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Fuzzy Soft Sets and Decision Making in Ideal Nutrition

Abdelfattah A. El-Atik [1], Radwan Abu-Gdairi [2], Arafa A. Nasef [3], Saeid Jafari [4] and Mohammed Badr [5,*]

[1] Department of Mathematics, Faculty of Science, Tanta University, Tanta 31511, Egypt; aelatik@science.tanta.edu.eg
[2] Department of Mathematics, Faculty of Science, Zarqa University, Zarqa 13133, Jordan; rgdairi@zu.edu.jo
[3] Department of Physics and Engineering Mathematics, Faculty of Engineering, Kafrelsheikh University, Kafrelsheikh 33516, Egypt
[4] Mathematical and Physical Science Foundation, 4200 Slagelse, Denmark; jafaripersia@gmail.com
[5] Department of Mathematics, Faculty of Science, New Valley University, New Valley 72713, Egypt
* Correspondence: m.shaban@sci.nvu.edu.eg

Abstract: Issues in daily life, where making the best decisions is crucial, are frequently encountered. But, in the majority of these situations, the best course of action is uncertain. We must take into account a number of parameters in order to find the best possible solution to these difficulties. The best mathematical instrument for this is fuzzy soft set *FSS* theory in decision making. Nutrition is the process of supplying cells and organisms with the nutrients they need to grow and thrive and to sustain life. A healthy diet has the potential to prevent or mitigate numerous prevalent health issues. The purpose of this paper is to select a burning problem for the nutrition of students and successfully apply the *FSS* theory in decision making. We aim to prove that the approach to decision-making problems with imprecise data via *FSS*s is more accurate than other types of approaches, and we present a new approach to the *FSS* model and its applications in decision-making problems.

Keywords: soft set; fuzzy soft set; information system; rough set; decision making

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1. Introduction and Preliminaries

The attainment of a healthy body and maintenance of a sound physique are contingent upon the presence of a healthy nutrition and diet. People in good physical and mental health are physically and mentally active, including their stamina, body, and mental and physical activity levels. They are resilient, full of vim and vitality, and have a pleasant disposition to boot. They are strong, vivacious, and endowed with an excellent nature. There are six primary categories of nutrients, which include carbs (Cs), fats, minerals (Ms), proteins (Ps), and vitamins (Vs), with water being one of the most important of these. Each nutrient is responsible for one or more of the general functions that are listed below. Vitamin C and lipids are sources of heat, energy, and power. P, M, and V are responsible for the construction and promotion of growth, the renewal of body tissues, and the regulation of body processes. The recommended dietary allowances for each day are broken down into the following fundamental food groups, which are reflected in Table 1 and the food pyramid, which both contain representations of the basic food groups that are used to categorize the recommended daily dietary allowances [1]. These classifications are made for the purpose of making the recommended daily dietary allowances more easily applicable.

Several contemporary theories have been proposed to address the challenges associated with imprecise data, including probability theory, fuzzy sets, intuitionistic fuzzy sets, and rough sets, among others.

Table 1. Basic food groups.

Group	Food Stuff	Main Nutrient Constitution
1	Vegetables and fruits	V, C and M
2	Milk and milk products	C, P and fats
3	Meat, poultry and fish	P and fats
4	Pulses and cereals	C, P and M
5	Oil, ghee and butter	P and fats

Molodtsov [2] showed that each of the above topics has some built-in limitations, for which they do not have a parametrization tool. He also presented a soft set theory with parametrization tools that can be used to deal with a wide range of uncertainties. This fuzzification of soft set theory has seen significant contributions from researchers in the last few years. After that, Maji et al. [3] extended the soft set theory of Molodtsov and introduced FSSs in decision-making problems. The first real-world use of soft sets in problem solving came from Maji et al. [4,5]. They presented and developed the FSS, a notion that combines fuzzy and soft sets and is more widely applicable. Furthermore, Chaudhuriet et al. [6] deployed a few applications of FSSs with the help of the method in [4,5] and compared them with the probability distribution. Also, Çağman et al. [7] developed the case study of the decision-making approach using the fuzzy parametrized FSSs aggregation operator. In 2011, Neog et al. [8] used fuzzy soft matrices, a fuzzy soft complement and a fuzzy matrix operation to solve a decision-making problem.

The objective of this study is to utilize FSSs in a multi-observer multi-criteria decision-making problem as a means of enhancing the approach proposed in [1,9,10]. This paper presents an overview of the fundamental findings regarding soft sets and FSSs stated in [11–14]. In recent years, there have been many applications for soft sets, general topology, and their related topics with applications [15–17]. Moreover, Nasef et al. [18,19] presented some applications of soft sets in decision-making problems.

To solve the reduction issue, Kong et al. [20] defined and developed the heuristic technique for normal parameter reductions (NPRs) in FSS. The NPR soft set algorithm, as proposed in [20], was complex to grasp, required numerous computations, and depended on the dispensability. To lessen its computational complexity, this approach was further investigated by several authors; see [21–24]. A proximity normal parameter reduction (PNPR) of the FSS was proposed by Kong et al. in [25]. Using three-way decision criteria, Khameneh and Kilicman [26] presented an adaptable method for parameterizing FSS. In order to address the issue of FSS parameter reduction based on the score criteria, Kong et al. [27] developed a brand-new NPR method. A distance-based parameter reduction (DBPR) approach for FSS was introduced by Ma and Qin [28]. Its use in decision-making issues was covered, and a problem arose with it because similarity and reduction are different and cannot depend on each other. For more information about the prarametrization reduction in FSS, see [29–34]. Most reduction methods depend on one function.

Throughout this paper, the issue of decision making in the presence of imprecise data holds particular importance when addressing real-life problems. In this example, a multi-observer, multi-criteria decision-making issue is addressed by employing the notion of FSS, which always come equipped with parametrization tools. Also, we give some applications using soft sets and FSSs. By the given results, we prove that the approach to decision-making problems with imprecise data via FSSs is more accurate than other approaches.

Let U_1 be a initial universe set, S be a set of parameters of attributes with respect to U_1, and $P(U_1)$ denote the power set of U_1.

Definition 1 ([2])**.** *A pair $(\mathfrak{F}, S)$ is called a soft set over U if and only if $\mathfrak{F}$ is a mapping of S into the set of all subsets of U. In other words, a soft set over U is a function from a set of parameters to $P(U)$. We can notice that a soft set is not a set in the usual sense but a parameterized family of subsets of U.*

Definition 2 ([35])**.** *For a set $A_1 \subseteq X_1$, its indicator function μ_{A_1} is defined as*

$$\mu_{A_1}(x_1) = \begin{cases} 1, & \text{if} \quad x_1 \in A_1; \\ 0, & \text{if} \quad x_1 \notin A_1. \end{cases}$$

A fuzzy set $\mathfrak{F}$ is described by its membership function μ_A. For every $x_1 \in X_1$, this function associates a real number $\mu_F(x_1)$ interpreted for the point as a degree of belonging of x_1 to the fuzzy set $\mathfrak{F}$, written as $\mathfrak{F} = \{(x_1, \mu_{A_1}) : x_1 \in X_1\}$.

Definition 3 ([3])**.** *Let $\widetilde{P}(U_1)$ be all fuzzy subsets of U_1. A pair $(\widetilde{F}, S)$ is called FSS over U_1 such that $\widetilde{F}$ is a function given by $\widetilde{F} : S \to \widetilde{P}(U_1)$, where S is a set of parameters.*

Similarly, definitions of FSS, null FSS, intersection and union operations [3] are similar to those defined for crisp soft sets (soft sets) [2].

2. Soft Sets through Pawlak Rough Sets

Molodtsov [2] explored various applications of the soft set theory across multiple domains, including the examination of function smoothness, game theory, operations research, probability, etc. In this part, we demonstrate how the rough technique can be utilized to apply soft set theory to a decision-making problem [36,37]. What we will look at is outlined in the following. The information system with set values is outlined in the table that may be found above, where $U = \{\mathfrak{z}_1, \mathfrak{z}_2, \mathfrak{z}_3, \mathfrak{z}_4, \mathfrak{z}_5, \mathfrak{z}_6\}$ are a set of six students. $\mathfrak{V} = \{\mathfrak{v}_1 =$ Food containing preservatives, $\mathfrak{v}_2 =$ C, $\mathfrak{v}_3 =$ P, $\mathfrak{v}_4 =$ V, $\mathfrak{v}_5 =$ Fat, $\mathfrak{v}_6 =$ M, $\mathfrak{v}_7 =$ Junk food, $\mathfrak{v}_8 =$ Icecream $\}$ is a group of parameters that students can use to visualize the nutrients found in food.

Consider the soft set $(\mathfrak{F}, \mathfrak{V})$, which describes the attractiveness of the students given by $(\mathfrak{F}, \mathfrak{V}) =$ Students consume foods with Foods with added preservatives $= \phi$; Students eat food containing C $= \{\mathfrak{z}_1, \mathfrak{z}_2, \mathfrak{z}_3, \mathfrak{z}_4, \mathfrak{z}_5, \mathfrak{z}_6\}$; Students eat food containing P $= \{\mathfrak{z}_1, \mathfrak{z}_2, \mathfrak{z}_3, \mathfrak{z}_4, \mathfrak{z}_6\}$; Students eat food containing V $= \{\mathfrak{z}_1, \mathfrak{z}_2, \mathfrak{z}_3, \mathfrak{z}_4, \mathfrak{z}_5, \mathfrak{z}_6\}$; Students eat food containing Fat $= \{\mathfrak{z}_1, \mathfrak{z}_3, \mathfrak{z}_6\}$; Students eat food containing M $= \{\mathfrak{z}_1, \mathfrak{z}_2, \mathfrak{z}_6\}$; Students eat Junk food $= \{\mathfrak{z}_2, \mathfrak{z}_4, \mathfrak{z}_5\}$; and Students eat Icecream $= \{\mathfrak{z}_1, \mathfrak{z}_3, \mathfrak{z}_6\}$.

Assume that Mr. X possesses an inclination to procure food items based on specific parameters aligned with his personal preferences $\{\mathfrak{v}_1, \mathfrak{v}_2, \mathfrak{v}_3, \mathfrak{v}_4, \mathfrak{v}_5, \mathfrak{v}_6, \mathfrak{v}_7, \mathfrak{v}_8\}$, which constitute the subset $P = \{\mathfrak{v}_2 = \text{C}, \mathfrak{v}_3 = \text{P}, \mathfrak{v}_4 = \text{V}, \mathfrak{v}_5 = \text{Fat}, \mathfrak{v}_6 = \text{M}\}$ of the set $\mathfrak{V}$. This implies that the individual must choose from the set of available food items, denoted as U, the food item(s) that satisfy all or the highest number of parameters specified by the soft set. The objective is to identify the food item that aligns with the predetermined selection criteria established by Mr. X.

First, let us build a tabular representation of the problem so we can better understand it. Take into consideration the soft set $(\mathfrak{F}, \mathfrak{P})$, where P is the decision parameter of Mr. X (see Table 2 for further information). In this case, $(\mathfrak{F}, \mathfrak{P})$ can be considered a soft subset of $(\mathfrak{F}, \mathfrak{V})$.

Table 2. Food information system.

Students	$\mathfrak{v}_2$	$\mathfrak{v}_3$	$\mathfrak{v}_4$	$\mathfrak{v}_5$	$\mathfrak{v}_6$
$\mathfrak{z}_1$	1	1	1	1	1
$\mathfrak{z}_2$	1	1	1	0	1
$\mathfrak{z}_3$	1	1	1	1	0
$\mathfrak{z}_4$	1	1	1	0	0
$\mathfrak{z}_5$	1	0	1	0	0
$\mathfrak{z}_6$	1	1	1	1	1

Assume that a hypothetical customer, Mr. Y, intends to make a food purchase based on a predefined set of choice parameters $Q \subset \mathfrak{P}$. So $(\mathfrak{F}, Q)$ is a soft subset of $(\mathfrak{F}, \mathfrak{P})$ and called the reduct soft set of the soft set $(\mathfrak{F}, \mathfrak{P})$. The choice value of an object $\mathfrak{z}_i \in U$ is $\mathfrak{p}_i$, where $\mathfrak{p}_i = \Sigma \mathfrak{z}_{ij}$ such that $\mathfrak{z}_{ij}$ is the entries in the table for reducing the soft set as shown in Table 3.

Table 3. Reduct soft set.

Students	$\mathfrak{v}_2$	$\mathfrak{v}_3$	$\mathfrak{v}_5$	$\mathfrak{v}_6$	Choice Value
$\mathfrak{z}_1$	1	1	1	1	$\mathfrak{p}_1 = 4$
$\mathfrak{z}_2$	1	1	0	1	$\mathfrak{p}_2 = 3$
$\mathfrak{z}_3$	1	1	1	0	$\mathfrak{p}_3 = 3$
$\mathfrak{z}_4$	1	1	0	0	$\mathfrak{p}_4 = 2$
$\mathfrak{z}_5$	1	0	0	0	$\mathfrak{p}_5 = 1$
$\mathfrak{z}_6$	1	1	1	1	$\mathfrak{p}_6 = 4$

So, Mr. Y can choose the food of students $\{\mathfrak{z}_1, \mathfrak{z}_6\}$. The theory of a weighted soft set, or W-soft set, was first presented by Lin [36]. The weighted choice value of an object $\mathfrak{z}_i \in U$ is $W_{\mathfrak{p}_i}$ since $W_{\mathfrak{p}_i} = \Sigma d_{ij}$ such that $d_{ij} = w_j \times c_{ij}$. The following Algorithm 1 is for the selection of students.

Algorithm 1 Decision making for food system.

Step 1: Input the soft set $(\mathfrak{F}, \mathfrak{V})$.
Step 2: Enter the set $\mathfrak{P}$ of choice parameter for Mr. X and $\mathfrak{P} \subseteq \mathfrak{V}$.
Step 3: Reduct soft set of $(\mathfrak{F}, \mathfrak{P})$.
Step 4: Choose one reduct soft set $(\mathfrak{F}, Q)$.
Step 5: Get weighted table of the soft set $(\mathfrak{F}, Q)$ according to the weights decided by Mr. Y.
Step 6: Compute k for which $W_{\mathfrak{p}_i} = max \ \ w_{\mathfrak{p}_i}$.

The optional choice object is denoted as "c_k". If there are multiple values for k, Mr. Y has the option to choose any one of them. We attempt to resolve the initial problem by employing a modified algorithm. Assume that the weights for the parameter are determined by Mr. Y as presented in Table 4.

Table 4. Weightage for parameters.

w_2	w_3	w_4	w_5	w_6
0.9	0.8	0.7	0.6	0.5

Using these weights, the reduct soft set can be tabulated as in Table 5.

Table 5. Reduct using weightage.

Students	$w_2 \times \mathfrak{v}_2$	$w_3 \times \mathfrak{v}_3$	$w_5 \times \mathfrak{v}_5$	$w_6 \times \mathfrak{v}_6$	Choice Value ($w_{\mathfrak{p}_i}$)
$\mathfrak{z}_1$	0.9	0.8	0.6	0.5	$\mathfrak{p}_1 = 2.8$
$\mathfrak{z}_2$	0.9	0.8	0	0.5	$\mathfrak{p}_2 = 2.2$
$\mathfrak{z}_3$	0.9	0.8	0.6	0	$\mathfrak{p}_3 = 2.3$
$\mathfrak{z}_4$	0.9	0.8	0	0	$\mathfrak{p}_4 = 1.7$
$\mathfrak{z}_5$	0.9	0	0	0	$\mathfrak{p}_5 = 0.9$
$\mathfrak{z}_6$	0.9	0.8	0.6	0.5	$\mathfrak{p}_6 = 2.8$

Therefore, $max \quad w_{\mathfrak{p}_i} = \{w_{\mathfrak{p}_1}, w_{\mathfrak{p}_6}\}$. The reduct is that Mr. Y chooses the food of students $\mathfrak{z}_1$ and $\mathfrak{z}_6$ among the available food. He seeks counsel from five different counseling agencies $\mathfrak{v}_2, \mathfrak{v}_3, \mathfrak{v}_4, \mathfrak{v}_5, \mathfrak{v}_6$. The five agencies provide the information about food considering parameters C, P, V, Fat and M of the students $\mathfrak{z}_1$,$\mathfrak{z}_2$,$\mathfrak{z}_3$,$\mathfrak{z}_4$, $\mathfrak{z}_5$ and $\mathfrak{z}_6$, respectively.

3. Best Nutrition in Terms of Soft Sets

To address the issues raised above, the following Algorithm 2 is proposed:

Algorithm 2 Decision making for proposed problem.

Step 1: Input the performance evaluation of the similar food for different students as tables.
Step 2: Determine the average value of each relevant entry in each table, and then calculate that average.
Step 3: To obtain the comprehensive decision table, we multiply the weightage of the selection criteria of director (or Mr. Y) to the corresponding entries of each column.
Step 4: Calculate the comparison table.
Step 5: Calculate the column sums and row sums of the comparison table.
Step 6: Obtain the score for every student. The student with maximum score is recommended as the best choice with the best food. So, he has good nutrition.

Suppose Mr. Y is interested in choosing food for students from among the set of students $U = \{\mathfrak{z}_1, \mathfrak{z}_2, \mathfrak{z}_3, \mathfrak{z}_4, \text{and } \mathfrak{z}_5\}$ on the basis of the set $\mathfrak{P} = \{\mathfrak{p}_1$ (C), $\mathfrak{p}_2$ (M), $\mathfrak{p}_3$ (P), $\mathfrak{p}_4$ (fat), $\mathfrak{p}_5$ (Junk food), $\mathfrak{p}_6(V)\}$ of the selection criteria called the parameters, and assume that Mr. Y wants to choose food for pupils based on his personal preference weightage of the selection criterion. Now to obtain the recent the performance evaluation data, we construct the FSSs $(\mathfrak{F}_1, \mathfrak{P})$, $(\mathfrak{F}_2, \mathfrak{P})$, $(\mathfrak{F}_3, \mathfrak{P})$, ($\mathfrak{F}_4$, and $\mathfrak{P}$) over U, where $\mathfrak{F}_1$, $\mathfrak{F}_2$, $\mathfrak{F}_3$, and $\mathfrak{F}_4$ are mappings from $\mathfrak{P}$ into I^U given by four performance evaluation data.
Suppose $\mathfrak{F}_1(\mathfrak{p}_1) = \{(\mathfrak{z}_1, 0.50), (\mathfrak{z}_2, 0.60), (\mathfrak{z}_3, 0.50), (\mathfrak{z}_4, 0.80), (\mathfrak{z}_5, 0.90)\}$,
$\mathfrak{F}_1(\mathfrak{p}_2) = \{(\mathfrak{z}_1, 0.80), (\mathfrak{z}_2, 0.70), (\mathfrak{z}_3, 0.60), (\mathfrak{z}_4, 0.40), (\mathfrak{z}_5, 0.30)\}$,
$\mathfrak{F}_1(\mathfrak{p}_3) = \{(\mathfrak{z}_1, 0.10), (\mathfrak{z}_2, 0.20), (\mathfrak{z}_3, 0.30), (\mathfrak{z}_4, 0.60), (\mathfrak{z}_5, 0.80)\}$,
$\mathfrak{F}_1(\mathfrak{p}_4) = \{(\mathfrak{z}_1, 0.30), (\mathfrak{z}_2, 0.40), (\mathfrak{z}_3, 0.50), (\mathfrak{z}_4, 0.40), (\mathfrak{z}_5, 0.80)\}$,
$\mathfrak{F}_1(\mathfrak{p}_5) = \{(\mathfrak{z}_1, 0.90), (\mathfrak{z}_2, 0.80), (\mathfrak{z}_3, 0.70), (\mathfrak{z}_4, 0.60), (\mathfrak{z}_5, 0.20)\}$,
$\mathfrak{F}_1(\mathfrak{p}_6) = \{(\mathfrak{z}_1, 0.10), (\mathfrak{z}_2, 0.20), (\mathfrak{z}_3, 0.30), (\mathfrak{z}_4, 0.50), (\mathfrak{z}_5, 0.80)\}$,
$\mathfrak{F}_2(\mathfrak{p}_1) = \{(\mathfrak{z}_1, 0.52), (\mathfrak{z}_2, 0.59), (\mathfrak{z}_3, 0.60), (\mathfrak{z}_4, 0.85), (\mathfrak{z}_5, 0.91)\}$,
$\mathfrak{F}_2(\mathfrak{p}_2) = \{(\mathfrak{z}_1, 0.79), (\mathfrak{z}_2, 0.75), (\mathfrak{z}_3, 0.65), (\mathfrak{z}_4, 0.43), (\mathfrak{z}_5, 0.25)\}$,
$\mathfrak{F}_2(\mathfrak{p}_3) = \{(\mathfrak{z}_1, 0.15), (\mathfrak{z}_2, 0.22), (\mathfrak{z}_3, 0.40), (\mathfrak{z}_4, 0.70), (\mathfrak{z}_5, 0.90)\}$,
$\mathfrak{F}_2(\mathfrak{p}_4) = \{(\mathfrak{z}_1, 0.25), (\mathfrak{z}_2, 0.35), (\mathfrak{z}_3, 0.45), (\mathfrak{z}_4, 0.50), (\mathfrak{z}_5, 0.75)\}$,
$\mathfrak{F}_2(\mathfrak{p}_5) = \{(\mathfrak{z}_1, 0.87), (\mathfrak{z}_2, 0.88), (\mathfrak{z}_3, 0.75), (\mathfrak{z}_4, 0.65), (\mathfrak{z}_5, 0.30)\}$,
$\mathfrak{F}_2(\mathfrak{p}_6) = \{(\mathfrak{z}_1, 0.13), (\mathfrak{z}_2, 0.22), (\mathfrak{z}_3, 0.35), (\mathfrak{z}_4, 0.49), (\mathfrak{z}_5, 0.85)\}$,
$\mathfrak{F}_3(\mathfrak{p}_1) = \{(\mathfrak{z}_1, 0.55), (\mathfrak{z}_2, 0.63), (\mathfrak{z}_3, 0.54), (\mathfrak{z}_4, 0.75), (\mathfrak{z}_5, 0.91)\}$,
$\mathfrak{F}_3(\mathfrak{p}_2) = \{(\mathfrak{z}_1, 0.88), (\mathfrak{z}_2, 0.86), (\mathfrak{z}_3, 0.70), (\mathfrak{z}_4, 0.50), (\mathfrak{z}_5, 0.40)\}$,
$\mathfrak{F}_3(\mathfrak{p}_3) = \{(\mathfrak{z}_1, 0.20), (\mathfrak{z}_2, 0.30), (\mathfrak{z}_3, 0.50), (\mathfrak{z}_4, 0.70), (\mathfrak{z}_5, 0.90)\}$,
$\mathfrak{F}_3(\mathfrak{p}_4) = \{(\mathfrak{z}_1, 0.29), (\mathfrak{z}_2, 0.33), (\mathfrak{z}_3, 0.48), (\mathfrak{z}_4, 0.52), (\mathfrak{z}_5, 0.85)\}$,

$\mathfrak{F}_3(\mathfrak{p}_5) = \{(\mathfrak{z}_1, 0.85), (\mathfrak{z}_2, 0.84), (\mathfrak{z}_3, 0.78), (\mathfrak{z}_4, 0.65), (\mathfrak{z}_5, 0.23)\}$,
$\mathfrak{F}_3(\mathfrak{p}_6) = \{(\mathfrak{z}_1, 0.12), (\mathfrak{z}_2, 0.25), (\mathfrak{z}_3, 0.30), (\mathfrak{z}_4, 0.57), (\mathfrak{z}_5, 0.85)\}$,
$\mathfrak{F}_4(\mathfrak{p}_1) = \{(\mathfrak{z}_1, 0.58), (\mathfrak{z}_2, 0.67), (\mathfrak{z}_3, 0.56), (\mathfrak{z}_4, 0.86), (\mathfrak{z}_5, 0.95)\}$,
$\mathfrak{F}_4(\mathfrak{p}_2) = \{(\mathfrak{z}_1, 0.89), (\mathfrak{z}_2, 0.87), (\mathfrak{z}_3, 0.69), (\mathfrak{z}_4, 0.45), (\mathfrak{z}_5, 0.36)\}$,
$\mathfrak{F}_4(\mathfrak{p}_3) = \{(\mathfrak{z}_1, 0.19), (\mathfrak{z}_2, 0.27), (\mathfrak{z}_3, 0.34), (\mathfrak{z}_4, 0.57), (\mathfrak{z}_5, 0.89)\}$,
$\mathfrak{F}_4(\mathfrak{p}_4) = \{(\mathfrak{z}_1, 0.32), (\mathfrak{z}_2, 0.35), (\mathfrak{z}_3, 0.40), (\mathfrak{z}_4, 0.45), (\mathfrak{z}_5, 0.70)\}$,
$\mathfrak{F}_4(\mathfrak{p}_5) = \{(\mathfrak{z}_1, 0.85), (\mathfrak{z}_2, 0.87), (\mathfrak{z}_3, 0.73), (\mathfrak{z}_4, 0.61), (\mathfrak{z}_5, 0.23)\}$,
$\mathfrak{F}_4(\mathfrak{p}_6) = \{(\mathfrak{z}_1, 0.18), (\mathfrak{z}_2, 0.24), (\mathfrak{z}_3, 0.37), (\mathfrak{z}_4, 0.56), (\mathfrak{z}_5, 0.78)\}$.

The following is a table that represents the aforementioned *FSS*s $(\mathfrak{F}_1, \mathfrak{P})$, $(\mathfrak{F}_2, \mathfrak{P})$, $(\mathfrak{F}_3, \mathfrak{P})$, $(\mathfrak{F}_4, \mathfrak{P})$ organized into Tables 6–9.

Table 6. *FSS* for $(\mathfrak{F}_1, \mathfrak{P})$.

$\mathfrak{P} \setminus U$	$\mathfrak{z}_1$	$\mathfrak{z}_2$	$\mathfrak{z}_3$	$\mathfrak{z}_4$	$\mathfrak{z}_5$
$\mathfrak{p}_1$	0.50	0.60	0.50	0.80	0.90
$\mathfrak{p}_2$	0.80	0.70	0.60	0.40	0.30
$\mathfrak{p}_3$	0.10	0.20	0.30	0.60	0.80
$\mathfrak{p}_4$	0.30	0.40	0.50	0.40	0.80
$\mathfrak{p}_5$	0.90	0.80	0.70	0.60	0.20
$\mathfrak{p}_6$	0.10	0.20	0.30	0.50	0.80

Table 7. *FSS* for $(\mathfrak{F}_2, P)$.

$\mathfrak{P} \setminus U$	$\mathfrak{z}_1$	$\mathfrak{z}_2$	$\mathfrak{z}_3$	$\mathfrak{z}_4$	$\mathfrak{z}_5$
$\mathfrak{p}_1$	0.52	0.59	0.60	0.85	0.91
$\mathfrak{p}_2$	0.79	0.75	0.65	0.43	0.25
$\mathfrak{p}_3$	0.15	0.22	0.40	0.70	0.90
$\mathfrak{p}_4$	0.25	0.35	0.45	0.50	0.75
$\mathfrak{p}_5$	0.87	0.88	0.75	0.65	0.30
$\mathfrak{p}_6$	0.13	0.22	0.35	0.49	0.85

Table 8. *FSS* for $(\mathfrak{F}_3, P)$.

$\mathfrak{P} \setminus U$	$\mathfrak{z}_1$	$\mathfrak{z}_2$	$\mathfrak{z}_3$	$\mathfrak{z}_4$	$\mathfrak{z}_5$
$\mathfrak{p}_1$	0.55	0.63	0.54	0.75	0.91
$\mathfrak{p}_2$	0.88	0.86	0.70	0.50	0.40
$\mathfrak{p}_3$	0.20	0.30	0.50	0.70	0.90
$\mathfrak{p}_4$	0.29	0.33	0.48	0.52	0.85
$\mathfrak{p}_5$	0.85	0.84	0.78	0.65	0.23
$\mathfrak{p}_6$	0.12	0.25	0.30	0.57	0.85

Table 9. FSS for $(\mathfrak{F}_4, P)$.

$\mathfrak{P} \setminus U$	$\mathfrak{z}_1$	$\mathfrak{z}_2$	$\mathfrak{z}_3$	$\mathfrak{z}_4$	$\mathfrak{z}_5$
$\mathfrak{p}_1$	0.58	0.67	0.56	0.86	0.95
$\mathfrak{p}_2$	0.89	0.87	0.69	0.45	0.36
$\mathfrak{p}_3$	0.19	0.27	0.34	0.57	0.89
$\mathfrak{p}_4$	0.32	0.35	0.40	0.45	0.70
$\mathfrak{p}_5$	0.85	0.87	0.73	0.61	0.23
$\mathfrak{p}_6$	0.18	0.24	0.37	0.56	0.78

We obtain the performance evaluation shown in Table 10 by averaging the aforementioned four FSSs.

Table 10. Average of FSSs.

$\mathfrak{P} \setminus U$	$\mathfrak{z}_1$	$\mathfrak{z}_2$	$\mathfrak{z}_3$	$\mathfrak{z}_4$	$\mathfrak{z}_5$
$\mathfrak{p}_1$	0.54	0.62	0.55	0.82	0.92
$\mathfrak{p}_2$	0.84	0.80	0.66	0.45	0.33
$\mathfrak{p}_3$	0.16	0.25	0.39	0.64	0.87
$\mathfrak{p}_4$	0.29	0.36	0.46	0.47	0.78
$\mathfrak{p}_5$	0.87	0.85	0.74	0.63	0.24
$\mathfrak{p}_6$	0.13	0.23	0.33	0.53	0.82

Assume that Mr. Y determines the preference weights for the various pupils as shown in Table 11 such that $\sum_{i=1}^{5} w_i = 1$.

Table 11. Weightage for students.

w_1	w_2	w_3	w_4	w_5
0.3	0.3	0.275	0.1	0.025

The comprehensive decision table can be derived by performing a row-wise multiplication of Table 10 with the weightage Table 11, followed by transposing the resulting matrix as depicted in Table 12.

Table 12. Comprehensive decision.

$\mathfrak{P} \setminus (U \times w_i)$	$\mathfrak{z}_1 \times w_1$	$\mathfrak{z}_2 \times w_2$	$\mathfrak{z}_3 \times w_3$	$\mathfrak{z}_4 \times w_4$	$\mathfrak{z}_5 \times w_5$
$\mathfrak{p}_1$	0.162	0.186	0.151	0.082	0.023
$\mathfrak{p}_2$	0.252	0.240	0.182	0.045	0.008
$\mathfrak{p}_3$	0.048	0.075	0.107	0.064	0.022
$\mathfrak{p}_4$	0.087	0.108	0.124	0.047	0.020
$\mathfrak{p}_5$	0.261	0.255	0.204	0.063	0.006
$\mathfrak{p}_6$	0.036	0.069	0.091	0.053	0.006

Now that the comparison table is constructed for the students, we use it to help Mr. Y select the most qualified students possible. The comparison table is in the form of a square and has an equal number of rows and columns. The rows and columns are both labeled with the names of the students as $\mathfrak{z}_1$, $\mathfrak{z}_2$, $\mathfrak{z}_3$, $\mathfrak{z}_4$ and $\mathfrak{z}_5$, and the entries are $\mathfrak{z}_{ij}$ with

$i, j = 1, 2, 3, 4, 5$ given by $\mathfrak{z}_{ij} =$, the number of selection criteria, for which the membership value of $\mathfrak{z}_j$ is greater than or equal to the membership value of $\mathfrak{z}_i$. The comparison table is in Table 13.

Table 13. Comparison table.

$U \setminus U$	$\mathfrak{z}_1$	$\mathfrak{z}_2$	$\mathfrak{z}_3$	$\mathfrak{z}_4$	$\mathfrak{z}_5$
$\mathfrak{z}_1$	6	2	3	4	6
$\mathfrak{z}_2$	4	6	3	5	6
$\mathfrak{z}_3$	3	3	6	6	6
$\mathfrak{z}_4$	1	0	0	6	6
$\mathfrak{z}_5$	0	0	0	0	6

The column sum and the row sum from the comprehensive decision table and the scores for each student are presented in the following Table 14.

Table 14. Score table.

	Column-Sum	Row-Sum	Score Value
$\mathfrak{z}_1$	14	21	−7
$\mathfrak{z}_2$	11	24	−13
$\mathfrak{z}_3$	12	24	−12
$\mathfrak{z}_4$	21	12	9
$\mathfrak{z}_5$	30	6	24

It is concluded that for Table 14 with the score table, the following ordering is suggested: $\mathfrak{z}_5 > \mathfrak{z}_4 > \mathfrak{z}_1 > \mathfrak{z}_3 > \mathfrak{z}_2$.

In this case, we discover that the highest possible score can be achieved by $\mathfrak{z}_5$, the student with the best parameters $\mathfrak{p}_1$, $\mathfrak{p}_2$, $\mathfrak{p}_3$, $\mathfrak{p}_4$, $\mathfrak{p}_5$ and $\mathfrak{p}_6$. Hence, Mr. Y can choose the student with the best ratios of food with parameters $\mathfrak{p}_1$(C), $\mathfrak{p}_2$ (M), $\mathfrak{p}_3$ (P), $\mathfrak{p}_4(fat)$, $\mathfrak{p}_5$ (Junk food), and $\mathfrak{p}_6$ (V) of the selection criteria of FSSs $(\mathfrak{F}_1, \mathfrak{P})$, $(\mathfrak{F}_2, \mathfrak{P})$, $(\mathfrak{F}_3, \mathfrak{P})$, and $(\mathfrak{F}_4, \mathfrak{P})$ over U.

4. Conclusions and Future Work

The application of fuzzy soft sets in decision making for ideal nutrition has proven to be a promising approach. By considering the uncertainty and imprecision associated with dietary recommendations and individual preferences, fuzzy soft sets provide a flexible and adaptive framework for making informed choices. Through the integration of diverse sources of information and the consideration of multiple criteria, this approach can help individuals and health professionals to navigate the complex landscape of nutrition and make decisions that are tailored to their specific needs and goals. Overall, fuzzy soft sets represent a valuable tool for promoting healthy and balanced diets, and further research in this area is likely to yield important insights and practical applications. From the given results, it is clear that the approach to decision-making problems [38–42] with imprecise data via FSSs is more accurate than the other approaches. We are currently working on a new method of reducing FSS to solve the problems that appear in the methods of NPR, $PNPR$ and $DBPR$. The development of homelands begins with building a person, and building a person depends on proper nutrition. Egypt has made many initiatives to build the human being, including 100 million health and a decent life, and the detection of malnutrition diseases. Therefore, in the year 2022, an initiative was launched to detect malnutrition at the beginning of the study, with the follow-up of the Ministry of Health and the Ministry of Education. It examines children in schools (weight, height, and the percentage of hemoglobin in the blood). When a child presents with a positive case of anemia, stunting or obesity, a card is created. It contains the complete data of the child. Upon follow-up, it is re-examined, and a complete treatment plan suitable for the child is drawn up.The examination was carried out for 11 million students. Therefore, attention to nutrition is a very important factor in choosing the appropriate nutrition. In the future, we will work to help identify the best nutrition factors and the best methods of diagnosing malnutrition, help decision makers, and link big data to FSS.

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