th>Target BFP</th>
<th>Expected Days to Reach Final Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>1804 Kcals</td>
<td>184 Kcals</td>
<td>17.7 %</td>
<td>16.9 %</td>
<td>15</td>
</tr>
</tbody>
</table>

We assume reevaluation in 15 days.

Scenario A
The reached BFP is 17.5 % and a weight of 66.45, resulting in a progress percentage of 25%.

Resulting recommendation:
Table 36: Case 1 Scenario A resulting caloric recommendation adjustment

<table>
<thead>
<tr>
<th>Adjusted CI</th>
<th>Adjusted Exercise amount per day</th>
<th>Expected Days to Reach Final Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>1500 Kcals</td>
<td>324 Kcals</td>
<td>4</td>
</tr>
</tbody>
</table>

The CI was reduced, yet not below the minimum “healthy” recommendations. The amount of exercise was increased as well.

Scenario B
The reached BFP is 17.3 %, resulting in a progress percentage of 50%.
Two options are possible in this case: (i) decreasing the amount of exercise and maintaining the same CI and (ii) increasing the amount of exercise while maintaining the same CI. In this case, the patient almost reached the target goal (cf. Table 10). A small adjustment is provided to keep the patient on track.

**Scenario C**

The patient reaches the target BFP as expected. In this case the agent will provide the following recommendation:

- Maintain current BFP and weight.

### 6.4.4.2. Case 2

**Table 38: Female case 2 input used for caloric recommendation adjustment example**

<table>
<thead>
<tr>
<th>Gender</th>
<th>Current CI</th>
<th>Current Exercise amount per day</th>
<th>Current BFP</th>
<th>Target BFP</th>
<th>Expected Days to Reach Final Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>1244 Kcals</td>
<td>253 Kcals</td>
<td>34.4 %</td>
<td>28.07 %</td>
<td>51</td>
</tr>
</tbody>
</table>

We assume reevaluation in 51 days, thus the first reassessment occurs at the 21-day mark.

**Scenario A**
The reached BFP is 33.9 % and a weight of 57.17 Kg, resulting in a progress percentage of 19.2%.

Resulting recommendation:

Table 39: Case 1 Scenario A resulting caloric recommendation adjustment

<table>
<thead>
<tr>
<th>Adjusted CI</th>
<th>Adjusted Exercise amount per day</th>
<th>Expected Days to Reach Final Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>1200 Kcals</td>
<td>459 Kcals</td>
<td>35</td>
</tr>
</tbody>
</table>

The CI was not reduced to avoid a recommendation below the minimum “healthy” recommendation of 1200 Kcals for females. The only option is to increase exercise.

Scenario B

The reached BFP is 33.3 % and the weight is 56.22 Kg, resulting in a progress percentage of 42%.

Table 40: Case 1 Scenario A resulting caloric recommendation adjustment

<table>
<thead>
<tr>
<th>Current CI</th>
<th>Current Exercise amount per day</th>
<th>Expected Days to Reach Final Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>1200 Kcals</td>
<td>369 Kcals</td>
<td>31</td>
</tr>
</tbody>
</table>

Since the patient is already at a very low CI, increasing exercise is the only possibility. In contrast to the pervious case where the progress is smaller, exercise is not increased as much. The slower the progress, the larger the modification to the CI and/or the exercise recommendation.

Scenario C

The patient reaches the target BFP and target weight as expected. In this case, the agent will provide an updated CI and exercise recommendation based on the new BMR of the patient.
Multiple CI/exercise amount options are provided for the patient to select from: 1236 kcals/252 kcals, 1486/252 Kcals, etc. Each option guides the patient to the target in a different duration.

6.5. Recommendation Ranking

The 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 expert’s way of recommending health solutions. Yet, this could turn out to be confusing for the patient more than helpful, if not presented properly. To handle the issue at hand, we design a mechanism to rank recommendations based on patient preferences concerning: (i) the amount of exercise, and ii) the size of the daily caloric deficit (i.e., the amount of food the patient would like to abstain from).

Here, determining that a patient requires a “high amount of exercise” or a “low amount of exercise” makes more sense than quantifying the amount of exercise or caloric deficit in calories; this is where fuzzy sets can be used to relate intuitive human descriptions to numerical values. A patient will express her preferences linguistically rather than with numerical values. The patient will be able to choose from the fuzzy linguistic variables related to (i) exercise percentage and (ii) caloric deficit as defined in Section 6.4.

For both exercise and caloric deficit, the patient will have the following options: (i) very low (ii), low (iii), normal (iv), high, and (v) very high. The patient has the ability to select multiple options.

The score function for a recommendation is defined based on the score of the recommendation in terms of both exercise membership and deficit membership. We define it as follows:

$$S = \alpha \ast S_e + \beta \ast S_d \quad (6)$$

where:
• S is the total normalized score
• $S_e$ is the fuzzy exercise score
• $\alpha$ is the exercise score factor set to 0.5
• $S_d$ is the fuzzy deficit score
• $\beta$ is the deficit score factor set to 0.5
• The factors can be fine-tuned based on the preference of the patient to highlight if
  the emphasis of the patient’s preferences is towards exercise or caloric restriction.

In the future, the defined model can be easily extended to include different other fuzzy
scores in ranking if other factors are to be integrated in CI recommendations.

6.5.1. Fuzzy Scores
We defined the fuzzy scores for each variable considering two factors: (i) the fuzzy sets
selected by the patient as desirable, and (ii) the actual value recommended by the agent.
To do so we compute the membership of the recommended value (whether exercise
percentage, or deficit) in terms of the selected sets by the patient. We average the
memberships greater than zero. The patient can make more than one selection/preference,
e.g., if the patient’s selected levels of exercise are low and very low, meaning the patient
desires having a very low amount of exercise or a low amount of exercise. As defined, if
the patient selects all possible options as acceptable values, all recommendations will
score the highest possible membership value of 1.

The fuzzy score can be formulated as follows:

$$\sum_{j=1}^{n} \frac{m_j}{n}$$  \hspace{1cm} (26)

Where:

i. $n$ is number of fuzzy sets selected by the patient where the membership is greater
   than 0
ii. $m_i$ 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.

6.5.2. Example

For example, for a patient with a BMR of 1770 Kcals, a TEE of 2434 Kcals and a goal of losing weight: we consider the two scenarios presented in Table 41 and Table 42 respectively

Table 41: Recommendation ranking example for low exercise and high restriction preferences

<table>
<thead>
<tr>
<th>Exercise preference</th>
<th>CI restriction preference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low or Low</td>
<td>Normal or High</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Resulting recommendations ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI (Kcals)</td>
</tr>
<tr>
<td>------------</td>
</tr>
<tr>
<td>1965</td>
</tr>
<tr>
<td>1715</td>
</tr>
<tr>
<td>1965</td>
</tr>
<tr>
<td>1715</td>
</tr>
<tr>
<td>2215</td>
</tr>
<tr>
<td>2215</td>
</tr>
</tbody>
</table>
Table 42: Recommendation ranking example for high exercise and low restriction preference

<table>
<thead>
<tr>
<th>Exercise preference</th>
<th>CI restriction preference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal or High</td>
<td>Very Low or Low</td>
</tr>
</tbody>
</table>

Resulting recommendations ranking

<table>
<thead>
<tr>
<th>CI (Kcals)</th>
<th>Additional exercise amount (Kcals)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2215</td>
<td>626</td>
</tr>
<tr>
<td>2215</td>
<td>310</td>
</tr>
<tr>
<td>1965</td>
<td>310</td>
</tr>
<tr>
<td>1965</td>
<td>0</td>
</tr>
<tr>
<td>1715</td>
<td>310</td>
</tr>
<tr>
<td>1715</td>
<td>0</td>
</tr>
</tbody>
</table>

In the first case, where the patient prefers to have a normal or high caloric deficit, and prefers not to perform exercise or perform very little exercise, the top four recommendations introduce caloric deficits of 469 and 719 Kcals: which fall in the normal and high categories based on our fuzzy sets defined for caloric deficit amount (Figure 35). The first two recommendations also do not add any exercise while the third and fourth recommendations add 316 Kcals of daily exercise; the equivalent of 17% of the BMR, which falls in the very low exercise amount category (Figure 36). While the last ranked recommendation introduces a minimal caloric deficit of 219 Kcals and a daily amount of exercise of 626 Kcals; the equivalent of 35% of the BMR (low exercise amount category)

On the other hand, in the second case where the patient has a high preference for exercise and a preference for keeping the caloric restriction minimal, the recommendation of minimal caloric deficit and highest amount of exercise is presented as the first option while recommendations with large deficit and small amount of exercise are ranked last.
6.6. Meal Plan Generation (MPG) Agent

After determining the appropriate CI for the patient, whether through initial caloric assessment, or evaluation and adjustment, the next phase of our nutrition process consists of recommending a meal plan that serves the patient’s health needs while catering to her food preferences. To do so, we introduce a dedicated meal plan generator (MPG) agent consisting of four main components:

**Component 1: Macronutrient Calculator.** It calculates the amount of macronutrient (carbohydrates, proteins, fats) in grams, based on the daily CI produced by the CIER agent in the previous step.

**Component 2: Serving Calculator.** It produces the daily amount of servings for the six primary food categories adopted from the food exchange list\(^4\) (i.e., starch, fruits, milk, vegetables, lean meat, and fats) based on the amounts of macronutrients produced by the macronutrient calculator.

\(^4\) The food exchange system is described section 2.4.2
**Component 3: Serving Assignor.** It splits the servings for each of the six primary food categories over the five meals (i.e., breakfast, snack one, lunch, snack two, dinner) based on sample meal plan serving assignments.

**Component 4: Food Assignor.** This component is designed based on a modified version of the transportation paradigm [69] [67] to allocate foods to the five daily meals while meeting the serving requirements.

We further describe each of the above components in the following sub-sections.

### 6.6.1. Macro-Nutrient Calculator

The macro-nutrient calculator adopts the calculation process defined in the nutrition literature, described in Section 2.4.1.

#### 6.6.1.1. Running Example

We consider a CI = 2107 Kcals. By applying equations (7), (8) and (9):

\[
grams_{\text{carbohydrates}} = \frac{2107 \times 50}{100 \times 4} = 263 \text{ grams}
\]

\[
grams_{\text{protein}} = \frac{2107 \times 20}{100 \times 4} = 105 \text{ grams}
\]

\[
grams_{\text{fat}} = \frac{2107 \times 30}{100 \times 9} = 70 \text{ grams}
\]

### 6.6.2. Servings Calculator

We presented in Section 2.4.2 the food list exchange system and the mathematical process adopted for transforming the grams of the three macronutrients into servings from the exchange categories. As previously presented, the savings are calculated using the following guidelines:

i. Select one serving of milk.
ii. For CI below 2200 Kcals select three 3 servings of fruits and 3 servings of vegetables. For CI above 2200 Kcals the servings of fruit are increased to 4 and the servings of vegetable are increased to 5.

iii. Apply equations (10), (11), and (12) respectively to produce the required servings of starch, protein and fat.

6.6.2.1. Running Example

\[ S_{\text{milk}} = 1, S_{\text{fruit}} = 3, S_{\text{vegetable}} = 3 \]

\[ S_{\text{starch}} = \frac{263 - 12 \times 1 + 5 \times 3 + 15 \times 3}{15} = 12.73 = 13 \text{ servings} \]

\[ S_{\text{meat}} = \frac{105 - 8 \times 1 + 5 \times 3 + 3 \times 13}{7} = 7.42 = 7 \text{ servings} \]

\[ S_{\text{fat}} = \frac{70 - 1 \times 1 + 2 \times 7 + 2 \times 13}{5} = 6 \text{ servings} \]

6.6.3. Servings and Food Assignment

As presented in Section 2.4.3, the final step in meal planning is to transform the number of servings from each category into an actual meal plan. Meal planning however goes beyond providing the numbers correctly. Important “logical” factors are to be considered, namely:

i. The food’s compatibility with the meal.

ii. The food preferences of the patient.

iii. The variety of the foods from day to day.

iv. The inter-compatibility between foods being assigned to the same meal.

In addition, we consider a fifth factor: producing a cost-efficient meal plan.

This multi-factor process depends on the common sense and expertise of the expert. In our approach we divide the process in two steps, that we explore in the upcoming subsections:

i. Servings Assignment

ii. Food Assignment

127
6.6.3.1. **Servings Assignment**

We adopt in our approach a five meal approach; three main meals (breakfast, lunch, dinner) and two snacks in between.

Once the total amount of servings for each of the food categories is determined, the servings for each category must be assigned over the five meals. This can be done by adopting a sample meal plan servings assignment and scaling based on the number of servings at hand.

6.6.3.2. **Running Example**

We adopt the following servings assignment extracted from a sample meal plan provided by a nutrition expert for a 2000 Kcals daily CI:

<table>
<thead>
<tr>
<th>Food Category</th>
<th>Total Servings</th>
<th>Breakfast servings</th>
<th>Snack one servings</th>
<th>Lunch servings</th>
<th>Snack two servings</th>
<th>Dinner servings</th>
</tr>
</thead>
<tbody>
<tr>
<td>cat&lt;sub&gt;1&lt;/sub&gt;</td>
<td><em>Milk</em></td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>cat&lt;sub&gt;2&lt;/sub&gt;</td>
<td><em>Fruit</em></td>
<td>3</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>cat&lt;sub&gt;3&lt;/sub&gt;</td>
<td><em>Vegetable</em></td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>cat&lt;sub&gt;4&lt;/sub&gt;</td>
<td><em>Starch</em></td>
<td>12</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>cat&lt;sub&gt;5&lt;/sub&gt;</td>
<td><em>Meat</em></td>
<td>7</td>
<td>1</td>
<td>0</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>cat&lt;sub&gt;6&lt;/sub&gt;</td>
<td><em>Fat</em></td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

In our running example for instance, the 2107 kcals intake results in 1, 3, 3, 13, 7 and 6 servings of milk, fruit, vegetable, starch, meat and fat respectively. By scaling the template to the problem at hand, the following serving plan is produced:
Table 44: 2107 Kcal CI servings plan

<table>
<thead>
<tr>
<th>Food Category</th>
<th>Total Servings</th>
<th>Breakfast servings</th>
<th>Snack one servings</th>
<th>Lunch servings</th>
<th>Snack two servings</th>
<th>Dinner servings</th>
</tr>
</thead>
<tbody>
<tr>
<td>cat(_1)</td>
<td>Milk</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>cat(_2)</td>
<td>Fruit</td>
<td>3</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>cat(_3)</td>
<td>Vegetable</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>cat(_4)</td>
<td>Starch</td>
<td>13</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>cat(_5)</td>
<td>Meat</td>
<td>7</td>
<td>1</td>
<td>0</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>cat(_6)</td>
<td>Fat</td>
<td>6</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

6.6.3.3. **Food Assignment**

The final step of the meal planning process is the food assignment process: assigning actual foods from the food exchange list based on the required servings. Here, we consider different factors that can affect the meal planning process, namely:

i. **Meal-food compatibility**: which governs which food should be assigned to which meal (ex., eggs at breakfast, milk at breakfast, fish at lunch, etc.).

ii. **Personal preferences**: the preferences of the patient regarding what foods are preferred and what foods are not pleasurable.

iii. **Food Occurrence**: nutrition experts aim to produce meal plans that insure variety from day to day by not recommending the same foods every day.

iv. **Inter-food compatibility**: a very important factor in meal planning is food compatibility, which is a factor directly related to human common sense on what foods go well with each other based on taste and appearance.

v. **Food prices**: In addition, food prices can be considered as well, in aims of producing cost efficient meals.

Other factors could be considered based on the patient or on the nutrition expert’s needs.

In the upcoming sub-sections, we describe how, and why, the food assignment process has been modeled as a transportation matrix. We design a modified version of the transportation problem that fits the requirements of the problem at hand, accounting for
multiple supply and demand types (i.e., the different food categories) as well as the different factors that play into the meal planning task described above.

Transportation Problem

In this section, we present a modification of the transportation problem (described in Section 5.2) that fits the requirements of our meal plan generation problem at hand.

With the required number of servings already assigned to the meals, the final step comes down to assigning the foods to the meals based on the required servings. This can be modeled through an adapted transportation matrix where:

i. The demand centers are the five meals: breakfast, 1st snack, lunch, 2nd snack, and dinner snacks.

ii. The supply centers designate the available foods from the food categories,

iii. The demand required at each demand center is the number of servings from each food category. This will be modeled as a 6-dimensional vector corresponding to each of the 6 categories of basic foods (2.4.2), in contrast with typical transportation problems where demands are represented as 1-dimensional scalar values.

iv. The supply capacity of each supply center, i.e., of each food, is the available amount from this food. Since the demand is modeled as a vector of serving requirements, supply is modeled as a 6-dimensional vector as well, representing the number of servings from each category the food is composed from, multiplied by the available amount from that food.

v. The cost function, associating a cost value with every transportation operation, is defined as an extensible aggregation function that combines the different cost factors considered in meal planning (e.g., meal-food compatibility, inter-food compatibility, etc., cf. Section 6.6.3).
Table 45: Food assignment transportation matrix

<table>
<thead>
<tr>
<th>Food</th>
<th>Cost per Food Distributed</th>
<th>Supply</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>C11, C12, ..., C1m</td>
<td>S1 * S1</td>
</tr>
<tr>
<td>2</td>
<td>C21, C22, ..., C2m</td>
<td>S2 * S2</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>n</td>
<td>Cn1, ..., Cnm</td>
<td>Sm * Sm</td>
</tr>
</tbody>
</table>

Demand

As previously described, each meal serves as a demand center. In meal planning, using the food exchange list system, a meal is not based on a single requirement. Each meal has requirements for each of the six basic food categories (cat1-to-cat6 from Table 5), i.e., milk, fruit, vegetable, starch, meat, and fat.

In order to account for this multi-dimensional requirement, we model demand as a vector of serving requirements:

$$\mathbf{D} = (d_1, d_2, d_3, d_4, d_5, d_6)$$  \hspace{1cm} (27)

where $d_1, d_2, d_3, d_4, d_5,$ and $d_6$ represent the requirements of the six food categories cat1-to-cat6 respectively.

Running Example

For example based on the serving plan presented in Table 44, the demands are modeled as follows:

$$\mathbf{D}_{\text{breakfast}} = (1, 0, 1, 3, 1, 2)$$
$$\mathbf{D}_{\text{snackone}} = (0, 1, 0, 2, 0, 1)$$
A demand is considered met, once all requirements in the demand vector are met.

Supply

As previously described, each food serves as a supply center. Here, we distinguish between: (i) the six basic food categories which can be mapped to the basic six categories (cat1-to-cat6) mentioned above, and (ii) composite foods which consist of combinations of basic foods. Foods, both basic and composite will serve as supply centers in aims to supply the serving demands at each meal.

Supply Vector

We represent supply as follows:

\[ \vec{S} = (s_1, s_2, s_3, s_4, s_5, s_6) \]  

where \( s_1, s_2, s_3, s_4, s_5, \) and \( s_6 \) represent the supply of milk, fruit, vegetable, starch, meat and fat respectively.

Based on the nature of the exchange list system, a basic food will supply requirements only for the category it belongs to. For example, one serving of yogurt will supply one serving of milk and one serving of chicken will supply one serving of meat. The corresponding vectors will be modeled as follows:

\[ \overrightarrow{S_{milk}} = (1,0,0,0,0,0) \]
\[ \overrightarrow{S_{chicken}} = (0,0,0,0,1,0) \]

On the other hand, combination foods supply multiple food servings based on the nature of the food. For example, a chicken sandwich can be modeled as follows:

\[ \overrightarrow{S_{cs}} = (0,0,3,4,0) \]
Where 3 and 4 signify the servings of starch and meat the chicken sandwich respectively supplies.

**Supply Amount**

We consider two factors while determining the supply amount: (i) the recommended amount to be consumed of a food per day and (ii) the available food stock. We define supply as follows:

\[
\text{Supply} = \begin{cases} 
\text{Recommended} & \text{if Recommended} < \text{InStock} \\
\text{InStock} & \text{otherwise}
\end{cases}
\]

This insures that we select the amount of servings from the available stock without surpassing recommended amounts. Thus the supply vector is now subject to the supply amount \(s\) and is presented as follows:

\[
\tilde{S} = s \cdot (s_1, s_2, s_3, s_4, s_5, s_6)
\]

**Additional Constraint**

After remodeling the transportation matrix into a multi-dimensional vector-based matrix, an essential constraint must be considered: if the supply center (i.e., food) is capable of supplying all the requirements in the demand center (i.e., meal).

We consider for example the following demand vector \(D_1\) and supply vectors \(S_1\), \(S_2\), and \(S_3\):

We consider for example the following demand vector and supply vectors.

\[
\overrightarrow{D_1} = (0, 2, 2, 2, 2, 1) \\
\overrightarrow{S_1} = 2 \cdot (1,0,0,0,0,0) \\
\overrightarrow{S_2} = 2 \cdot (0,1,0,0,0,0) \\
\overrightarrow{S_3} = 2 \cdot (0,0,2,2,2,0)
\]

\(S_1\) cannot supply \(D_1\) since the meal does not require any milk servings (dimension 1). \(S_2\) can supply \(D_1\) with 2 serving since \(D_1\) requires 2 servings of fruits (dimension 2). \(S_3\) can supply only one serving to \(D_1\) to avoid over supplying.
**Cost**

The transportation matrix is a cost-based matrix, where each supply center is related to each demand center through a cost of supplying a demand center from a supply center, i.e. in our case: supplying a meal with a food.

We propose the following definition for the cost function: the inverse of the likelihood of a food being associated with a meal; meaning the higher the cost the less likely the food well be assigned to a meal, and vice versa. This definition of the cost is adopted since, when meal planning, a human expert tends to consider the foods that are more likely to be assigned rather than eliminating all foods that are not likely to be selected.

The cost function is defined as an extensible weighted sum:

\[
C_{Total} = w_1 \times c_1 + w_2 \times c_2 + w_3 \times c_3 + w_4 \times c_4 + w_5 \times c_5
\]  

where:

i. \( c_i \) is the cost associated with each of the five following factors respectively:
   1. meal-food compatibility (1)
   2. food preferences (2)
   3. food occurrence (3)
   4. inter-food compatibility (4)
   5. food price (5)

ii. \( w_i \) is the weight assigned to each cost, where \( \forall w_i \in [0, 1] \) and \( \sum_{i=1}^{5} w_i = 1 \)

Elaboration on the cost function is presented in the upcoming sub-sections.

**Meal-food compatibility cost**

This cost automates the human decision-making process when assigning a food to meal, relating each food with a meal as follows:

i. Very likely food (I) in meal (M): \( C_1(I, M) = 0 \)
ii. Likely food (I) in meal (M): \( C_1(I, M) = 0.25 \)
iii. Somehow likely food (I) in meal (M): \( C_1(I, M) = 0.5 \)
iv. Unlikely likely food (I) in meal (M): \( C_1(I, M) = 0.75 \)
v. Very unlikely food (I) in meal (M): \( C_1(I, M) = 1 \)
Numerical values are chosen empirically with the help of the nutrition expert and are normalized $\in [0, 1]$.

**Preferences cost**

Each food is associated with a personal preference cost. The costs are determined by the patient to express her personal preferences regarding foods considered in meal planning.

The preference cost relates each food with all meals as follows:

1. Very liked food (I) $C_2 I = 0$
2. Liked food (I) $C_2 I = 0.25$
3. Patient neutral towards food (I) $C_2 I = 0.5$
4. Not-liked food (I): $C_2 I = 0.75$
5. Hated food (I): $C_2 I = 1$

Numerical values are defined in accordance with meal-food compatibility scores defined above, to be comprised $\in [0, 1]$.

**Occurrence cost**

The occurrence cost factor is included to avoid repetitive occurrences of foods. The cost is normalized $\in [0, 1]$ similarly to the previous cost factors. This can be achieved by increasing the cost of foods that are being selected, using a certain scaling factor, until the food is no longer selected, then the cost is reset to 0. As for the scaling factor $\alpha$, we chose an initial value of 0.25. By setting the scaling factor to 0.25 the occurrence cost will fall in the set $\{0, 0.25, 0.5, 0.75, 1\}$, as shown in eq. (32) which is the same set of cost values for preference and meal-food compatibility costs, yet any other value can be used (depending on the impact the patient wishes to assign to repeated foods: increasing the cost at a faster or slower pace, following the value of $\alpha$):

$$C_3(I) = Nb_{occ} * \alpha$$

where $Nb_{occ}$ is the number of consecutive daily appearances of the food.

**Inter-food compatibility cost**

This cost parameter designates the distance (similarity) between two foods. To compute the latter, a food graph was built connecting foods following their direct compatibility
relationship. If items are directly connected (inter-distance =1 edge), it means they are directly compatible together. If not, the graph is used to identify the smallest distance (highest compatibility) between two items using legacy (Dijkstra) shortest path computations.

The distance between a food node and itself is 0. While the distance between two disconnected food nodes is \textit{infinity}.

The cost between two foods, is normalized between [0, 1]:

$$C(I, I') = 1 - \frac{1}{1 + \text{distance}(I, I')}$$  \hspace{1cm} (33)

If the distance between two items is 0, the cost is 0. This only occurs when comparing a food with itself, i.e., a food is most compatible with itself. If the distance between two items is \textit{infinity}, the cost is a maximum of 1. This only occurs when comparing non-connected (totally incompatible) foods.

In general, multiple foods will be assigned to a meal. Thus, the inter-food compatibility cost relating the food to each meal depends on the foods already assigned to this meal. We define the inter-food cost relating food $I_i$ with a meal $M$ having foods $I_{(i, 2, \ldots, j)}$ assigned to it as:

$$C_4(I_i, M) = \frac{\sum_{j=1}^{n} C(I_i, I_j)}{n} \in [0, 1]$$  \hspace{1cm} (34)

Every time a food is assigned to a meal, the costs in the transportation matrix is updated automatically based on the assigned foods. This maps to the human thought process when assigning foods while trying to match the next selected food to pre-assigned foods.

\textit{Economic (Price) cost}

We define an economic cost normalized $\in [0, 1]$. For each food the price will be collected. The price will be computed in terms of 1 serving of a food. For a food $I_i$ from a specific
category the economic cost is defined as the price of the item divided by the most expensive item from the same food category:

\[ C_5(I_i) = \frac{p_i}{\max\{p_1, p_2, \ldots, p_j\}} \]  

(35)

where \( p \) represents the price of a single food.

**Dynamically updated cost**

Another modification we introduce to the transportation problem is the automatic update of the costs at each iteration. This is due to the fact that \( C_4(I, M) \), the cost related to inter-food compatibility is updated for each food every time a new food is assigned to a meal.

**Running Example**

For example, we assume that bread from the starch category is already assigned to lunch while no foods are assigned to breakfast yet. Hence, we compute the cost for two items from the meat category as follows. For this example, we only consider breakfast and lunch meals:

i. **Cheese** with:
1. Compatibility cost of 0.25 with breakfast and 0.5 with lunch
2. A neutral preference (\( C = 0.5 \))
3. A single previous occurrence the day before
4. Distance of 1 from bread.
5. An economic cost of 0.3

ii. **Chicken** with:
1. Compatibility cost of 0 with lunch, and 1 with breakfast
2. A liked preference (\( C = 0.25 \))
3. No previous occurrences
4. Distance of 3 from bread.
5. An economic cost of 0.5
Table 46: Food assignment example

<table>
<thead>
<tr>
<th></th>
<th>Costs for Breakfast Meal</th>
<th></th>
<th>Costs for Lunch Meal</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C₁</td>
<td>C₂</td>
<td>C₃</td>
<td>C₄</td>
</tr>
<tr>
<td>Cheese</td>
<td>0.25</td>
<td>0.5</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>Chicken</td>
<td>1</td>
<td>0.25</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

In this example, cheese will be assigned to breakfast and chicken will be assigned to lunch. The weights assigned to each cost factor can be modified to modify how decision making is done. For example, by raising the weight of $C_4$ (i.e. the inter-compatibility factor), and decreasing the other weights, cheese will be selected for lunch because of its compatibility with bread which is already assigned to lunch.

**Solving the Matrix**

We adopt the least cot method presented in Section 5.2, while applying the following modifications:

i. If there is a tie between foods, then we choose arbitrarily. This is important since it insures variety.

ii. We consider the supply constraint introduced in the vector based modification presented in Section 6.6.3.3, which states that the supply center (i.e., food) must be capable of supplying all the requirements in the demand center (i.e., meal).

*A sample meal plan produced for the 2107 CI is presented in*.

. In this example, we assume all factors $w_i = 0.2 \ \forall i \in \{1, 2, 3, 4, 5\}$. We also assume that the patient preference toward all foods is neutral (i.e., equal/no preference).

6.7. **Self-Evaluation**

In this section, we present a technique to evaluate the meal plans generated in terms of several parameters considered in our meal plan generation task, including:

i. *Meal-food compatibility*: the agent’s performance in terms of matching the foods to the meals in terms of the costs defined with the help of nutrition experts.
ii. *Food Preferences:* the agent’s performance in meeting the patient’s preferences.

iii. *Inter-food compatibility:* the agent’s ability of properly matching foods in the same meal.

iv. *Food cost:* the agent’s performance in terms of producing cost efficient costs based on the available meals.

This mechanism will allow our MPG (meal plan generator) agent to self-evaluate its performance and produce score as an error percentage, for each aspect. This will reflect the effect of changing the cost weights ($w_1, w_2, w_3, w_4, w_5$) in equation (31) on the meal plan produced.

Note that we do not include *food occurrence* among the considered parameters for self-evaluation since the mechanism applies to a daily meal plan in isolation of previous meal plans, while the occurrence factor impacts the occurrence of foods between consecutive days.

### 6.7.1. Meal-food compatibility

A meal plan that focus only on meal-food compatibility will not necessarily produce the best meal plan in terms of preferences, inter-food compatibility and economic cost. meal-food compatibility error percentage is computed as follows:

$$S_1 = \frac{|C_{\text{experimental}} - C_{\text{theoretical}}|}{|C_{\text{theoretical}}|}$$  \hspace{1cm} (36)

Where $C$ in this case represents the total cost of the meal plan in terms of meal-food compatibility, defined as:

the average of meal-food compatibility costs associated with every food $C_1(I_i, M)$ selected in a meal plan where $i \in [1, n]$.

$$C = \sum_{i=1}^{n} \frac{C_1(I_i, M_i)}{n}$$  \hspace{1cm} (37)

where $M_i$ is the meal to which $I_i$ belongs.

$C_{\text{experimental}}$ is computed from the generated meal plan, while $C_{\text{theoretical}}$ is computed by generating a meal where the meal-food compatibility factor is maximal ($w_1 = 1$) and all
other factors are set to 0. This insures that we perform a fair evaluation against a meal plan generated from foods available in stock.

### 6.7.2. Preferences

A meal plan that focuses only on preferences will not necessarily produce the best meal plan in terms of meal-food compatibility, inter-food compatibility, and price since the main focus is to meet the preferences of the patient.

Since each individual food has a score for preference, the overall score is calculated as a percentage percent error as follows:

\[ S_2 = \frac{|CP_{\text{experimental}} - CP_{\text{theoretical}}|}{|CP_{\text{theoretical}}|} \quad (38) \]

Where CP in this case represents the average preference cost of a daily meal plan.

CP is defined as: the average preference cost of all foods selected \( C_2(I_i) \) where \( i \in [1, n] \). We do not need to consider the number of servings here since this is a measure of quality (preferences) regardless of the quantity.

\[ CP = \frac{\sum_{i=1}^{n} C_2(I_i)}{n} \quad (39) \]

CP \(_{\text{experimental}}\) computed from the generated meal plan, while CP \(_{\text{theoretical}}\) is computed from the meal plan where the preference factor is maximal \((w_2 = 1)\) and all other factors are set to 0. This insures that we are performing a fair comparison against a meal plan generated from foods available in stock.

### 6.7.3. Inter-Food Compatibility

In order to evaluate inter-food compatibility, we evaluate the ability of our solution to match items one-to-one. This is based on how human experts usually match foods: by matching items one-to-one. We compute the inter-food compatibility score is calculated as a percentage percent error as follows:
\[ S_3 = \frac{|CI_{experimental} - CI_{theoretical}|}{CI_{theoretical}} \]  

where CI represents the number of 1-to-1 connections with respect to the total number of possible connections in the meal plan, and is defined as:

\[ CI_n = \sum_{i=1}^{M} \frac{n_i}{N} \cdot \frac{k_i}{n_i} \]  

i. \( n_i \): is the number of connections in a meal \( M_i \).
   
   o if a meal has \( j \) foods, the number of connections is:
   \[ (j - 1) + (j - 2) + \ldots + 1 = \frac{i(j-1)}{2} \]
   
   N: is the total number of connections in the meal plan computed by summing the number of connection in each meal \( M_i \).

ii. \( n/N \): is the weight of each meal plan based on the number of connections within this meal with respect to the total number of connections in the meal plan.

iii. \( k_i \) is the number of 1-to-1 connections in meal \( i \).

iv. \( k/n \) is the percentage of 1-to-1 connections in a meal.

The function simplifies as follows:

\[ CI_n = \sum_{i=1}^{M} \frac{k_i}{N} \]  

This represents the total number of 1-to-1 connections with respect to the total number of possible connections in the meal plan.

\( CI_{experimental} \) computed from the generated meal plan, while \( CI_{theoretical} \) is computed from the meal plan where the preference factor is maximal (\( w_4 = 1 \)) and all other factors are set to 0.

6.7.4. Economic Cost

The economic cost can be evaluated in terms of the cheapest possible meal. The latter will not necessarily evaluate well in terms of preferences, variety, and compatibility since the
focus is on finding the cheapest possible meal from the available items in stock. The score is calculated based as a percentage error as follows:

$$S_4 = \frac{|CE_{\text{experimental}} - CE_{\text{theoretical}}|}{|CE_{\text{theoretical}}|}$$

where CE in this case represents the average economic cost of the meal plan.

CE is defined as: the average of number of servings of a food $m_i$ selected multiplied by the economic cost of the food $C_5(I_i)$ for all foods selected in a meal plan where $i \in [1, n]$. This function evaluates the economic cost of the meal plan which is affected by the number of servings selected from each food, hence we consider the number of servings of each assigned food.

$$CE = \frac{\sum_{i=1}^{n} C_5(I_i) \times m_i}{n}$$

CE$_{\text{experimental}}$ is computed from the generated meal plan, while CE$_{\text{theoretical}}$ is computed from the meal plan where the economic cost factor is maximal ($w_5 = 1$) and all other factors are set to 0.

### 6.7.5. Example

For example, by applying the self-evaluation functions to the meal plan presented in Appendix D. The following resulting scores are produced:

<table>
<thead>
<tr>
<th>Function</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meal-food compatibility</td>
<td>0.91</td>
</tr>
<tr>
<td>Preferences</td>
<td>1.00</td>
</tr>
<tr>
<td>Inter-food compatibility</td>
<td>0.83</td>
</tr>
<tr>
<td>Economic Cost (Price)</td>
<td>0.59</td>
</tr>
</tbody>
</table>
For this example, all preferences are set to neutral, assigning equal importance to all considered factors in producing the overall meal plan evaluation score.
Chapter 7

Experimental Evaluation

This chapter describes our PIN prototype implementation design and details in Section 7.1, our experimental protocols and evaluation metrics in Section 7.2, our experimental data in Section 7.3, and the corresponding experimental results in Section 7.4.

7.1. Prototype Implementation

![PIN Implementation general architecture](image)

We have implemented our PIN framework as a web-based application to allow easy access for patients and experts using and evaluating the system. On the server-side, we adopted a three-layer architecture:

i. **Web API** layer that allows client-side applications to communicate with the server to request data and services. We used the SPRING framework [70] to build the Web API.

ii. **Business Logic** layer where the decision making logic is implemented.
iii. **Data Access** layer where data storing and retrieval is handled. This layer is built on top of **Hibernate** [71] Object Relationship Mapper [72].

**MySQL** is used for data storage. The **JDBC** driver is used to communicate with the database.

At the **Business Logic**, the **JFuzzyLogic** java library [73][74] is adopted to implement the fuzzy models.

On the client-side, we develop a web application, implemented using **Angular 6**, through which the services provided by the framework can be accessed. Communication between the client-side and server-side applications is established through REST API over HTTP.

### 7.2. Evaluation Protocols and Metrics

As presented in Chapter 6, the designed framework consists of four main components:

i. **WAR agent**: responsible for recommending target weight and BFP recommendations based on the current state of the patient (age, gender, weight, height and BFP).

ii. **CIER agent**: responsible for producing daily CI (caloric intake) and exercise amount recommendations.

iii. **PERA agent**: responsible for monitoring and assessing the progress of a patient, as well as adjusting the CI and exercise recommendation in case of lack of progress.

iv. **MPG agent**: responsible for generating meal plans based on the required CI, taking into account different factors including: (i) meal-food compatibility, (ii) preferences, (iii) occurrence; to insure variety, (iv) inter-food compatibility and (v) price of the food.

In order to evaluate the performance of the **PIN** framework, we design multiple sets of experiments, which we categorize in two main groups: experiments dedicated to evaluating system performance in terms of: (i) accuracy: by comparing the recommendations of each of three of the components of PIN (i.e. WAR, CIER, and PERA) with the recommendations of human expert testers, and (ii) correctness: by requiring the
expert testers to evaluate and rate the recommendations of PIN’s four agents on a scale from 1 to 5; 5 being strong agreement and 1 being strong disagreement. Experimental protocols were designed with the help of nutrition experts. Each experiment was performed by four different expert testers. A total of eleven testers where involved in conducting all experiments, each tester participated in one or multiple experiments.

7.2.1. WAR Agent Evaluation

7.2.1.1. Recommendation Accuracy

In this experiment, we provide expert testers with data input for 25 males and 25 female patient cases. The input data includes: the age, height, weight, and BFP of the patient. For each case, the expert tester is requested to provide: (i) a goal recommendation (i.e., patient needs to \textit{lose} weight, \textit{gain} weight, or \textit{maintain} her/his current weight), (ii) a short term target BFP and (iii) a short term target weight.

Here, we evaluate:

i. Average \textit{inter-tester agreement} (in terms of similarity) between the sets of goal recommendations (i.e. lose weight, gain weight or maintain weight) produced by the experts for the of 25 male cases and the of 25 female cases. Where we define the similarity between two recommended goals $g_x$ and $g_y$ as follows:

$$s = \begin{cases} 1 & \text{if } g_x = g_y \\ 0 & \text{otherwise} \end{cases}$$

ii. Average \textit{PIN-tester agreement} (in terms of similarity) between the sets of goal recommendation produced by PIN and those produced by each expert for the 25 male cases and 25 female cases.

iii. Average \textit{agreement} (in terms of similarity) between the recommendations produced by the experts, for both BFP and weight respectively. We define the similarity between two data points $x$ and $y$ as follows:

$$s = \frac{|x - y|}{\text{Max}(x, y)}$$
iv. Average *PIN-tester agreement* (in terms of similarity) between the recommendations produced by *PIN* and those produced by the experts, for both the BFP and weight respectively.

7.2.1.2. *Recommendation Correctness*

In this experiment, we provide four different experts with *PIN*’s goal, BFP, and weight recommendations for each of the 25 male and 25 female cases, and ask the experts to evaluate and rate them on a scale from 1 (strong disagreement) to 5 (strong agreement). We compute average ratings and their and standard deviations, per case, for both BFP and weight expert ratings.

7.2.2. *CIER Agent Evaluation*

7.2.2.1. *Recommendation Accuracy*

In this experiment, we require the expert testers to produce *CI* and *exercise recommendations* for patient cases. We present the experts with 20 male and female patient cases organized in three groups: (i) 5 cases of patients 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: (i) the exercise preference i.e. the amount of exercise the patient desires to perform per day (*low, high, etc.*), and (ii) the caloric deficit preference, i.e. the amount of calories the patient desires to abstain from per day (*low, high, etc.*) (cf. Section 6.5).

Each recommendation produced by the expert tester is represented as a doublet (I, E), where I represents the recommended CI and E the additional amount of calories that the patient needs to spend per day by performing physical exercise.

Since a CIER recommendation consists of a doublet of (I, E) values, we treat the latter as a single recommendation, and define the similarity between two recommendations (I₁, E₁) and (I₂, E₂) as the average similarity between the *CI*’s I₁ and I₂, and *exercise amounts* E₁ and E₂:
\[
s = \frac{1}{2} \times \frac{|I_x - I_y|}{\max(I_x, I_y)} + \frac{1}{2} \times \frac{|E_x - E_y|}{\max(E_x, E_y)}
\]

(47)

Here, we compare the recommendations produced by CIER with those of experts, while first quantifying cross-expert agreement, and then PIN-expert agreement by evaluating:

i. **Average inter-tester agreement** (in terms of similarity), and standard deviation, between the recommendations produced by the expert tester pair-wise.

ii. **Average PIN-tester agreement** (in terms of similarity) and standard deviation between the recommendations produced by PIN’s CIER and those produced by experts.

Each expert will produce multiple possible options, between 1 and 3. PIN provides multiple options as well; up to 6, this is due to the nature of the condition-action rules of the designed fuzz agent (cf. Section 6.3.1.4). Thus when comparing recommendations multiple combinations are considered. We apply two types of analysis: (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.

### 7.2.2.2. Recommendation Correctness

In this experiment, we present the expert testers with the CI and exercise recommendations produced by CIER for the same cases used in the previous experiment, and we ask different experts to rate the produced system recommendations on a scale from 1 (strong disagreement) to 5 (strong agreement).

In addition, we define two metrics for rating:

i. **Recommendation feasibility**: evaluating whether the recommendations are feasible from a healthiness point of view.

ii. **Preference compliance**: evaluating whether the recommendations meet the preferences of the patient in terms of daily caloric restriction and amount of exercise. This only applies in the case of weight loss cases where we require a caloric restriction and additional exercise recommendations.
The total rating is computed as the average of both feasibility and compliance ratings.

In all cases, PIN provides multiple recommendations for patients (as described in the previous section). Hence, we apply two types of analysis methods: (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 compute the average rating per case and the standard deviation by averaging the recommendation ratings produced by experts in the previous step.

### 7.2.3. PERA Agent Evaluation

#### 7.2.3.1. Progress Evaluation Accuracy

In this experiment, we present the experts with a set of cases, where each case represents (i) the profile of a patient, (ii) the target BFP and target weight of the patient, (iii) multiple scenarios of different BFP/weight targets reached by the patient. Four main scenarios for progress percentage evaluation, in terms of reached BFP/weight, are considered: (i) 20%, (ii) 40%, (iii) 50% and (iv) 75%. The selected values represent the boundaries of the progress classification and fuzzy memberships presented respectively in Table 32 and Figure 47. Experts would then rate progress as: (i) slow, (ii) moderate, or (iii) good.

Here, we define the similarity between two recommendations as follows:

\[
s = \frac{|c_1 - c_2|}{Max(c_1, c_2)} \tag{48}
\]

Where

\[
c = \begin{cases} 
1 & \text{if progress is slow} \\
2 & \text{if progress is moderate} \\
3 & \text{if progress is good} 
\end{cases} \tag{49}
\]

Similarly, to the previous experiments, we compare the recommendations produced by PERA with those of human expert testers, while first quantifying cross-expert agreement:
i. Average *inter-tester agreement* (in terms of similarity) and standard deviation between the recommendations produced by the experts pair-wise.

And then quantifying PIN-tester agreement

ii. Average *PIN-tester similarity* (in terms of similarity) and standard deviation between the recommendations produced by PIN’s PERA agent and those produced by experts.

### 7.2.3.2. Recommendation Accuracy

In this experiment, we provide the experts with 10 patient cases similar to the cases provided in the previous experiment. We provide two scenarios for each case in terms of weight and body fat percentage recommendations: (i) slow progress: 10% and (ii) moderate progress: 50-60%

We only consider slow and moderate progress here since in the case of good progress the is covered in two previous experiments (cf. Sections 7.2.1 and 7.2.2) where the patient undergoes a weight assessment or a CI recommendation.

Similarly, to previous experiments, we aim to evaluate the similarity between PIN’s and the experts’ recommendations, while first quantifying cross-expert agreement: To do so, we define two scenarios where the progress is clearly either moderate (50-60% progress) or slow (10% progress) and compute:

i. Average *inter-tester agreement* (in terms of similarity), and standard deviation, between the recommendations of the experts.

ii. The average *PIN-tester agreement* (in terms of similarity), and standard deviation, between the recommendations of PIN and those of the experts.

### 7.2.3.3. Recommendation Correctness

In this experiment, we ask the experts to rate the recommendations produced by PIN’s PERA, on a scale of 1 (strong disagreement) to 5 (strong agreement) for the same cases
processed in the previous experiment, considering both slow and moderate progress scenarios. We compute the average rating and standard deviation per case.

7.2.4. MPG Agent Evaluation

In order to evaluate the MPG agent, we define a set of experiments that evaluate the different aspects involved in meal planning presented throughout Section 6.6.

7.2.4.1. Meal Plan Quality

The objective of this experiment is to evaluate PIN’s ability to generate healthy and feasible meal plans. We present the experts with meal plans each consisting of four three-day meal plans (covering typical patient CIs):

i. A three-day meal plan for 1200 Kcals intake
ii. A three-day meal plan for 1600 Kcals intake
iii. A three-day meal plan for 2000 Kcals intake
iv. A three-day meal plan for 2400 Kcals intake

Meal plans were organized in two main groups: those including basic foods (e.g., bread, milk, apples), and those containing both basic foods and combination foods (lasagna, hamburger, cf. Section 2.4.2).

MPG evaluates a cost function that defines how foods are selected based on weight factors defined for each factor involved in the meal plan generation process, i.e., meal-food compatibility, preference, occurrence, inter-food compatibility, and price (cf. equation (31)). For this experiment, we set the weight factors of the price constraint to 0 (since financial price is not a health-related parameter), while we split all other (health-related) factors equally. We leave out the price at this point, since experts do not usually consider food prices while producing meal plans.

The following three criteria are considered:

i. Daily Meal-Food Compatibility: If the foods are assigned to the meals correctly.
ii. **Daily Inter-Food Compatibility**: If the foods are matched well within the same meal.

iii. **Daily Food Diversity**: If the daily meal plan has a variety of foods.

In addition, we consider:

iv. **Overall Meal Plan Diversity**: which signifies the variety of meal plans from day to day.

### 7.2.4.2. Patient Preferences and Variation

In addition, we asked four non-expert testers to evaluate the meal plans. We generated three-day meal plans based on the CI requirements and the preferences of the testers and asked the testers to rate the generated meal plans based on the following criteria:

i. **Daily Preference Satisfaction**: If the foods selected meet the preferences set by the tester.

ii. **Daily Food Variation**: If the daily meal plans have non-repetitive and changing foods that satisfy the tester. Here, we distinguish between food diversity evaluated in the previous experiment, which represents the presence of diverse combinations of foods in every meal plan: a basic requirement that most nutritionists seek to achieve; and food variation which represents the non-repetitive and changing foods among different consecutive meal plans.

iii. **Overall Meal Plan Variation**: which designates the non-repetitive and changing nature of meal plans recommended from day to day.

### 7.2.4.3. Cost Function Weights Variation

In the MPG agent description, we introduced a cost function (cf. equation (31)) which defines how foods are selected based on multiple factors, including meal-food compatibility, preference, occurrence, inter-food compatibility and price. In this experiment, we vary some of the cost function weights in order to evaluate their effect on the agent’s self-evaluation criteria described in Section 6.7. For every combination of
weight factors we produced 40 meal plans, 10 for each of the following typical CIs: 1200, 1600, 2000, 2400 Kcals.

7.3. Test Data

7.3.1. Empirically Collected Data

For our male body composition data, we select 25 cases out of a dataset of 252 male cases collected and published by experts from Carleton College [75]. For female cases, due to the fact that no published complete dataset was found, we collected data from local pharmacies where body composition machines are available. We selected the data in fashion that covers different cases ranging from low body fat percentages to overweight and obsess cases.

*Table 48: Male data summary*

<table>
<thead>
<tr>
<th>Input</th>
<th>Age</th>
<th>Weight(KG)</th>
<th>Height (Meters)</th>
<th>Body Fat %</th>
<th>BMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>33.64</td>
<td>84.52</td>
<td>1.81</td>
<td>18.18</td>
<td>25.89</td>
</tr>
<tr>
<td>Min</td>
<td>23.00</td>
<td>56.36</td>
<td>1.72</td>
<td>5.30</td>
<td>18.89</td>
</tr>
<tr>
<td>Max</td>
<td>65.00</td>
<td>163.42</td>
<td>1.97</td>
<td>36.30</td>
<td>48.52</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>10.36</td>
<td>19.96</td>
<td>0.07</td>
<td>8.39</td>
<td>5.93</td>
</tr>
</tbody>
</table>

*Table 49: Female data summary*

<table>
<thead>
<tr>
<th>Input</th>
<th>Age</th>
<th>Weight(KG)</th>
<th>Height (Meters)</th>
<th>Body Fat %</th>
<th>BMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>28.92</td>
<td>62.99</td>
<td>1.65</td>
<td>29.30</td>
<td>23.24</td>
</tr>
<tr>
<td>Min</td>
<td>18.00</td>
<td>50.00</td>
<td>1.56</td>
<td>16.10</td>
<td>18.94</td>
</tr>
<tr>
<td>Max</td>
<td>59.00</td>
<td>88.40</td>
<td>1.75</td>
<td>46.20</td>
<td>30.23</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>11.49</td>
<td>8.76</td>
<td>0.05</td>
<td>7.63</td>
<td>2.90</td>
</tr>
</tbody>
</table>
7.3.2. System Generated Data

For the WAR, CIER and PERA recommendation correctness experiments, we used PIN to generate different recommendations for different cases and asked the experts to evaluate and rate. Similarly, for the MPGA agent, we used PIN to generate different meal plans and we asked the experts to rate the meal plans.

Finally, we produced sets of meals plans with different cost function weight factors, in order to evaluate their effects on the scores produced by the self-evaluation functions.

7.4. Experimental Results

7.4.1. WAR Agent Recommendations Evaluations

7.4.1.1. Recommendation Accuracy Results

Evaluation of Goal Recommendations

In this experiment we evaluate the similarity between: (i) the health nutrition goal (i.e., lose, maintain, or gain weight) suggested by the experts, and (ii) the goal suggested by PIN’s WAR agent. We evaluate: (i) the average agreement (in terms of similarity) between each of the four experts recommended goals one-by-one, and (ii) the average agreement (in terms of similarity) between PIN and each of the four experts. When comparing the experts’ recommendations w.r.t. each other, in the case where an expert provides multiple options for the same patient (e.g., maintain weight, or gain weight while performing additional physical exercises), we consider the recommendation which is most similar to the other experts’ recommendations, i.e., the one producing the highest inter-tester correlation.

Similarly, in the case where PIN provides multiple options for the same case, we consider the one with the highest correlation with the expert’ recommendation. Results are provided in Figure 58 and Figure 59.

Figure 58 presents the inter-tester average similarity results produced for the 25 male and 25 female cases considered in our study, and Figure 59 provides PIN-tester average similarity for the same cases. Various observations can be made here:
i. 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 is average inter-tester similarity is 0.6 and is obtained between experts 1 and 3. In the case of PIN vs testers, the highest average similarity is 0.96 for both PIN vs expert 1 and PIN vs expert 2, while the smallest similarity is 0.64 between PIN and expert 1. Also, PIN scores 0.8 and 0.87 similarity on average for male and female cases respectively, which is higher than average inter-tester similarity. This shows that PIN’s goal recommendations highlight an overall accuracy similar (and even surpassing) those of human experts.

Figure 58: Inter-tester recommended goal average similarity
ii. For male and female cases, the inter-tester average similarity is 0.73 and 0.8 respectively, indicating that there is no single correct decision regarding the nutrition goal of a patient, and that different options might be possible (as briefly discussed in Section 6.2). This highlights the need for producing multiple possible recommendation options which PIN successfully provides.

iii. 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 experts among each other as well as PIN tend to agree on more similar goals when evaluating female cases, compared with male cases. This reflects more flexibility when dealing with male cases, where males are given options between maintain or losing weight, while in female cases a general agreement exists regarding when a patient should maintain the current weight or lose more weight.

In addition, as shown in Figure 60, for male cases with high BFP scores are generally agreed upon among testers since the obvious recommendation would be to lose weight. Yet, conflicting recommendations might appear when evaluating cases with small BFP
where some experts might recommend maintaining the patient weight while others might recommend weight gain. Also, some dissimilarities appeared in cases where $\text{BFP} \in [14\%, 17.8\%]$ where some experts considered that the patient can maintain the current weight and others considered that the patient should lose additional weight.

![Average inter-tester similarity per male case with respect to the BFP](image)

**Figure 60: Average inter-tester similarity per male case with respect to the BFP**

**Evaluation of Target BFP and Weight Recommendations**

Previously presented Figure 58 and Figure 59 represent the agreement in terms of target goal (lose, gain or maintain weight). On the other hand

Figure 61 and Figure 62 below represent the agreement in terms of target BFP and weight values. The graphs show very close agreements when comparing inter-tester similarity and PIN-tester similarity in terms of both BFP (0.94 and 0.92 respectively) and weight (0.98 and 0.97 respectively). This indicates PIN’s ability of producing ‘human-like’ BFP and weight recommendations.
Figure 61: Average inter-tester recommendation similarity and standard deviation
Two main observations can be made here:

i. Here, by comparing the experts’ recommendations for both weight and BFP, we notice very high 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.

ii. From Figure 62, we notice that the similarity between the recommendations of PIN and experts fall within the same range of inter-tester recommendations similarity, considering BFP and weight. Similarly, the standard deviations are relatively low, signifying high general agreement for most cases between PIN and the experts.
7.4.1.2. **Recommendation Correctness Results**

In this experiment we evaluate the ratings provided by the experts evaluating the nutrition goal recommendations produces by the PIN framework.

![Bar charts showing average scores and standard deviations for male cases sorted in descending order.](image)

*Figure 63: Average score, and standard deviation, per case for male cases sorted in descending order*
Results in Figure 63 and Figure 64, show an almost opposite correlation between average tester rating and standard deviation: 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 PIN’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 PIN’s goal recommendations.

In addition, we notice that 18% of the ratings are equal to or greater than 4.5, 46% fall between 3.75 and 4.5, 24% of the ratings fall between 3 and 3.5, and 12% of the ratings fall between 2.25 and 2.75.

7.4.1.3. Discussion
Experiments show high correlation between the nutrition goal recommendations of the PIN framework and those of the 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. This highlights the observation that PIN could be considered or viewed as “yet another human tester”, an observation which will be further reinforced in the following experiments. In addition, expert testers’ ratings of PIN’s results demonstrate the system’s ability of producing good weight and body fat percentage recommendations.

7.4.2. CIER Agent Recommendations Evaluation

The CIER agent is responsible for producing CI and exercise recommendations based on (i) the current weight, (ii) the target weight, (iii) the level of activity and (iv) the preferences regarding exercise and caloric deficit.

7.4.2.1. Recommendation Accuracy Results

In this experiment we evaluate the similarity between the CI and exercise recommendations of expert testers versus the recommendations of other experts (inter-tester results), as well as the recommendations of PIN versus the recommendations of the experts (PIN-tester results).

As previously described (cf. Section 7.2.2), patient cases are classified in three categories; (i) weight loss cases, (ii) weight gain cases and (iii) weight maintenance cases. Where (i) patients in the weight loss cases require a CI and exercise recommendation which invokes weight loss, (ii) patients in the weight gain cases require a CI which invokes weight gain and (iii) patient in the weight maintenance cases requires the appropriate CI to maintain the current weight.

Weight Loss Cases
Figure 65: Average inter-tester similarity, and standard deviation, of CI and exercise recommendations for weight loss cases.

Figure 66: Average PIN vs tester similarity, and standard deviation, of CI and exercise recommendations for weight loss cases.
We apply two types of analysis methods: (i) maximum analysis, where we select the combination with the highest similarity, (ii) average analysis, where we compute the average similarity of all recommendation combinations.

**Maximum Analysis**

When applying maximum analysis, as observed in Figure 65 and Figure 66, PIN scores higher agreement (in terms of similarity) with experts, 0.94 on average, compared to an inter-tester agreement of 0.84 on average. We also notice a smaller standard-deviation of 0.04 on average in the case of PIN versus tester similarity, compared to a 0.14 standard deviation for inter-tester agreement. This signifies that PIN’s CI/exercise recommendation are homogeneous with human expert recommendations, demonstrating PIN’s ability of producing ‘human-like’ recommendations for weight loss cases.

**Average Analysis**

When applying average analysis, the average similarity for PIN vs tester similarity is 0.64, slightly lower than the average similarity of 0.67 in the case of inter tester similarity, with a smaller standard deviation of 0.06 in comparison to 0.13.

The smallest similarity observed is 0.61 when comparing recommendations of PIN to expert one, which is higher than the smallest agreement (in terms of similarity), of 0.57 observed between experts 1 and 3 in the case of inter-tester similarity. This means that the smallest similarity between PIN and a human expert tester is not lower than a similarity we can observe between two human experts, thus the recommendations produced by PIN fall within the range of human recommendations for weight loss cases.
Weight Gain Cases

Figure 67: Average inter tester similarity, and standard deviation, of CI and exercise recommendations for weight gain cases
When applying maximum analysis, as shown in Figure 67 and Figure 68, we notice very high average agreements (in terms of similarity) of 0.99 (0.01 std. dev) and 0.99 (0.01 std. dev) for inter-tester and PIN-tester agreements respectively. The high similarities and small standard deviations demonstrate, yet again, PIN’s ability of producing ‘human-like’ recommendations for weight gain cases.

When applying average analysis, we notice average agreements of 0.84 (0.11 std. dev) and 0.90 (0.07) for inter-tester and PIN-tester agreements respectively. Given the average agreement between human expert tester, the PIN-tester agreement value emphasizes the fact that PIN can be considered an ‘other human tester’ when dealing with recommendations for weight gain cases.
Discussion

By comparing, weight loss cases CI/exercise recommendation similarities (Figure 65, Figure 66) to weight gain cases CI/exercise recommendation similarities (Figure 67, Figure 68) we notice higher similarities and smaller standard deviations, when comparing inner-tester agreement; as per maximum analysis we notice average similarities of 0.84 (0.14 std. dev) and 0.99 (0.01) for weight loss cases and weight gain cases respectively, while per average analysis we notice average similarities of 0.84 (0.11) and 0.9 (0.07 std. dev) for weight loss cases and weight gain cases respectively.

This indicates a general higher agreement among human experts when dealing with weight gain cases compared to weight loss cases; this is due to an observed emphasis on the weight loss rate. As per our discussions with nutrition experts, we deduce that weight loss is the most delicate case, and human experts might recommend different recommendations, in contrast to weight gain and weight maintenance cases where a general agreement regarding recommendations exists.

We notice that PIN adheres to this observation and displays higher agreements with human experts both in maximum and average analysis in weight gain cases when compared to weight loss cases. This observation can be associated with multiple factors, including (i) the exercise recommendations in case of weight loss that increase the possible different recommendations and (ii) the previously mentioned nature of weight loss and weight gain cases.

Weight Maintenance Cases

Based on our discussion with nutrition experts in contrast to weight loss and weight gain cases, and as previously presented in 2.2.2, usually a single recommendation exists for weight maintenance cases: recommendation a CI equal to the TEE (Total energy expenditure). However, experimental results show that some experts adhere to the mentioned approach that we adopt in our framework, while some experts recommend additional exercise recommendations and increase the CI accordingly.
As shown in Figure 69 and Figure 70, similar to weight loss and weight gain cases, we observe high agreement (in terms of similarity), when comparing PIN-tester similarity compared to inter-tester similarity.

**Figure 69: Inter-tester average similarity, and standard deviation, for weight maintenance cases**

**Figure 70: PIN vs tester average similarity, and standard deviation, for weight maintenance cases**
Discussion

PIN’s CIER agent produces CI/ exercise recommendations to guide the patient to the target weight. When evaluating the agreement between PIN’s recommendations and human expert testers recommendations, while accounting for the inter-tester agreement, we notice high agreements based on both maximum and average analysis. Thus, we conclude that PIN’s recommendations are comparable, and indistinguishable to those of human expert recommendations.

7.4.2.2. Recommendation Correctness Results

In addition to similarity analysis, we require experts to rate the CI/exercise recommendations produced by PIN. To do so, we separated the recommendations in three categories:

i. **Weight Loss cases**: where we have two rating criteria, as previously explained: (i) feasibility of the recommendation, and (ii) preference w.r.t. the patient. Since multiple options are provided, we look at the maximum and averages scores per case.

ii. **Weight Gain cases**: where only a feasibility score is available. Since multiple options are provided, we look at the maximum and average scores per case.

iii. **Weight Maintenance cases**: where a single option is provided and graded solely on the feasibility criteria.
Weight Loss Cases

We notice, high scores for the CI (caloric intake) and exercise recommendations, in terms of feasibility, preference and total grades. The lowest grade of 3.75 for the preference criteria in case 9 is associated with the highest standard deviation.

In addition, we apply average analysis and present the results in Figure 72 below. We notice that lowest grades are associated with preferences, and thus leading to a drop in the total average drop. This is expected, since PIN produces all the possible feasible options and them attempts to sort them based on patient preferences without eliminating any recommendation. Out of the possible recommendation, few will meet the preferences of the patient, and this will result in an expected low average grade.

The results indicate a high human expert approval of PIN’s CI/exercise recommendations for weight loss cases.
Figure 72: Average grade, and standard deviation, of CI and exercise recommendations for weight loss cases based on average Analysis

By referring to Table 50, we notice that even in the average analysis case, the feasibility average grade is 3.93 and average total grade is 3.51. In both maximum analysis and average analysis, expert testers provide satisfying rating in both maximum and average analysis. The same observation applies for the total ratings. As previously mentioned, an expected decrease of the preference rating is observed based on average analysis, this is due to PIN’s mechanism that produces multiple healthy feasible options sorted based on the patient preferences, without eliminating any option.

Table 50: Aggregate average rating for CI and exercise recommendations grades for weight loss cases

<table>
<thead>
<tr>
<th>Analysis Type</th>
<th>Feasibility Rating</th>
<th>Preference Rating</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Analysis</td>
<td>4.75</td>
<td>4.63</td>
<td>4.65</td>
</tr>
<tr>
<td>Average Analysis</td>
<td>3.93</td>
<td>3.08</td>
<td>3.51</td>
</tr>
</tbody>
</table>
Weight Gain Cases

For gain, we provide the experts with five cases. As previously mentioned, for both weight gain and weight maintenance, our design considers that additional exercise recommendations are not necessary, and thus we only need to evaluate the feasibility criterion here. As shown in Figure 73, based on both maximum and average analysis, we notice satisfying human expert ratings for PIN’s CI recommendations for weight gain cases, indicating a high human expert approval.

Yet, experimental results showed that some experts would recommend additional exercise for patients with low activity levels, even if their goal is not to lose weight. The additional exercise is accounted for by increasing the CI. PIN does not consider the latter scenario (i.e., recommending exercise event when the goal is not to lose weight). We report this special case to a dedicated future work specifically focused on fitness and exercise.

![Graph showing average grades and standard deviations for weight gain cases.]

Figure 73: Average rating, and standard deviation, of CI and exercise recommendations for weight gain cases

Weight Maintenance Cases

As previously described in Section 7.4.2.1, in the case of weight maintenance we adopt the approach of recommending a single CI equal to the TEE. Experts were provided with
only one option, thus there is no need for maximum and average analysis. We also provide the experts with five different weight maintenance cases. As shown in Figure 74, human expert testers provided satisfying ratings, indicating PIN’s ability of recommending proper CI’s for weight maintenance.

![Figure 74: Average rating, and standard deviation, of CI and exercise recommendations for weight maintenance cases](image)

### 7.4.2.3. Discussion

We notice PIN’s ability of producing CI and exercise recommendations that are very similar to human expert recommendations. The recommendations were also approved by the experts as reflected by their ratings discussed in the previous section. We highlight the fact the exercise recommendations should be included in weight gain and weight maintenance recommendations in future works.
7.4.3. PERA Agent Recommendations Evaluation

7.4.3.1. Progress Classification Results

PIN’s PERA agent, as presented in Section 6.4, is responsible for evaluating the progress of the patient, based on the (i) current BFP, (ii) expected reached BFP and (iii) reached BFP. After evaluating and classifying the progress (as slow, moderate or good), the agent adjusts the CI/exercise recommendations in case of slow or moderate progress accordingly.

In this experiment, we assess patient progress evaluation based on different scenarios of different progress percentage. As previously explained in 7.2.3.1, we select different progress percentages (20%, 40%, 50% and 75%). This experiment, helped define the classification for progress and the fuzzy memberships presented respectively in Table 32 and Figure 47.

We present in Figure 75 and Figure 76 the inter-tester agreement (in terms of similarity) and PIN-tester similarity respectively. Based on the progress classification adopted in our design, results show that PIN-expert classification similarity scores are very close, and in fact slightly higher, that the inter-tester classification similarities, which means that PIN shows once again that it can be on a par with (and can even surpass) human nutrition experts in its recommendations.
Figure 75: Inter-tester average similarity, and standard deviation, for progress classification.

Figure 76: PIN-tester average similarity, and standard deviation for patient progress classification.
7.4.3.2. Recommendation Accuracy Results

As previously explained, we distinguish between two scenarios: (i) slow progress and (ii) moderate progress. We first present the inter-tester similarity for the adjusted recommendations and the PIN-tester similarities, for both scenarios.

In this experiment, human expert testers provided a single recommendation for each scenario in each case. On the other hand, PIN provides one or two recommendations for moderate progress cases and only one adjusted recommendation for slow progress. Thus, in the slow progress case we have a single couple of values to compare. While in the moderate progress scenario, one or two couples might be compared per case, thus we adopt maximum analysis in the case of moderate progress.

![Figure 77: Average inter-tester similarity, and standard deviation, for adjust CI recommendations](image-url)
By observing Figure 77 and Figure 78, we notice that the PIN-tester agreement (in terms of similarity) and standard deviation results are almost identical to inter-tester results, which means that PIN’s adjusted recommendations for both slow progress and moderate progress cases are very similar to human expert recommendations.

7.4.3.3. Recommendation Correctness Results

In addition to the above results, we asked the expert testers to evaluate the correctness of PIN’s recommendations by rating them from 1 (strongly disagree) to 5 (strongly agree). Figure 79 and Figure 80 show results for both maximum rating analysis and average rating analysis. As previously discussed we distinguish two scenarios, slow progress and moderate progress. For slow progress, PIN provides only one option, while for moderate progress, PIN provides two or three options, this is due to the nature of the designed fuzzy agent, where based on the condition-action rules, in the case of moderate progress a patient will be provided of more options, in contrast to slow progress where both CI decrease and exercise increase will be required. Therefore, in the case of moderate
progress we apply both maximum and average analysis similarly to the previous experiments.

**Figure 79:** Average rating per case for CI and exercise readjustment in case of slow progress

**Figure 80:** Average rating per case for CI and exercise readjustment in case of slow progress

178
As observed in Figure 79, for slow progress, we notice a minimum expert rating of 3.5 with a standard deviation of 1.12 (case 2), and a maximum rating of 4.75 with a standard deviation of 0.43 (case 10). The average rating for all cases combined is 4.20 with a standard deviation of 0.68. Which signifies a high, and agreed upon human expert approval of PIN’s adjusted CI/exercise recommendations in the case of slow progress.

In the case of moderate progress, by referring to Figure 80, based on average analysis, the minimum expert rating is 3.33 with a standard deviation of 0.41 (case 1), while in the case of maximum analysis the minimum expert rating on average is 4.0 with standard deviation 0.71 (case 6). We notice average ratings of 4.5 (0.48 std. dev) and 4.04 (0.54 std. dev) based on maximum and average analysis respectively. Similar to slow progress, results show a high and agreed upon expert approval of PIN’s adjusted CI/exercise recommendations in the case of moderate progress.

The ratings demonstrate satisfying results, both on a case by case basis and on average.

7.4.3.4. Discussion
Results clearly show that PIN-tester similarity results are on a par with inter-tester similarity results, highlighting (yet again) that PIN’s recommendations are in strong agreement with those of testers, where PIN can pass for another expert. In addition, the satisfying ratings provided by the expert testers demonstrate PIN’s ability in adjusting the recommendation for a patient that is facing issues reaching his target.

7.4.4. MPG Agent Meal Plans Evaluation
7.4.4.1. Meal Plan Quality
In this experiment we provide the experts with sets of produced meal plans and we require the experts to grade the meal plans based on different criteria (meal-food compatibility, inter-food compatibility, daily diversity and overall diversity) presented in Section 7.2.4.1.

We present the experts with two sets of plans: set A, consisting of basic foods (e.g., milk, white bread, apples, etc.) and set B including basic and composite foods (e.g., noodles, lasagna, etc.). Each set consists of four three-day meal plans corresponding to each of the
following CI: 1200, 1600, 2000, 2400 Kcals. The experts rated the meal plans for each of the three days based on the different defined criteria. A meal plan rating score for a chosen criterion consists of the experts’ ratings averaged over the three days covered by the plan. Figure 81 and Figure 82 show meal plan ratings’ averaged over all four expert testers, along with their standard deviation for sets A and B.

*Figure 81: Average meal plan ratings, and standard deviation, per CI for Set A*
For both sets, PIN performs best in terms of meal-food compatibility, daily food diversity and meal plan diversity. The average rating scores for set A fall between 3.5 and 3.9. Figure 82 shows a slight drop in the ratings (of almost 6.2 %), wrt. to all factors (criteria), when considering composite foods, expect for variety which remained the same. We also notice higher standard deviations in set B, highlighting a wider variety of opinions among testers when composite foods are considered).

As shown in Figure 81 and Figure 82, both when considering or not considering composite foods the inter-food compatibility criterion receives the lowest rating among all criteria (3.54 and 3.06 for sets A and B respectively). The inner food compatibility KB (knowledge base) was constructed with the help of two experts (different from the four experts who evaluated the mean plans). Yet subjectivity comes into play when matching food items, and testers might have different points of view on this point. A possible approach is to allow testers to define their personal matching of foods instead of adopting the predefined food compatibility KB.
In addition, the overall meal plan diversity can be improved by expending the database and including more food items in the future. The addition of food items to the database reduces the probability of repetitive foods items from day to day.

7.4.4.2. Patient Preferences and Variation

In this experiment, we involved five non-expert participants by asking them to set their food preferences. Then, using PIN’s MPG agent, we generated a three-day meal plan based on the required CI of each tester. Consequently, we asked each tester to rate every meal of the generated daily meal plan considering two criteria: (i) meeting the testers’ preferences, and (ii) including food variation (non-repetitiveness) as well as overall meal plan variation. The rating of the meal plan for each criteria is the averaged over three days. The average ratings of all five meal plans for each criterion is then computed. The average meal plan ratings and standard deviation results are shown Figure 83.

![Figure 83: Meal plan non-experts average ratings and standard deviation](image)

Recall that food/meal plan variation is different from food/meal plan diversity, where diversity underlines the combination of different foods (meals) in a single meal (meal plan) whereas variation underlines the occurrence of different foods (meals) in different consecutive meals (meal plans).
Results show a slightly lower rating of the overall variation criterion (3.8) when compared to the other criteria (4.7 and 4.47). As previously described, extending PIN’s food database is likely to improve the overall diversity, as well as the overall variation by adding more possible food options.

7.4.4.3. Cost Function Weights Variation

We evaluate the effect of varying the weight factors of the cost function (31), using the self-evaluation functions defined in Section 6.7. In order to do so, for every different weight combination, we generate 40 sets of meal plans, 10 for each one of adopted CI values (1200, 1600, 2000 and 2400 Kcals). We define the following weight combinations:

i. Set 1: \( w_1 = w_2 = w_3 = w_4 = w_5 = 0.2 \). Where all weights are equal.

ii. Set 2: \( w_1 = w_2 = w_3 = w_4 = 0.25 \), \( w_5 = 0 \). Where all weights are equal, except for the price, since the price is not a healthy factor usually considered by human in the meal planning process.

iii. Set 3: \( w_1 = 0.6 \), \( w_2 = w_3 = w_4 = w_5 = 0.1 \). To emphasis meal-food compatibility.

iv. Set 4: \( w_4 = 0.6 \), \( w_1 = w_2 = w_3 = w_5 = 0.1 \). To emphasis inter-food compatibility.

v. Set 5 \( w_2 = 0.6 \), \( w_1 = w_3 = w_4 = w_5 = 0.1 \). To emphasis preferences.

vi. Set 6: \( w_3 = 0.6 \), \( w_1 = w_2 = w_4 = w_5 = 0.1 \). To emphasis occurrence (which primarily impacts daily diversity and variation).

We compute the average score for each self-evaluation function. In addition, we randomize food preferences in order to have in each food category foods with all possible preferences: hate, dislike, neutral, like and love. The complete average results of this experiment are presented in Appendix F. We present a summary of our findings in Figure 84.

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6 The cost function (31) depends on five variables: \( w_1, w_2, w_3, w_4, w_5 \) which represent weight factors for: meal-food compatibility, preferences, occurrence, inner-food compatibility and price respectively.
Results in Figure 84, highlight the following observations:

i. When increasing one of the weights to 0.6 (or above, i.e. sets 3-6) and minimizing all other weight factors to 0.1 (or below), the self-evaluation function related to the weight factor in question produces high average scores while other functions produces low scores.

ii. When setting all weight factors to 0.2 (Set 2), we observe the following results on average: 0.56, 0.04, 0.72 and 0.16 for meal-food compatibility, preference, inner-food compatibility, and price respectively. This signifies that a fully balanced weight distribution does not guarantee good scores.
iii. As previously discussed in our expert and patient experiment we set the price factor to 0 and all other factors to 0.25. When the latter weight factor distribution is adopted (Set 2), we observe the following results: 0.7, 0.11, 0.71, and 0.02 for meal-food compatibility, preference, inner-food compatibility, and price respectively. We notice that by removing the price constraint, meal-food compatibility improves. By observing the produced meal plans, we also notice improved variety when disregarding the price factor. We realize that adding a price constraint might lead to dismissing some of the more expensive foods such as beef and exotic fruits, which are selected less often.

iv. We notice a low preference self-evaluation score, even though the patient preference experience yielded a score of 4.07 over 5 when evaluating if the meal plans meet the requirements. This is because the evaluation function evaluates the difference between the generated meal plan versus the ideal meal plan that only emphasizes meeting preferences where all the patient’s favorite foods are required to be included in every meal of each daily meal plan (following the food preference factor). On the other hand, from the point of view of a patient, the preference requirement is met if some of the patient’s preferred foods are included in the meal plan, without requiring including all of her favorite food.

The meal plan evaluation experiments presented above demonstrate PIN’s ability of producing healthy, personalized, and feasible meal plans that fit the preferences of the patient or patient.

7.4.5. Discussion

Results, in terms of BFP and weight recommendations, recommendation adjustments, exercise recommendations, as well as meal planning highlight PIN’s result quality, where its different modules produce results which are on a par (and sometimes even surpass) those of human experts. This being said, PIN can be further improved to better handle certain aspects. We present the potential areas of improvements in our conclusion.
Chapter 8

Conclusion and Future Works

In this research project, we design, implement, and evaluate a novel framework titled PIN: a computerized solution for Personalized Intelligent Nutrition recommendations. PIN consist of four main modules allowing four essential complementary functionalities: (i) WAR module allowing weight assessment and recommendation, (ii) CIER module for CI and exercise recommendation, (iii) PERA module for progress evaluation and recommendation adjustment and (iv) MPG module for personalized meal plan generation and adaptation following patient chosen parameters (e.g., food preference, food compatibility, price, etc.). While most existing solutions focus solely on the meal plan generation task, PIN provides the first full-fledged solution for nutrition health assessment, which results are required to run the meal planning task. PIN relies on the fuzzy logic paradigm to simulate human expert health assessment and reasoning in order to perform: (i) weight/BFP recommendations, (ii) CI/exercise recommendations, (iii) progress evaluation and CI/exercise recommendations adjustment. PIN also provides a novel contribution in meal planning, introducing an adaptation of the transportation optimization problem to dynamically generate, change, adapt, and self-evaluate meal plans following the patient’s needs, compared with most existing meal planning solutions which fail to integrate all the different essential factors (meal-food compatibility, inner-food compatibility, preferences, diversity and variety) while producing meal plans.

The framework was implemented as a web application using: (i) the Java Spring Framework on the server side to implement the decision making logic, and (ii) Angular 6 on the application side to provide a light weight and multi-platform accessible front-end. We ran a large battery of experiments, involving 50 patient profiles, 11 nutrition expert evaluators, and 5 non-expert testers, to evaluate PIN’s quality. Empirical results led to very interesting observations, mainly:
i. PIN produced BFP, weight, CI, adjustment, and exercise recommendations which are on a par with (and sometimes surpass those of) human experts.

ii. PIN produced dynamic meal plans to fulfill the patient’s nutrition needs while catering to their preferences, where meal plan quality matches (and sometime surpasses) the quality of meal plans produced by expert nutritionists.

Despite its quality and promising results, yet several PIN improvements lay ahead in the near future:

i. Including exercise recommendations even for weight gain and weight maintenance cases, where the level of activity of the patient is too low, and accounting for the additional exercise by increasing the CI.

ii. Integrating an exercise planning mechanism that incorporates and schedules multiple exercise types based on the (i) time availability of the patient and (ii) patient preference towards specific exercises.

iii. Expanding our food KB to group simple food items under dishes, i.e., grouping together simple foods that can be incorporated to prepare a single dish in the same meal, and suggesting the dish (alongside the content foods), rather than recommending separate foods.

iv. Providing an improved servings assignment mechanism to better handle the integration of composite foods and their combination with basic foods, rather than fixing the servings from each category corresponding to every meal before solving the transportation matrix.

v. Extending the meal planning cost function to include potential factors such as: (i) region specific foods, (ii) season specific foods, (iii) preparation time.

Other issues and aspects can also be investigated on the long run, mainly:

i. Optimizing the selection of the weight factors in the meal planning cost function, using auto-calibration and optimization techniques, e.g., [76][77][78], allowing to choose the different parameter values in order to adapt the generated meal plans to the nutrition health needs and preferences of the target patients.
ii. In our food KB, the *inner-food* and *meal-food* compatibility are manually defined by nutrition experts. This could result in subjective and maybe incomplete KBs, following the experts’ judgements. A future direction is to give the expert the capability to define the model, and then allow PIN to build it (semi)automatically by mining large meal plan corpora. The main challenge in this regard would be to identify reliable meal plan corpora which could be hard to come by.

iii. Applying a learning mechanism that adjusts the cost function weights and the various costs of foods based on the patient’s own selections, adjustments, and choices of foods and meal plans over time.
Bibliography


Appendices
Appendix A

Body Fat Percentage Classification

The body fat percentage as suggested by the American college of Sports Medicine [16] for males and females:

*Table 51: Body fat percentage for males by ACSM*

<table>
<thead>
<tr>
<th>Age</th>
<th>Classification</th>
<th>20-29</th>
<th>30-39</th>
<th>40-49</th>
<th>50-59</th>
<th>60-69</th>
<th>70-79</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Lean</td>
<td></td>
<td>4.2-6.3</td>
<td>7.0-9.9</td>
<td>9.2-12.8</td>
<td>10.9-14.4</td>
<td>11.5-15.5</td>
<td>13.6-15.2</td>
</tr>
<tr>
<td>Excellent</td>
<td></td>
<td>7.9-10.5</td>
<td>11.9-14.5</td>
<td>14.9-17.4</td>
<td>16.7-19.1</td>
<td>17.6-19.7</td>
<td>17.8-20.4</td>
</tr>
<tr>
<td>Good</td>
<td></td>
<td>11.5-14.8</td>
<td>15.5-18.2</td>
<td>18.2-20.6</td>
<td>19.9-22.1</td>
<td>20.6-22.6</td>
<td>21.1-23.1</td>
</tr>
<tr>
<td>Fair</td>
<td></td>
<td>15.8-18.6</td>
<td>19.0-21.3</td>
<td>21.3-23.4</td>
<td>22.7-24.6</td>
<td>23.2-25.2</td>
<td>23.7-24.8</td>
</tr>
<tr>
<td>Poor</td>
<td></td>
<td>19.6-23.1</td>
<td>22.1-24.9</td>
<td>24.1-26.6</td>
<td>25.3-27.8</td>
<td>26.0-28.4</td>
<td>25.4-27.6</td>
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<tr>
<td>Very Poor</td>
<td></td>
<td>24.6-33.3</td>
<td>26.2-34.3</td>
<td>27.7-35.0</td>
<td>28.9-36.4</td>
<td>29.4-36.8</td>
<td>28.9-35.5</td>
</tr>
</tbody>
</table>

*Table 52: Body fat percentage for females by ACSM*

<table>
<thead>
<tr>
<th>Age</th>
<th>Classification</th>
<th>20-29</th>
<th>30-39</th>
<th>40-49</th>
<th>50-59</th>
<th>60-69</th>
<th>70-79</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Lean</td>
<td></td>
<td>9.8-13.6</td>
<td>11.0-14.0</td>
<td>12.6-15.6</td>
<td>14.6-17.2</td>
<td>13.9-17.7</td>
<td>14.6-16.6</td>
</tr>
<tr>
<td>Excellent</td>
<td></td>
<td>14.8-16.5</td>
<td>15.6-17.4</td>
<td>17.2-19.8</td>
<td>19.4-22.5</td>
<td>19.8-23.2</td>
<td>20.3-24.0</td>
</tr>
<tr>
<td>Good</td>
<td></td>
<td>17.3-19.4</td>
<td>18.2-20.8</td>
<td>20.8-23.8</td>
<td>23.8-27.0</td>
<td>24.8-27.9</td>
<td>25.0-28.6</td>
</tr>
<tr>
<td>Fair</td>
<td></td>
<td>20.1-22.7</td>
<td>21.7-24.6</td>
<td>24.8-27.6</td>
<td>27.9-30.4</td>
<td>28.7-31.3</td>
<td>29.7-31.8</td>
</tr>
<tr>
<td>Poor</td>
<td></td>
<td>23.6-27.1</td>
<td>25.6-29.1</td>
<td>28.5-31.9</td>
<td>31.4-34.5</td>
<td>32.5-35.4</td>
<td>32.7-36.0</td>
</tr>
<tr>
<td>Very Poor</td>
<td></td>
<td>28.9-38.9</td>
<td>30.9-39.4</td>
<td>33.5-39.8</td>
<td>35.6-40.4</td>
<td>36.0-40.8</td>
<td>37.4-40.5</td>
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</table>
## Appendix B

### Ideal Body Weight Formulas

*Table 53: Ideal body weight formulas*

<table>
<thead>
<tr>
<th>Formula</th>
<th>Year</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>G. J. Hamwi Formula</td>
<td>1964</td>
<td>48.0 kg + 2.7 kg per inch over 5 feet</td>
<td>45.5 kg + 2.2 kg per inch over 5 feet</td>
</tr>
<tr>
<td>B. J. Devine Formula</td>
<td>1974</td>
<td>50.0 + 2.3 kg per inch over 5 feet</td>
<td>45.5 + 2.3 kg per inch over 5 feet</td>
</tr>
<tr>
<td>J. D. Robinson Formula</td>
<td>1983</td>
<td>52 kg + 1.9 kg per inch over 5 feet</td>
<td>49 kg + 1.7 kg per inch over 5 feet</td>
</tr>
<tr>
<td>D. R. Miller Formula</td>
<td>1983</td>
<td>56.2 kg + 1.41 kg per inch over 5 feet</td>
<td>53.1 kg + 1.36 kg per inch over 5 feet</td>
</tr>
</tbody>
</table>
Appendix C
BMI and Body Fat Percentage Fuzzy Sets

Figure 85: BMI fuzzy sets

Figure 86: BPF fuzzy sets for males between 20 and 29
Figure 87: BPF fuzzy sets for males between 30 and 39

Figure 88: BFP fuzzy sets for males between 40 and 49
Figure 89: BFP fuzzy sets for males between 50 and 59
Figure 90: BFP sets for males between 60 and 69

Figure 91: BFP sets for males between 70 and 79
Figure 92: BFP fuzzy sets for females between 20 and 29

Figure 93: BFP fuzzy sets for females between 30 and 39
Figure 94: BFP fuzzy sets for females between 40 and 49

Figure 95: BFP fuzzy sets for females between 50 and 59
Figure 96: BFP fuzzy sets for females between 60 and 69

Figure 97: BFP fuzzy sets for females between 70 and 79
## Appendix D

### Sample Meal Plan

*Table 54: Sample meal plan for 2107 CI*

<table>
<thead>
<tr>
<th>Day 1</th>
<th>Calories: 2107</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meal</td>
<td>Food Compatibility : 0.9</td>
</tr>
<tr>
<td></td>
<td>Preference: 1.0</td>
</tr>
<tr>
<td></td>
<td>Inter Food Compatibility: 0.83</td>
</tr>
<tr>
<td></td>
<td>Price: 0.59</td>
</tr>
</tbody>
</table>

### Breakfast
- Bread, whole grain, Serving size: 1 slice (28 grams), Serving Amount: 2
- Oil: canola, olive, Serving size: 1 tea spoon, Serving Amount: 1
- Cottage cheese, Serving size: 1/4 cup, Serving Amount: 2
- Peanuts, Serving size: 10 nuts, Serving Amount: 1
- Carrot, Serving size: One piece (60 grams), Serving Amount: 1
- Milk, Serving size: 1 cup, Serving Amount: 1

### Snack One
- Jam, Serving size: 1 tablespoon, Serving Amount: 1
- Biscuit, Serving size: 1 piece, Serving Amount: 1
- Peanut Butter, Serving size: 1/2 tablespoon, Serving Amount: 1

### Lunch
- Green peas, Serving size: 1/2 a cup, Serving Amount: 4
- Carrot, Serving size: One piece (60 grams), Serving Amount: 1
- White rice, cooked, Serving size: 1/3 a cup, Serving Amount: 1
- Oil: canola, olive, Serving size: 1 tea spoon, Serving Amount: 2
- Lamb: chop, leg or roast, Serving size: 28 grams, Serving Amount: 4
- Strawberries, Serving size: 1.25 cup, Serving Amount: 1

### Snack Two
- Blueberries, Serving size: 3/4 cup, Serving Amount: 1
- Rice cake, Serving size: 2 pieces, Serving Amount: 2
- Biscuit, Serving size: 1 piece, Serving Amount: 1

### Dinner
- White rice, cooked, Serving size: 1/3 a cup, Serving Amount: 2
- Lamb: chop, leg or roast, Serving size: 28 grams, Serving Amount: 3
- Olives, Serving size: 8 pieces, Serving Amount: 1
- Carrot, Serving size: One piece (60 grams), Serving Amount: 1
Appendix E
Case by Case Similarity of BFP & Weight Recommendations for
Males and Females

Figure 98: BFP recommendation case by case average similarity for males
Figure 99: BFP recommendation case by case average similarity for females

Figure 100: Weight recommendation case by case average similarity for males
Figure 101: Weight recommendation case by case average similarity for females
Appendix F

Self-Evaluation Functions Results

\[ C_{Total} = w_1 \times c_1 + w_2 \times c_2 + w_3 \times c_3 + w_4 \times c_4 + w_5 \times c_5 \]

Where \( c_i \) is the cost associated with each of the five following factors respectively:

i. meal-food compatibility (1)
ii. food preferences (2)
iii. food occurrence (3)
iv. inter-food compatibility (4)
v. food price (5)

Set 1

*Table 55: Set 1 weights combination*

<table>
<thead>
<tr>
<th></th>
<th>w1</th>
<th>w2</th>
<th>w3</th>
<th>w4</th>
<th>w5</th>
</tr>
</thead>
<tbody>
<tr>
<td>w1</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

*Table 56: Set 1 self-evaluation results*

<table>
<thead>
<tr>
<th>CI</th>
<th>Meal Food Compatibility Score</th>
<th>Food Preference Score</th>
<th>Inter Food Compatibility Score</th>
<th>Price Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average 1200</td>
<td>0.52</td>
<td>0.00</td>
<td>0.85</td>
<td>0.16</td>
</tr>
<tr>
<td>Average 1600</td>
<td>0.50</td>
<td>0.00</td>
<td>0.69</td>
<td>0.09</td>
</tr>
<tr>
<td>Average 2000</td>
<td>0.48</td>
<td>0.04</td>
<td>0.66</td>
<td>0.19</td>
</tr>
<tr>
<td>Average 2400</td>
<td>0.74</td>
<td>0.13</td>
<td>0.68</td>
<td>0.19</td>
</tr>
<tr>
<td>Average</td>
<td>0.56</td>
<td>0.04</td>
<td>0.72</td>
<td>0.16</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.30</td>
<td>0.12</td>
<td>0.20</td>
<td>0.16</td>
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</table>
Set 2

Table 57: Set 2 weights combination

<table>
<thead>
<tr>
<th>$w_1$</th>
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<th>$w_3$</th>
<th>$w_4$</th>
<th>$w_5$</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
<td>0</td>
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</table>

Table 58: Set 2 self-evaluation results

<table>
<thead>
<tr>
<th>CI</th>
<th>Meal Food Compatibility Score</th>
<th>Food Preference Score</th>
<th>Inter Food Compatibility Score</th>
<th>Price Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average 1200</td>
<td>0.61</td>
<td>0.01</td>
<td>0.71</td>
<td>0.02</td>
</tr>
<tr>
<td>Average 1600</td>
<td>0.69</td>
<td>0.00</td>
<td>0.73</td>
<td>0.01</td>
</tr>
<tr>
<td>Average 2000</td>
<td>0.67</td>
<td>0.06</td>
<td>0.77</td>
<td>0.00</td>
</tr>
<tr>
<td>Average 2400</td>
<td>0.81</td>
<td>0.37</td>
<td>0.64</td>
<td>0.05</td>
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<tr>
<td>Average</td>
<td>0.70</td>
<td>0.11</td>
<td>0.71</td>
<td>0.02</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.22</td>
<td>0.27</td>
<td>0.23</td>
<td>0.06</td>
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</table>
Set 3

Table 59: Set 3 weights combination

<table>
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<tr>
<th>w1</th>
<th>w2</th>
<th>w3</th>
<th>w4</th>
<th>w5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
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</table>

Table 60: Set 3 self-evaluation results

<table>
<thead>
<tr>
<th>CI</th>
<th>Meal Food Compatibility Score</th>
<th>Food Preference Score</th>
<th>Inter Food Compatibility Score</th>
<th>Price Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average 1200</td>
<td>0.95</td>
<td>0.00</td>
<td>0.69</td>
<td>0.04</td>
</tr>
<tr>
<td>Average 1600</td>
<td>0.96</td>
<td>0.00</td>
<td>0.65</td>
<td>0.01</td>
</tr>
<tr>
<td>Average 2000</td>
<td>0.99</td>
<td>0.00</td>
<td>0.70</td>
<td>0.08</td>
</tr>
<tr>
<td>Average 2400</td>
<td>0.96</td>
<td>0.01</td>
<td>0.63</td>
<td>0.12</td>
</tr>
<tr>
<td>Average</td>
<td>0.96</td>
<td>0.00</td>
<td>0.67</td>
<td>0.06</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.08</td>
<td>0.02</td>
<td>0.20</td>
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</table>
Set 4

Table 61: Set 4 weights combination

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<th>w_2</th>
<th>w_3</th>
<th>w_4</th>
<th>w_5</th>
</tr>
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<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.6</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Table 62: Set 4 self-evaluation results

<table>
<thead>
<tr>
<th>CI</th>
<th>Meal Food Compatibility Score</th>
<th>Food Preference Score</th>
<th>Inter Food Compatibility Score</th>
<th>Price Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average 1200</td>
<td>0.45</td>
<td>0.00</td>
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<td>0.16</td>
</tr>
<tr>
<td>Average 1600</td>
<td>0.41</td>
<td>0.00</td>
<td>0.90</td>
<td>0.12</td>
</tr>
<tr>
<td>Average 2000</td>
<td>0.54</td>
<td>0.01</td>
<td>0.87</td>
<td>0.20</td>
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<tr>
<td>Average 2400</td>
<td>0.66</td>
<td>0.03</td>
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</tr>
<tr>
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<td>0.51</td>
<td>0.01</td>
<td>0.87</td>
<td>0.17</td>
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<td>0.35</td>
<td>0.04</td>
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</table>
Set 5

Table 63: Set 5 weights combination

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<tr>
<th>W_1</th>
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<th>W_3</th>
<th>W_4</th>
<th>W_5</th>
</tr>
</thead>
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<td>0.1</td>
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</tbody>
</table>

Table 64: Set 5 self-evaluation results

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<th>Food Preference Score</th>
<th>Inter Food Compatibility Score</th>
<th>Price Score</th>
</tr>
</thead>
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<tr>
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<td>0.14</td>
<td>0.78</td>
<td>0.48</td>
<td>0.00</td>
</tr>
<tr>
<td>Average 1600</td>
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<td>0.00</td>
</tr>
<tr>
<td>Average 2000</td>
<td>0.03</td>
<td>0.86</td>
<td>0.74</td>
<td>0.00</td>
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<tr>
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<td>0.54</td>
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<tr>
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<td>0.82</td>
<td>0.58</td>
<td>0.00</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.20</td>
<td>0.20</td>
<td>0.17</td>
<td>0.01</td>
</tr>
</tbody>
</table>
### Set 6

#### Table 65: Set 6 weights combination

<table>
<thead>
<tr>
<th>(w_1)</th>
<th>(w_2)</th>
<th>(w_3)</th>
<th>(w_4)</th>
<th>(w_5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.1</td>
<td>0.6</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

#### Table 66: Set 6 self-evaluation results

<table>
<thead>
<tr>
<th>CI</th>
<th>Meal Food Compatibility Score</th>
<th>Food Preference Score</th>
<th>Inter Food Compatibility Score</th>
<th>Price Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average 1200</td>
<td>0.27</td>
<td>0.00</td>
<td>0.71</td>
<td>0.10</td>
</tr>
<tr>
<td>Average 1600</td>
<td>0.21</td>
<td>0.13</td>
<td>0.57</td>
<td>0.07</td>
</tr>
<tr>
<td>Average 2000</td>
<td>0.21</td>
<td>0.00</td>
<td>0.60</td>
<td>0.12</td>
</tr>
<tr>
<td>Average 2400</td>
<td>0.35</td>
<td>0.03</td>
<td>0.54</td>
<td>0.12</td>
</tr>
<tr>
<td>Average</td>
<td>0.26</td>
<td>0.04</td>
<td>0.60</td>
<td>0.10</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.27</td>
<td>0.13</td>
<td>0.19</td>
<td>0.12</td>
</tr>
</tbody>
</table>