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AN INTEGRATED FULL CONSISTENT LOPCOW-EDAS FRAMEWORK FOR MODELLING CONSUMER DECISION MAKING FOR ORGANIC FOOD SELECTION

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Abstract: Over the years, there has been an upsurge in the buying and consuming green products like organic foods. However, past studies are limited to exploring the effects of behavioral factors on consumers' buying decisions for green products. The present paper fills the gap in the literature by providing a multi-criteria decision-making (MCDM) framework for consumer decision-making for selecting organic foods. To set the criteria for comparing organic foods, the theoretical foundation of the consumers' black box model concerning the intention-behavior gap is applied. The present paper proposes an intuitionistic fuzzy number (IFN) based hybrid Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) and Evaluation based on Distance from Average Solution (EDAS) model with an inherent capability to check the consistency in the calculation of the criteria weights with the help of the Full Consistency Method (FUCOM). The results have shown that greenwashing has changed the customers' mindset and they are considering mostly the factors of organic food selection that same as traditional products in the market. The output has provided a valid, robust and reliable solution, further established by performing sensitivity analysis.

Keywords: Organic Food, Green Consumerism, Consumer Black Box Model, MCDM, Intuitionistic Fuzzy Numbers (IFNs), Full Consistency Method (FUCOM)

MSC: 03B52, 62A86, 62C86, 62P25.

1. INTRODUCTION

Industrialization and rapid economic expansion have steered to enormous consumption and deterioration of natural resources. Mother Earth has been undergoing various ecological challenges like water, air, soil pollution, global warming, etc. Food consumption is allied with these ecological matters like enhanced greenhouse gas emissions, water utilization and quality, soil quality, biodiversity damages, inherently modified organisms (GMOs), and pesticide use [1]. There has been an upsurge in the preference and consumption of green products, recognizing the importance of protecting the environment for sustainable living. There has been a notable expansion of the organic food market. Organic food is considered to be without chemicals and pesticides and has minor influences on the environment [2]. The pandemic has considerably influenced Indian customers' health consciousness, concern for the environment, price, and purchase intention of organic food [3].

The extant literature shows impressive growth in investigating consumer behaviors regarding selecting and consuming organic foods. It is noted that demographic factors significantly influence consumers' purchase intention for organic foods [4-5]. Organic certification logos influence customers to buy organic products [6]. However, some eco-friendly products could be more transparent and helpful [7], confusing consumers when identifying authentic organic products [8]. This green skepticism stimulates customers to find additional product-related information, flashes negative word of mouth (WOM) to society, and prevents purchase intentions [9]. Therefore, to formulate an effective green marketing strategy and product design, organizations must understand consumers' decision-making for the selection of green products like organic foods.

The history of organic food started with consumer activism, whose primary anxiety was the impact of human activity on Mother Earth. The drive began with establishing the International Federation of Organic Agricultural Movement (IFOAM) [10]. This driving force constantly supports this movement by bringing them to the global level. The term "organic" was formally acknowledged in the 1990s as a food manufacturing method, backed by factors like government support and altering customers' tastes and preferences. Consuming organic food is a vigorous and contextual phenomenon that is determined by various parameters such as moral norms [11], subjective norms [12], green pressure [13], and geographical differences [14]. Food purchasing is a low-involvement process [15]. However, the selection is more difficult for organic food because it is ever-changing, mainly in nature and uncertain, and its associations have complex attributes like health, environment protection, and animal welfare. Consumers cogitate multiple trust factors when buying a credence good, like organic food [14]. However, credence features such as taste, experience, and environmental elements are fundamentally authoritarian to review even after buying, even though organic markets and trade fairs are experiencing higher growth rates.

There are various intrinsic and extrinsic factors behind organic food consumption based on the recommendations from previous studies. The research has suggested that intrinsic cues influence organic food purchase purposes more than extrinsic cues. The appearance, smell, color, taste, and texture are the intrinsic attributes, whereas brand, certification, price, and packaging are part of the extrinsic factors [16]. The organic food market has achieved the value of $1,278 million in 2022 and is projected to be tentatively at $4,602 million by 2028, with a compound annual growth rate (CAGR) of 23.8% during the phase. It is noteworthy to investigate the organic food selection problem based on factors influencing the customers' willingness to purchase organic food and the obstacles they perceive. Consumers' decision-making for the selection of an appropriate product is complex. It is influenced by several behavioral factors (suffered by subjective bias), product attributes, and external factors. The stimuli that trigger the purchase intentions are often not explicitly known and explained. Green perceived value consumers have been observed to affect consumer attitudes [17], which triggers eco-friendly product purchases [18]. Similarly, social influence considerably encourages pessimistic consumers for organic food selection [19].

The black box consumer behavior model, sometimes called a stimulus-response model [20], has been used to understand customers' organic purchase behavior. This model has three components. First is the environment, where the customers come into contact with external stimuli. The external stimuli combine the internal marketing stimuli like product, price, place, and promotion and other stimuli like economics, technology, society, and culture. This model is a mental process that cannot be quantified or examined [21]. The second one is the buyer's black box, which entails buyers' characteristics (social, cultural, personal, and psychological elements), their pre-existing knowledge, and the decision-making process. The buyer's decision process- starting from need recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior –initiates long before the buying decision and remains long after. The last is the buyer's response, which is the outcome of a conscious and rational decision process. Factors like the marketers' relentless promotion of organic and sustainable products, customers' selective attention like health consciousness, eco-friendliness blended with their lifestyles, and green trust drive the purchase decision for green products like organic foods [8]. Most often, customers' positive attitudes towards green products are not reflected in their actual purchase [22], leading to an attitude-behavior gap [23]. A review of previous literature advocates the utilization of different theories like TPB, TRA, stimulus-organism-response model, value-attitude system model, self-construal theory, social identification, and identity theories to understand the consumption behavior of organic food. The observations above instigate the application of the consumer black box model to study the consumption pattern of foods grown organically.

The present paper considers the black box model to formulate the multi-criteria based consumer decision making model to buy the organic foods. It aims to develop a multi-criteria decision making (MCDM) framework to model the selection of organic foods. MCDM models are widely popular and find extensive applications in complex decision-making problems for selection of an appropriate choice [24]. The selection of organic foods depends both objective information related to the products and subjective opinions of the decision makers. To deal with the imprecise information (associated with subjectivity) the current work resorts to uncertain decision models. In this regard, the ongoing study uses an intuitionistic fuzzy set (IFS) based approach. IFS [25] finds its root in the classical Fuzzy set (FS) theory [26] which was the pioneering work in the domain of decision making under uncertainties and imprecise information. FS only considers the varying degree of membership (M). However, in many real-life complex problems like selection of organic foods, also, it is important to consider the degree of non-membership (N) [27]. IFS provides the decision makers with the flexibility to work with both μ and ϑ subject to the condition $M + N \leq 1$.

In the current work, the researchers propose a hybrid IFS based MCDM framework of integrated Full Consistency Method (FUCOM) [28] and Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) [29] for calculating the criteria weights and Evaluation Based on Distance from Average Solution (EDAS) [30] for comparing the organic food options. FUCOM uses a pairwise comparison approach to figure out the comparative priorities of the criteria. FUCOM conducts (n-1) number of such comparisons which is much lower than the other methods like AHP and CRITIC. Hence, it is less suffered from the subjective bias. Further, FUCOM provides an inherent consistency check for the result as it measures the deviation from the full consistency (DFC) value (indicated by the value of the objective function) while deriving the criteria weights. The LOPCOW has been developed for deriving the criteria weights primarily using objective information. It extends the advantages like the ability to provide a reliable calculation of criteria weights under the conditions such as presence of zero or negative performance values in the decision matrix, a large number of criteria or alternatives and rational distribution of the criteria weights. Hence, an integration of LOPCOW and FUCOM brings forth a robust model to calculate the criteria weights. EDAS is a widely used method for ranking the alternatives that uses the center line (i.e., average performance values of the alternative subject to the effect of each criterion) as the reference solution. In effect, EDAS balances the extreme effects of the ideal (positive and negative) solutions. Hence, EDAS provides a realistic approach. Further, it can work fine with a large number of criteria and alternative and does not suffer from the rank reversal phenomenon. Thus, the framework used in this research (IFS based LOPCOW-FUCOM-EDAS) proffers a reliable model to the analysts for solving the complex selection problems.

The motivation for the present paper stems from two major gaps in the literature. It is noticed that there has been a number of studies conducted in past mainly in the area of consumers' purchase behavior for the organic foods and the influencing factors. But the research on intention- behavior gap of organic food selection based on the theoretical framework like – consumers black box model is quite uncommon in the previous studies. Hardly any research is found on the application of MCDM for selection of organic food and related intention- behavior gap. Further, LOPCOW is a very recently developed model. It is apparent that there is a scantiness of past studies that aimed to assess the consistency level by integrating FUCOM model with LOPCOW while using IFS.

Therefore, broadly the contributions of the present paper is twofold. First, based on the theoretical foundation of consumer black box model, this study puts forth a model of mathematical analysis for selection of organic food using MCDM framework. Second, from the technical perspectives the ongoing work develops an apparently rare IFS based hybrid LOPCOW-EDAS model with an inherent capability to check the consistency in calculation of the criteria weights with the help of the FUCOM. The application of IFN-based MCDM model, provide coherent and balanced results for addressing the organic food selection problem.

The rest of the paper is unfolded as follows. Section 2 highlights the related research work; Section 3 provides the research framework with the computation steps of FUCOM-EDAS model; Section 4 delivers the summary of the data analysis; Section 5 unveils the output of sensitivity and validity analysis. Section 6 uncovers the discussion and implications of the research. Lastly Section 7 concludes the paper followed by some future scope and limitations of the research in Section 8.

2. INVESTIGATION OF THE PAST STUDIES

This section revisits some of the past research related work into sub-sections like organic food market, applications of IFS, related work in EDAS algorithms, and FUCOM algorithms and investigates the contributions.

2.1. Past studies on consumer behavior related to organic foods

Organic food can be defined as organically manufactured food based on 'organic philosophy' or food produced without any synthetic inputs like pesticides, chemical fertilizers, or any other type of chemicals [31] or does not hold genetically modified organisms [32]. The organic market has exploded in the last few decades, with companies in various industries, such as food, fashion, and cosmetics, to mention a few. Food consumption considerably affects the surroundings, and organic food purchase is vastly considered sustainable behavior [33]. Consumers grow their perceptions of organic products based on personal experiences or evidence from other sources (media, word of mouth, and so on). One study has shown that purchasing organic milk is progressively affected by their trust in farmers, which is insignificant for government, manufacturers, and retailers [34]. Few customers consider that it is not essential to purchase organic products only because of the current marketing trend. However, with the rise of consumers' green attitude, companies have started malpractice by providing false or incomplete information to showcase, which their public imager termed "Greenwashing" [35], making customers struggle to recognize if the product is green [8]. Conversely, initiating green certification and strategic controls make customers believe that organic food is less vulnerable than traditional food [36]. The price of organic food is high. However, the research suggests that price consciousness does not affect Indian customers' buying intention during the pandemic [3]. Nevertheless, on the other way, the customers' belief in organic food is not converting into their behavior creates consistency, which is well accepted in literature and termed as the green attitude-behavior gap [23], the green intention-behavior gap [37], or the motivation-behavior gap [38]. So, the extant literature focuses on the progression of organic food consumption, but there is a knowledge gap about the motives that propagate its actual consumption [39].

In recent years there has been an upsurge in the research work on organic food market. It is evident that several researchers have examined consumers' perception and their behavioral intentions to buy organic foods. For example, Guru et al. [40] applied a combined fuzzy AHP and SAW model to discern the drivers for purchasing and consumption of organic food products. The authors noted the significant influence of the hygiene factors for purchasing and consuming organic food products. The study of Bazhan et al. [41] and Bhutto et al. [42] corroborated the views of [40]. Aljanabi et al. [43] used fuzzy AHP-TOPSIS framework, grounded on cognitive-affective perspective, in their work to investigate the impulse buying behavioral factors and compare the organic foods. The study of Jánská et al. [44] focused on consumer lifestyles while explaining their behavior for buying organic products. The authors used non-parametric hypothesis testing and classification algorithm like decision tree. Packaging is an important aspect that often influences consumers' buying decisions. The issue of selection of eco-friendly packaging was reflected in the work of Lombardi et al. [45]. The authors considered the theoretical base of the Theory of Planned Behavior (TPB) and the Rational-Emotional Model (REM). The authors advocated for exploring consumers' emotion while selecting the packages. Sometimes it is seen that the buying decisions are made to follow the decisions of the mass. In their work [46], the authors put forth a vital question whether health consciousness or follow-the-mass behavior that controls the buying decisions.

Most of the former researchers had carried out the study on organic food mostly in developed countries with higher awareness and knowledge of food, whereas the smaller number of studies have been observed in countries like India. Table 1 displays the summary of the methods used in past research. Indian organic food market is at a nascent phase of its progress. It is significant to understand the consumer behavior for organic food in India for overall understanding of the food market. Currently, Indian fruits and vegetables are at its peak demand in organic food classifications [47] (Nandi et al., 2017). The domestic market for organic products is restricted to mostly in the metro cities of India. However, the modern Indian lifestyles are inclining towards healthy lifestyles.

Table 1: Examples of methodologies used in past studies

Methodology Used	Authors
Exploratory factor analysis, confirmatory factor analysis, Structural Equation Modeling (SEM), Partial least square SEM (PLS-SEM)	Parashar et al. [48]; Khan et al. [49]; Roh et al. [17]; Kashif et al. [50]; Konuk [51]; Nguyen et al. [33]; Pham et al. [52]
Systematic Literature Review	Kushwah et al. [53]; Carrión et al. [54]
Comparative mixed-methods approach	Pedersen et al. [55]

From Table 1 it is apparent that SEM has been dominantly applied by various past studies to build causal models to explain the consumer buying behavior for the green products. However, applications of MCDM models are limited in the stated field.

2.2. Some applications of IFNs in real-life problems

With IFNs, the opinions are quantified in a much comprehensive way as vagueness and imprecisions can be coped more conveniently by both the membership and non-membership degrees. That is the reason it has been applied vastly in several real-life situations to depict the ambiguous reasoning of experts. Table 2 demonstrates a summary of researches in relation to some applications of IFNs.

Table 2: Studies related to applications of IFN

Applications	Authors
Research proposals evaluation for grant funding	Alkan and Kahraman [56]
Pattern classification and medical diagnosis	Wu et al. [57]
Cloud vendor selection	Krishankumar et al. [58]
Similarity measure in face recognition and software quality evaluation	Patel et al. [59]
Coronavirus vaccine selection in the age of COVID-19	Ecer [60]
Evaluation of information security management	Azam et al. [61]
Multi-Mobile Agent Itinerary Planning Approach in Wireless Sensor Networks	Alsboui et al. [62]
An application in software bug triaging	Panda and Nagwani [63]
An application in software quality evaluation	Thao and Chou [64]
Preferred hospitalization of COVID-19 patients	Si et al. [65]

From Table 2 we observe that IFNs have been applied in many complex decision-making issues across the disciplines. It has been applied in selection problems. It supports the use of IFN in our case. However, the application of IFNs in green product selection is apparently rare.

2.3. Some applications of EDAS model for decision-making

EDAS delivers an optimistic and pessimistic evaluation of alternatives. For instance, research has applied EDAS method with Dombi function for aggregation to determine the final ranking along with Dombi norms based Logarithmic Methodology of Additive Weights (LMAW) for calculating criteria weights for calculation of metaverse integration of freight fluidity measurement [66]. In another recent work, interval rough number (IRN) with best worst method (BWM) and EDAS has been applied for solving a supplier selection problem in an Indian textile mill [67]. The application of EDAS along has been observed also in the areas like-green finance [68], 3D Printer selection [69], for comparative assessment of the flood-susceptible zones [70], additive manufacturing process selection for automotive industry [71] etc. However, the extant literature shows a limited application of EDAS model in the green marketing.

2.4. Applications of FUCOM for finding criteria weights in complex problems

The FUCOM is one of the extensively applied comparison-based MCDM procedure for calculating the criteria weights. Table 3 exhibits some of the recent applications of this mathematical modelling techniques.

Table 3: Applications of FUCOM

Applications	Authors
Artificial Neural Network	[72]
Software adoption in banking industry	[73]
Video games experiences	[74]
Evaluation of Indian national parks	[75]
Distribution channel selection	[76]
Critical Success Factors for 5G Technology Adaptation	[77]
Site selection for maize cultivation	[78]
Health care performance management	[79]
Health care waste treatment selection	[80]
Evaluating the sustainability of farm tourism sites	[81]

Table 3 reflects the increasing use of FUCOM model in determining the criteria weights in various problems. However, it is seen that FUCOM has not been combined with another model for finding out the criteria weights.

2.5. Research gaps evident from revisit of the past studies

Researchers have directed to study and explore the gap among consumers' consumption, intention and attitude by focusing on that aspects which influence actual consumption [12] [82]. From the review of the extant literature the following gaps are observed.

Research gap 1. It is noted that there is a scantiness of contributions that worked on comparison of the organic foods subject to the influence of the end customers. The prior studies mostly focused on discovering various factors influencing consumers' purchase decisions for organic foods. The literature shows some evidences of comparison of green products but that too is not a sizeable number. Also, the organic food segment shows a little attention on comparing the products.

Research gap 2. It has been opinionated in many researches that some of the factors like-price, perceived risks, trust etc. are not aspects the customers look for while going for organic food purchase. In contrast, there are research papers where it has been suggested that the companies must decrease their greenwash as it is negatively associated with green trust and green consumer confusion.

Research gap 3. The choice of products depends on several factors entailing consumers' decision making before buying. The decisions are based on subjective opinions and objective information on product attributes. Hence, it calls for a holistic multi-criteria based assessment. The application of MCDM in organic food selection is stagnant at an initial phase.

Research gap 4. The subjective opinions of the customers influencing the buying decision are uncertain and imprecise in nature and are biased. To offset the bias, it is therefore necessary to use the uncertain models. However, the studies on organic food segment with application of the uncertainty models are not widely visible.

The present work therefore plugs in the gaps in the literature by providing an IFS based MCDM framework using opinions of the focused group members (representing the views of the consumers) to compare a set of organic foods.

3. PRELIMINARIES

The traditional fuzzy set (TFS) was brought into existence [26] to deal with the uncertainty regarding the degree of membership (M) to a set. However, TFS was silent about the degree of non-membership (N) of the elements. In several instances it was felt to define N. To remove this obstacle, Atanassov [25] introduced a new variant of TFS known as intuitionistic fuzzy sets (IFS) that considers both M and N. Besides, it provides a way to calculate the degree of indeterminacy (I). As a result, IFS provides a greater scope of applications in solving real-life issues [83]. IFS has been widely applied in numerous problems pertaining to the domains of engineering, management, social science, basic science and others (examples may be found in [60, 64, 84-97]). In this section some of the fundamental concepts, definitions and operations on the IFS are discussed briefly.

Definition 1. IFS

Let, U is the universe of discourse. Then an IFS Θ in defined as

$$\Theta = \{\langle x, M(x), N(x)\rangle | x \in U\} \tag{1}$$

Where, for all $x \in U \to [0,1]$ in Θ, the degrees of membership and non-membership such as $M(x)$ and $N(x)$ satisfy the condition,

$$0 \leq M(x) + N(x) \leq 1 \tag{2}$$

For each IFS in U, the degree of indeterminacy (I) is derived as

$$I(x) = 1 - M(x) - N(x) \tag{3}$$

Without losing the meaning of the general terms, an intuitionistic fuzzy number (IFN) is defined as $\alpha = \{M, N\}$ for computational convenience.

Definition 2. Fundamental operations

Let, $\alpha = \{M, N\}, \alpha_1 = \{M_1, N_1\}, \alpha_2 = \{M_2, N_2\}$ are the three IFNs. Then, following are some of the basic operational laws [98-99].

$$\alpha_1 \oplus \alpha_2 = (M_1 + M_2 - M_1 M_2, N_1 N_2) \tag{4}$$

$$\alpha_1 \otimes \alpha_2 = (M_1 M_2, N_1 + N_2 - N_1 N_2) \tag{5}$$

$$\lambda\alpha = (1 - (1 - M)^{\lambda}, N^{\lambda}) \text{ (Multiplication by scalar)} \tag{6}$$

(λ is a scalar quantity and $\lambda > 0$)

$$\alpha^{\lambda} = (M^{\lambda}, 1 - (1 - N)^{\lambda}); \lambda > 0 \text{ (Power)} \tag{7}$$

$$\alpha^{c} = (N, M) \text{ (Complement)} \tag{8}$$

Definition 3. Basic definitions of the score and accuracy functions

The basic definition of the score function for the IFN α is given as [98-101]

$$Sf(\alpha) = M - N;\ Sf(\alpha) \in [-1,1] \tag{9}$$

The accuracy function is given as

$$Af(\alpha) = M + N;\ Af(\alpha) \in [0,1] \tag{10}$$

To compare the IFNs the following rules are being followed

If $Sf(\alpha_1) > Sf(\alpha_2)$ then $\alpha_1 > \alpha_2$

If $Sf(\alpha_1) < Sf(\alpha_2)$ then $\alpha_1 < \alpha_2$

If $Sf(\alpha_1) = Sf(\alpha_2)$ then if $Af(\alpha_1) < Af(\alpha_2)$ then $\alpha_1 < \alpha_2$

Definition 4. Modified definitions of the score function

There has been a number of modifications done to improve the basic score functions. Some of them are given below

Improved score function [102]

$$Sf^*(\alpha) = M - N + (M^2 - N^2)I \tag{11}$$

Generalized score function (GSF) [97]

$$GSf(\alpha) = M[1 + (\varepsilon_1 + \varepsilon_2)(1 - M - N)] \tag{12}$$

Here, $\varepsilon_1 + \varepsilon_2 = 1$, $\varepsilon_1, \varepsilon_2 > 0$ indicate the attitudinal behavior of the score function.

Definition 5. Basic aggregation operators (AO)

Let, $\alpha_1, \alpha_2, \alpha_3 \ldots\ldots \alpha_n$ be a set of n IFNs with usual definitions as provided in the expressions (1) to (3). In what follows are some of the basic AOs used for averaging the IFNs.

Intuitionistic fuzzy weighted average (IFWA)

$$IFWA(\alpha_1, \alpha_2, \alpha_3 \ldots\ldots \alpha_n) = \bigoplus_{i=1}^{n} (w_i \alpha_i) = \left(1 - \prod_{i=1}^{n} (1 - M_i)^{w_i}, \prod_{i=1}^{n} N_i^{w_i}\right) \tag{13}$$

Intuitionistic fuzzy weighted geometric aggregation (IFWGA)

$$IFWGA(\alpha_1, \alpha_2, \alpha_3 \ldots\ldots \alpha_n) = \bigotimes_{i=1}^{n} (\alpha_i^{w_i}) = \left(\prod_{i=1}^{n} M_i^{w_i}, 1 - \prod_{i=1}^{n} (1 - N_i)^{w_i}\right) \tag{14}$$

Generalized Intuitionistic fuzzy weighted aggregation (GIFWA) [103]

$$GIFWA(\alpha_1, \alpha_2, \alpha_3 \ldots\ldots \alpha_n)(\bigoplus_{i=1}^{n} (w_i \alpha_i^{\lambda}))^{\frac{1}{\lambda}} \left\langle \begin{array}{c} (1 - \prod_{i=1}^{n} (1 - M_i^{\lambda})^{w_i})^{\frac{1}{\lambda}}, \\ 1 - \left(1 - \prod_{i=1}^{n} (1 - (1 - N_i)^{\lambda})^{w_i}\right)^{\frac{1}{\lambda}} \end{array} \right\rangle \tag{15}$$

Here, $\alpha_i = (M_i, N_i); i = 1, 2, \ldots n$ is the set of IFNs with the weights $w_1, w_2, w_3 \ldots\ldots w_n (w_i \geq 0; \sum_{i=1}^{n} w_i = 1)$ and $\lambda > 0$ If $\lambda = 1$ then GIFWA becomes IFWA operator.

4. MATERIALS AND METHODS

In section concisely explains the research methodology steps. Figure 1 illustrates the research methodology stepwise in a flow diagram.

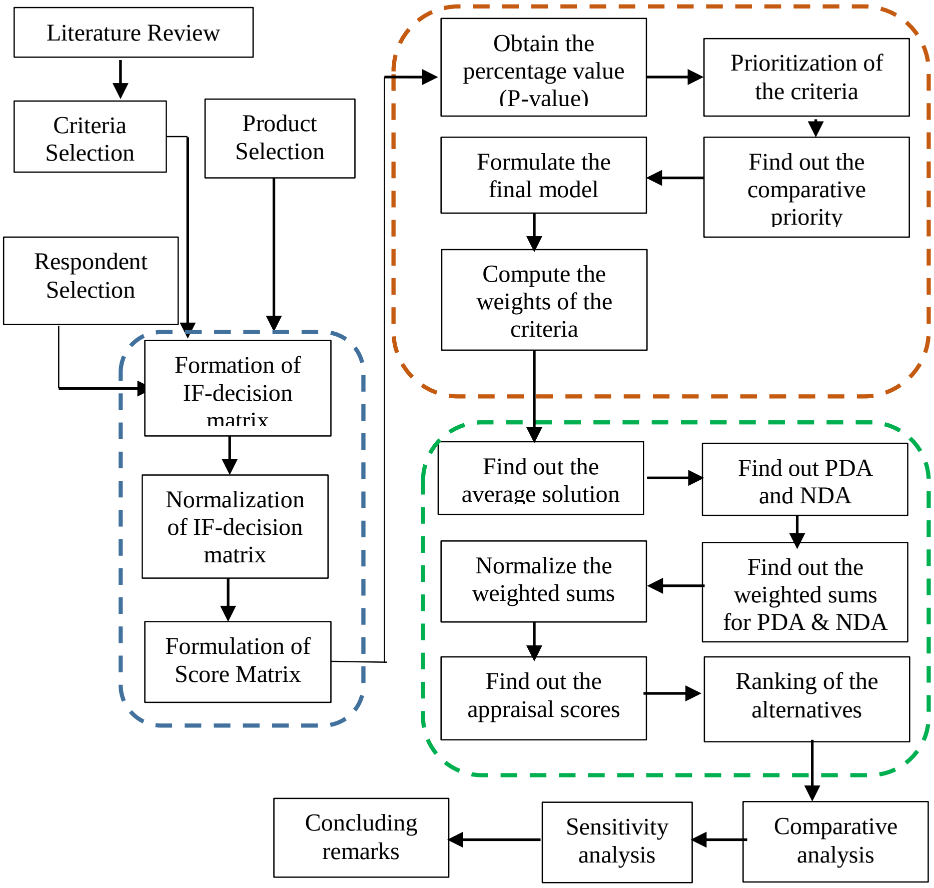

Figure 1: Flowchart of the study

4.1. Sample

This paper studies the top 10 organic food products (as preferred by the consumers) in India based on the record available in the frequently used rating website of Statista[1] . The foods are heterogeneous in nature in terms of cost and attributes. In this paper our endeavor is to compare the popular organic foods from the perspective of consumers' choice factors. The present study does not consider the intra-segment comparative analysis. Here, the sample units are denoted as $F_1, F_2, ...F_{10}$.

4.2. Selection of criteria to compare organic foods

It has been noted that no earlier work was made to determine the factors for organic food purchase behavior. Hence, in order to compare the organic food, first some of the attributes based on the finding of former researches are identified. The researchers have developed various models to explain customer actions. However, an understanding of customer behavior can be gained from the consumer black box model. This model provides a glimpse of the decision-making and behavior-transfer processes behind customer choices. Consumers need a clearer understanding of the factors that impact their purchasing decisions. Their choices are frequently suppressed within the customer's mind. The model has three main parts: the environment, the buyer's black box, and the buyer's responses. Since the Value-Belief-Norm (VBN) theory explains how environmentalist values impact human behavior, many studies have already been conducted on organic food. The integrated application of the VBN theory with the theory of planned behavior (TPB) and consumers' trust has also been observed. Uses-gratification is allied with the media consumption choices of the customers, i.e., how to select media to satisfy these needs. The following few decades saw a concentration in the uses and gratifications literature on the benefits that media consumers receive, so we refrain from applying the uses-gratification theory. However, in the future, this comment from the respected reviewer encouraged us to come up with research papers in allied theory.

The criteria have been finalized after a round of discussions with the respondents. Accordingly, the present work uses 10 user centric criteria (that customers' purchase decision) to compare the organic foods. The criteria list is provided in Table 4.

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[1] https://www.statista.com/statistics/1008571/india-preferred-organic-food-products-by-type/.

Table 4: List of factors (i.e., criteria) stimulating customers' selections for choosing the Organic Foods

S/L	User centric criteria	Effect Direction
UA 1	Trust	(+)
UA 2	Perceived Risk	(-)
UA 3	Easy availability	(+)
UA 4	Better Taste	(+)
UA 5	Price	(-)
UA 6	Information	(+)
UA 7	Trendy	(+)
UA 8	Curiosity	(+)
UA 9	More nutritious	(+)
UA 10	Word of Mouth (WOM)	(+)

Now, the respondents were requested to rate the organic food based on the factors listed in table 1. A five-point linguistic scale is used as provided in table 5. The rating of the alternatives by the customers for the criteria selected for the comparison are given in Appendix A.

Table 5: Five-point linguistic scale and corresponding IFNs (Adopted from Sangaiah et al., 2015)

Definition of Linguistic Terms	Code	μ	ϑ
Very high influence	VH	0.90	0.10
High influence	H	0.75	0.20
Medium influence	M	0.50	0.45
Low influence	L	0.35	0.60
Very Low/ No influence	N	0.10	0.90

4.3. Respondents' profile

This study is mainly conducted in urban areas of Eastern India. The respondents have been selected through convenience sampling. A number of super malls have been identified. These respondents regularly visit those malls and buy organic food products. The respondents are sufficiently well-versed with all of the organic foods considered in this study. Initially, we figured out 20 such respondents who regularly buy and prefer organic food products for a number of years and are knowledgeable on product characteristics and usage. While selecting the initial group of respondents we tried to make it heterogeneous in demographic profile for better capturing the consumers' views. Out of 20 respondents, we got the consent from 12 people. After getting their responses and carefully scrutinizing the responses (for any missing values) finally we found 10 such responses complete. Hence, in this study the number of respondents is 10 which also confirms the minimum requirement for the sample size for a group decision analysis (Rabiee, 2004; Biswas, 2019). The profile of the 10 respondents (R_1, R_2, R_3, …… R_{10}) is exhibited in Table 6.

Table 6: Demographic Profile of the respondents (n=10)

Experts	Gender	Age (In Years)	Use experience (In Years)	Current Industry	Current Designation
R1	Male	41-55	23	Media and Entertainment	Artist
R2	Female	26-40	6	Education	Research Scholar
R3	Male	41-55	9	Self-Employed	Founder
R4	Male	18-25	15	Telecom	Associate Partner
R5	Male	18-25	10	Consumer Services	Regional Manager
R6	Male	41-55	8	Consulting	HR Head
R7	Male	41-55	23	Financial Services	Associate Director
R8	Female	26-40	7	IT	Senior Brand Manager
R9	Female	26-40	5	Software	HR and PR Head
R10	Male	26-40	8	IT	Associate Partner

4.4. Integrated IFS- FUCOM-EDAS Framework

Let,
$i = 1,2....m$ is the number of alternatives (i.e., types of organic foods). In this paper $m = 10$ (i.e., $F_1, F_2, ...F_{10}$)
$j = 1,2....n$ is the number of criteria for comparing the alternatives (i.e., types of organic foods). In this work, $n = 10$ $(i.e., UA_1, UA_2, ... UA_{10})$.
$k = 1,2.....r$ is the number of decision makers who rated the alternatives. In our work, $k = 10$ $(i.e., R_1, R_2, ... R_{10})$
ψ_{ij}^{k} is the performance rating of the i^{th} alternative subject to j^{th} criterion as rated by the k^{th} decision maker. It may be noted that the rating is an IFN, i.e., $\psi_{ij}^{k} = (M_{ij}^{k}, N_{ij}^{k})$
In what follows are the procedural steps using the combined LOPCOW and EDAS methodology based on IFN.

<u>Phase 1. Formulation of the decision analysis framework</u>

Step 1. Formation of the IF-decision matrix

At this step the ratings of all decision makers for each alternative subject to each criterion are aggregated using the IFWA operator as given in expression (13). Finally, an IF-decision matrix is formulated as $\Psi = [\psi_{ij}]_{m\times n}$

$$\psi_{ij} = IFWA(\psi_{ij}^{1}, \psi_{ij}^{2}, ..., \psi_{ij}^{r}) = \bigoplus_{k=1}^{r} (w_k \psi_{ij}^{k}) = \left(1 - \prod_{k=1}^{r} (1 - M_{ij}^{k})^{w_k}, \prod_{k=1}^{r} (N_{ij}^{k})^{w_k}\right) \quad (16)$$

Here, w_k is the weight of the k^{th} decision maker. In this work it is assumed that $w_1 = w_2 = ... = \frac{1}{r}$

Step 2. Normalization of the IF-decision matrix

Using the definition given by the expression (8), the normalized IF-decision matrix $\Phi = \left[\phi_{ij}\right]_{m\times n}$ is obtained as

$$\phi_{ij} = \left.\begin{matrix}\psi_{ij} = (M_{ij}, N_{ij});\ j \in j^{+} \\ \psi_{ij} = (N_{ij}, M_{ij});\ j \in j^{-}\end{matrix}\right\} \tag{17}$$

Step 3. Formation of the score matrix

In the next step, the score values of all elements of the normalized IF-decision matrix $\Phi = \left[\phi_{ij}\right]_{m\times n}$ are calculated using GSF (see expression (13)) as follows

$$GSf(\phi_{ij}) = M_{ij}[1 + (\varepsilon_1 + \varepsilon_2)(1 - M_{ij} - N_{ij})] \tag{18}$$

Accordingly, we get a score matrix $Y = \left[y_{ij}\right]_{m\times n}$ where the elements are given by the expression (18), i.e., $y_{ij} = GSf(\phi_{ij})$

Phase 2. Computation of the criteria weight (F-LOPCOW method)

In phase 2, first the procedural steps of the LOPCOW method [29] are followed to calculate the initial percentage values of the criteria which are then used as inputs to the steps of the FUCOM method [28] for obtaining the criteria weights. In effect, the present paper provides a hybrid FUCOM-LOPCOW method (F-LOPCOW). The steps under phase 2 are described below.

Step 4. Obtain the percentage value (P-value)

The P-values for the criteria are obtained as

$$P_j = \left| \ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m} y_{ij}^2}{m}}}{\sigma}\right).100 \right| \tag{19}$$

σ denotes the standard deviation.

Step 5. Prioritization of the criteria

The P-values are used to set the prioritized order of the criteria as $UA_j(1) \succ UA_j(2) \succ UA_j(3) \succ ......UA_j(t)$ where, $1, 2....t$ denote the positional rank of the corresponding criteria. The criterion with rank 1 is treated as having the highest priority or preference (i.e., highest P_j value compared to others). It may also be mentioned that for some criteria with equal priorities, "=" holds good.

Step 6. Derive the comparative priority of the criteria

The comparative priority of the criterion having rank t with respect to one having the rank $(t+1)$ is expressed as $\wp_{\frac{t}{t+1}}$. The comparative priority of the most preferred criterion is 1 or it may be determined by the decision maker.

Step 7. Compute the final weights of the criteria

The final weights of the criteria (ω_j) are computed by satisfying the following two mathematical conditions:

$$\frac{\omega_{j(t)}}{\omega_{j(t+1)}} = \wp_{t/(t+1)} \tag{20}$$

Mathematical transitivity:

$$\frac{\omega_{j(t)}}{\omega_{j(t+2)}} = \wp_{(t+1)/(t+2)} \tag{21}$$

The final model for solving for the deviation from the full consistency (DFC) is constructed as

$$\begin{gathered} Min\ \chi \\ s.t \\ \left|\frac{\omega_{j(t)}}{\omega_{j(t+1)}} - \wp_{t/(t+1)}\right| \leq \chi, \forall j \\ \left|\frac{\omega_{j(t)}}{\omega_{j(t+2)}} - \wp_{t/(t+1)} \otimes \wp_{(t+1)/(t+2)}\right| \leq \chi, \forall j \\ \sum\omega_j = 1, \omega_j \geq 0, \forall j \end{gathered} \tag{22}$$

The model is said to be consistent if χ is significantly small. After solving the final model, we get the final weights of the criteria.

<u>Phase 3. Ranking of the alternatives (EDAS model)</u>

Next the ranking of the alternative models using the criteria weights is conducted following the algorithmic steps of the EDAS model [30]. The score matrix Y is used for this purpose.

$$Y = \begin{pmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{pmatrix}$$

Step 8. Find out the average solution

The average solution for the j^{th} criterion is obtained as

$$av_j = \frac{\sum_{i=1}^{m} y_{ij}}{m} \tag{23}$$

Step 9. Determine the positive deviation from the average (PDA) and the negative deviation from the average (NDA)

The PDA and NDA values are obtained as

$$D_{ij}^{+} = \begin{cases} \frac{\max(0,(y_{ij}-av_j))}{av_j}; j \in j^{+}(beneficial) \\ \frac{\max(0,(av_j-y_{ij}))}{av_j}; j \in j^{-}(non-beneficial) \end{cases} \tag{24}$$

$$D_{ij}^{-} = \begin{cases} \frac{\max(0,(av_j-y_{ij}))}{av_j}; j \in j^{+}(beneficial) \\ \frac{\max(0,(y_{ij}-av_j))}{av_j}; j \in j^{-}(non-beneficial) \end{cases} \tag{25}$$

Step 10. Compute the weighted sum of PDA and NDA for all alternatives
The weighted sums are computed as

$$S_i^{+} = \sum_{j=1}^{n} \omega_j D_{ij}^{+} \tag{26}$$

$$S_i^{-} = \sum_{j=1}^{n} \omega_j D_{ij}^{-} \tag{27}$$

ω_j is the weight of the j^{th} criterion.

Step 11. Normalization of the values of the weighted sums for all alternatives
The normalized weighted sums are calculated as

$$NS_i^{+} = \frac{S_i^{+}}{\max(S_i^{+})} \tag{28}$$

$$NS_i^{-} = 1 - \frac{S_i^{-}}{\max(S_i^{-})} \tag{29}$$

Step 12. Derive the appraisal score (AS) for all alternatives
The appraisal score of the i^{th} alternative is calculated as

$$AS_i = \frac{1}{2}(NS_i^{+} + NS_i^{-}) \tag{30}$$

$0 \leq AS_i \leq 1$

The alternative with a higher AS_i value is ranked first than the others.

5. FINDINGS

This section provides stepwise findings of the data analysis briefly. The opinions of the respondents are obtained through online questionnaires. Next, the intuitionistic fuzzy weighted (IFWA) operation [102] is carried out to get an aggregated rating of each food with respect to each criterion. Aggregated response (IF-Decision Matrix) is provided in Table 7. In this study, it is considered that the all respondents are having equal weightage. Therefore, λ1= λ2=…. = λ10=1/10.

Table 7: IF-Decision Matrix (aggregated response)

Food	UA1		UA2		UA3		UA4		UA5	
F1	0.597	0.385	0.088	0.499	0.088	0.385	0.067	0.394	0.067	0.452
F2	0.435	0.452	0.022	0.412	0.022	0.341	0.067	0.359	0.067	0.429
F3	0.549	0.394	0.058	0.412	0.058	0.331	0.067	0.520	0.067	0.508
F4	0.506	0.385	0.022	0.314	0.022	0.322	0.067	0.339	0.067	0.452
F5	0.473	0.417	0.022	0.380	0.022	0.369	0.067	0.401	0.067	0.505
F6	0.365	0.587	0.058	0.499	0.058	0.485	0.067	0.526	0.067	0.412
F7	0.447	0.442	0.022	0.355	0.022	0.365	0.067	0.378	0.067	0.355
F8	0.556	0.505	0.206	0.380	0.206	0.471	0.011	0.541	0.011	0.529
F9	0.551	0.345	0.022	0.351	0.022	0.369	0.011	0.447	0.011	0.437
F10	0.556	0.505	0.206	0.460	0.206	0.468	0.011	0.580	0.011	0.389
Food	UA6		UA7		UA8		UA9		UA10	
F1	0.067	0.505	0.067	0.365	0.067	0.380	0.067	0.280	0.067	0.434
F2	0.067	0.442	0.067	0.376	0.067	0.557	0.067	0.339	0.067	0.520
F3	0.067	0.493	0.067	0.380	0.067	0.429	0.067	0.412	0.067	0.466
F4	0.067	0.535	0.067	0.401	0.067	0.520	0.067	0.349	0.067	0.417
F5	0.067	0.557	0.067	0.391	0.067	0.550	0.067	0.331	0.067	0.477
F6	0.067	0.474	0.067	0.429	0.067	0.339	0.067	0.564	0.067	0.493
F7	0.067	0.541	0.067	0.369	0.042	0.309	0.067	0.580	0.067	0.452
F8	0.011	0.520	0.011	0.460	0.067	0.401	0.011	0.460	0.011	0.493
F9	0.011	0.493	0.011	0.355	0.067	0.424	0.011	0.529	0.011	0.535
F10	0.011	0.614	0.011	0.442	0.067	0.353	0.011	0.629	0.011	0.622

After preparing the decision matrix, now the normalized decision matrix is constructed. Normalized Matrix is given in Table 8.

Table 8: Normalized IF-Decision Matrix

Food	UA1		UA2		UA3		UA4		UA5	
F1	0.597	0.385	0.499	0.088	0.088	0.385	0.067	0.394	0.452	0.067
F2	0.435	0.452	0.412	0.022	0.022	0.341	0.067	0.359	0.429	0.067
F3	0.549	0.394	0.412	0.058	0.058	0.331	0.067	0.520	0.508	0.067
F4	0.506	0.385	0.314	0.022	0.022	0.322	0.067	0.339	0.452	0.067
F5	0.473	0.417	0.380	0.022	0.022	0.369	0.067	0.401	0.505	0.067
F6	0.365	0.587	0.499	0.058	0.058	0.485	0.067	0.526	0.412	0.067
F7	0.447	0.442	0.355	0.022	0.022	0.365	0.067	0.378	0.355	0.067
F8	0.556	0.505	0.380	0.206	0.206	0.471	0.011	0.541	0.529	0.011
F9	0.551	0.345	0.351	0.022	0.022	0.369	0.011	0.447	0.437	0.011
F10	0.556	0.505	0.460	0.206	0.206	0.468	0.011	0.580	0.389	0.011
Food	UA6		UA7		UA8		UA9		UA10	
F1	0.067	0.505	0.067	0.365	0.067	0.380	0.067	0.280	0.067	0.434
F2	0.067	0.442	0.067	0.376	0.067	0.557	0.067	0.339	0.067	0.520
F3	0.067	0.493	0.067	0.380	0.067	0.429	0.067	0.412	0.067	0.466
F4	0.067	0.535	0.067	0.401	0.067	0.520	0.067	0.349	0.067	0.417
F5	0.067	0.557	0.067	0.391	0.067	0.550	0.067	0.331	0.067	0.477
F6	0.067	0.474	0.067	0.429	0.067	0.339	0.067	0.564	0.067	0.493
F7	0.067	0.541	0.067	0.369	0.042	0.309	0.067	0.580	0.067	0.452
F8	0.011	0.520	0.011	0.460	0.067	0.401	0.011	0.460	0.011	0.493
F9	0.011	0.493	0.011	0.355	0.067	0.424	0.011	0.529	0.011	0.535
F10	0.011	0.614	0.011	0.442	0.067	0.353	0.011	0.629	0.011	0.622

Now, score based normalized value is calculated. Score based Normalized Decision Matrix is given in Table 9.

Table 9: Score based Normalized Decision Matrix

Criteria/ Foods	UA1 (+)	UA2 (-)	UA3 (+)	UA4 (+)	UA5 (-)	UA6 (+)	UA7 (+)	UA8 (+)	UA9 (+)	UA10 (+)
F1	0.608	0.705	0.134	0.103	0.670	0.096	0.105	0.104	0.111	0.100
F2	0.484	0.645	0.036	0.105	0.646	0.100	0.104	0.092	0.107	0.095
F3	0.580	0.631	0.094	0.095	0.724	0.096	0.104	0.101	0.102	0.098
F4	0.562	0.523	0.037	0.107	0.670	0.094	0.103	0.095	0.106	0.102
F5	0.525	0.607	0.036	0.103	0.721	0.092	0.103	0.093	0.107	0.098
F6	0.383	0.720	0.085	0.094	0.627	0.098	0.101	0.107	0.092	0.096
F7	0.497	0.576	0.036	0.104	0.560	0.093	0.105	0.070	0.091	0.099
F8	0.522	0.538	0.272	0.015	0.772	0.015	0.016	0.103	0.016	0.016
F9	0.609	0.570	0.036	0.016	0.678	0.016	0.017	0.101	0.015	0.015
F10	0.522	0.614	0.273	0.015	0.623	0.014	0.016	0.106	0.014	0.014

Now, once normalization matrix is formulated, the Percentage Value (PV) for each criterion using the procedural steps of LOPCOW (see expressions (4)) is evaluated. Table 10 displays the calculated PVs for each criterion.

For example,

For UA1,

$$P_j = \left| \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^{\ 2}}{m}}}{\sigma} \right) . 100 \right| = 206.9408$$

It can be noted that while calculating PV, min (Square) of the normalized value with respect to the standard deviation (SD) of the corresponding cell is taken and this natural log is applied in the ratio to get the percentage value. By taking the square the negative value effect is removed and dividing it with SD the outlier effect is removed and most importantly this gives an even distribution of the PV because of the presence of the natural log operator. Now, the criteria based on their PV values are arranged and we calculate the final weights using equations (5), (6), and (7). Table 11 and 12 exhibit the comparative priorities and the final weights of the criteria respectively.

Table 10: Calculation of the PV values

Criteria	UA1	UA2	UA3	UA4	UA5
Mean Square	0.284	0.379	0.019	0.007	0.451
SD	0.067	0.065	0.095	0.042	0.06
PV	206.94	224.35	36.795	71.447	240.91
Criteria	UA6	UA7	UA8	UA9	UA10
Mean Square	0.007	0.008	0.001	0.007	0.007
SD	0.039	0.042	0.011	0.043	0.04
PV	72.625	72.755	218.35	70.589	72.012

Table 11: Comparative priorities of the criteria

Criteria	PV	φ(k/k+1)	w(k/k+1)	w(k/k+2)	W
UA5	240.9149	1.0738	1.0738	1.1033	0.1872
UA2	224.3507	1.0275	1.0275	1.0841	0.1743
UA8	218.3519	1.0551	1.0551	3.0012	0.1697
UA1	206.9408	2.8443	2.8443	2.8494	0.1608
UA7	72.755	1.0018	1.0018	1.0103	0.0565
UA6	72.6254	1.0085	1.0085	1.0165	0.0564
UA10	72.0115	1.0079	1.0079	1.0202	0.056
UA4	71.4467	1.0122	1.0122	1.9417	0.0555
UA9	70.589	1.9184	1.9184		0.0549
UA3	36.7952				0.0286

(DFC = 0.000037)

Table 12: Final weights of the criteria

Criteria	UA1	UA2	UA3	UA4	UA5
Weight	0.1608	0.1743	0.0286	0.0555	0.1872
Criteria	UA6	UA7	UA8	UA9	UA 10
Weight	0.0564	0.0565	0.1697	0.0549	0.056

(UA1: Trust; UA2: Perceived Risks; UA3: Easy Availability; UA4: Better Taste; UA5: Price; UA6: Information; UA7: Trendy; UA8: Curiosity; UA9: More Nutritious; UA10: WOM)

The DFC (χ) value is achieved as $\chi = 0.00003654889 \approx 0$ which recommends the validity of the criteria weight calculation and has furnished a consistent solution by LOPCOW-FUCOM. The order of preference of the organic food products is found as

$$UA_5 \succ UA_2 \succ UA_8 \succ UA_1 \succ UA_7 \succ UA_6 \succ UA_{10} \succ UA_4 \succ UA_9 \succ UA_3$$

We use Lingo software (version 20) to calculate the criteria weights.

We now move to rank the alternatives using the steps of EDAS method. Using the equations (24) and (25), PDA and NDA have been formulated (Table 13 and 14). It may be noted that criteria 2 and 5 are non-beneficial (i.e.- minimizing effects) type. Next, the weighted sums of PDA and NDA, termed as SP and SN are calculated as sum products (see expressions (26), (27)). Then the normalized weighted sum of PDA (NSP) and NDA values (NSN) are constructed (see expressions (28), (29)). The appraisal score of the ith alternative is computed (see expressions (30)). The alternatives are ranked as per their appraisal scores in descending order. Table 15 represents ranking of the organic foods along with the values of SP, SN, NSP, NSN, AS etc.

Table 13: PDA matrix

	UA 1	UA 2	UA 3	UA 4	UA 5	UA 6	UA 7	UA 8	UA 9	UA 10
F1	0.149	0.000	0.291	0.362	0.000	0.339	0.357	0.072	0.455	0.369
F2	0.000	0.000	0.000	0.393	0.035	0.398	0.347	0.000	0.404	0.291
F3	0.097	0.000	0.000	0.250	0.000	0.350	0.344	0.038	0.339	0.340
F4	0.061	0.147	0.000	0.410	0.000	0.311	0.326	0.000	0.395	0.385
F5	0.000	0.009	0.000	0.356	0.000	0.290	0.334	0.000	0.411	0.330
F6	0.000	0.000	0.000	0.245	0.063	0.369	0.301	0.101	0.206	0.315
F7	0.000	0.061	0.000	0.375	0.163	0.305	0.353	0.000	0.191	0.352
F8	0.000	0.123	1.627	0.000	0.000	0.000	0.000	0.058	0.000	0.000
F9	0.150	0.069	0.000	0.000	0.000	0.000	0.000	0.042	0.000	0.000
F10	0.000	0.000	1.633	0.000	0.069	0.000	0.000	0.091	0.000	0.000

Table 14: NDA matrix

	UA 1	UA 2	UA 3	UA 4	UA 5	UA 6	UA 7	UA 8	UA 9	UA 10
F1	0.000	0.151	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
F2	0.085	0.053	0.651	0.000	0.000	0.000	0.000	0.050	0.000	0.000
F3	0.000	0.029	0.098	0.000	0.082	0.000	0.000	0.000	0.000	0.000
F4	0.000	0.000	0.647	0.000	0.001	0.000	0.000	0.024	0.000	0.000
F5	0.008	0.000	0.657	0.000	0.078	0.000	0.000	0.045	0.000	0.000
F6	0.276	0.175	0.184	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F7	0.061	0.000	0.656	0.000	0.000	0.000	0.000	0.283	0.000	0.000
F8	0.013	0.000	0.000	0.799	0.154	0.784	0.793	0.000	0.789	0.786
F9	0.000	0.000	0.657	0.786	0.014	0.780	0.779	0.000	0.799	0.792
F10	0.013	0.002	0.000	0.805	0.000	0.798	0.790	0.000	0.813	0.804

Table 15: Ranking of alternatives

Product	SP	SN	NSP	NSN	AS	Rank
F1	0.149	0.027	1.000	0.895	0.947	1
F2	0.109	0.050	0.728	0.801	0.765	5
F3	0.113	0.023	0.754	0.908	0.831	3
F4	0.138	0.023	0.920	0.909	0.915	2
F5	0.098	0.042	0.653	0.832	0.742	6
F6	0.109	0.080	0.731	0.681	0.706	7
F7	0.129	0.077	0.865	0.696	0.780	4
F8	0.078	0.252	0.520	0.000	0.260	9
F9	0.043	0.241	0.290	0.042	0.166	10
F10	0.075	0.226	0.502	0.101	0.301	8

(F1: Vegetables and Fruits; F2: Milk and Dairy Products; F3: Cereals and Grains Products; F4: Eggs and Poultry; F5: Meats(excluding Poultry); F6: Condiments and Seasonings; F7: Snack Foods; F8: Baby Foods; F9: Non-alcoholic Beverages (excluding milk and dairy); F10: Alcoholic Beverages)

It may be noted that extreme low values of DFC imply that this model has given a consistent solution. Also, it can be observed that F1>F4>F3>F2>F7>F5>F6>F10>F8>F9. Hence, Vegetables and Fruits, Eggs and Poultry, Cereals and Grains Products, Milk and Dairy Products are found to be more popular selection alternatives. Indians are still believing on the traditional baby food available in the market. Also, it can be highlighted that the high-end brands and multinational brands are very much preferred for alcoholic beverages than the organic one as per the ranking is concerned. So, the result is justified in that sense.

5.1. Sensitivity Analysis

For any MCDM model it is required to check the stability of the solution using sensitivity analysis. Sensitivity analysis is performed for determining the robustness and stability of the results by testing the degree the original ranking given by a MCDM model. MCDM model becomes susceptible because of the changes in the given situations [104-106]. In this paper the succeeding situations is created [107-108].

We reduce the criterion with highest weight (i.e., UA5) by 2% at each stage and then increase the weights of the other criteria proportion form for confirming the sum of weights = 1. This way 10 such situations are generated. Table 16 displays the various scenarios for sensitivity analysis (i.e., the ranking of the organic foods using different experimental cases).

Table 16: Experimental cases for sensitivity analysis

Cases	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
Initial	0.1608	0.1743	0.0286	0.0555	0.1872	0.0564	0.0565	0.1697	0.0549	0.0560
Exp1	0.1612	0.1748	0.0290	0.0559	0.1868	0.0569	0.0570	0.1701	0.0553	0.0564
Exp2	0.1617	0.1752	0.0294	0.0564	0.1864	0.0573	0.0574	0.1705	0.0557	0.0568
Exp3	0.1621	0.1756	0.0298	0.0568	0.1860	0.0577	0.0578	0.1709	0.0561	0.0572
Exp4	0.1625	0.1760	0.0303	0.0572	0.1856	0.0581	0.0582	0.1714	0.0565	0.0576
Exp5	0.1629	0.1764	0.0307	0.0576	0.1851	0.0585	0.0586	0.1718	0.0569	0.0580
Exp6	0.1633	0.1768	0.0311	0.0580	0.1847	0.0589	0.0590	0.1722	0.0574	0.0585
Exp7	0.1637	0.1773	0.0315	0.0584	0.1843	0.0594	0.0595	0.1726	0.0578	0.0589
Exp8	0.1642	0.1777	0.0319	0.0589	0.1839	0.0598	0.0599	0.1730	0.0582	0.0593
Exp9	0.1646	0.1781	0.0323	0.0593	0.1835	0.0602	0.0603	0.1734	0.0586	0.0597
Exp10	0.1650	0.1785	0.0328	0.0597	0.1831	0.0606	0.0607	0.1738	0.0590	0.0601

Table 17 exhibits that there is no much variation the comparative positions of the organic foods to notify in spite of variations in the criteria weights. Figure 2 also pictorially displays the outcome of the sensitivity analysis by plotting the ranks based on the success factors. The figure highlights that there are fewer variations. Hence it can be inferred that the model gives a quite stable solution.

Table 17: Result of sensitivity analysis (Ranking under experimental cases)

	Ranking of alternatives									
Cases	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Initial	1	5	3	2	6	7	4	9	10	8
Exp1	1	5	3	2	6	7	4	9	10	8
Exp2	1	5	3	2	6	7	4	9	10	8
Exp3	1	5	3	2	6	7	4	9	10	8
Exp4	1	5	3	2	6	7	4	9	10	8
Exp5	1	5	3	2	6	7	4	9	10	8
Exp6	1	5	3	2	6	7	4	9	10	8
Exp7	1	5	3	2	6	7	4	9	10	8
Exp8	1	5	3	2	6	7	4	9	10	8
Exp9	1	5	3	2	6	7	4	9	10	8
Exp10	1	6	3	5	7	4	2	10	8	9

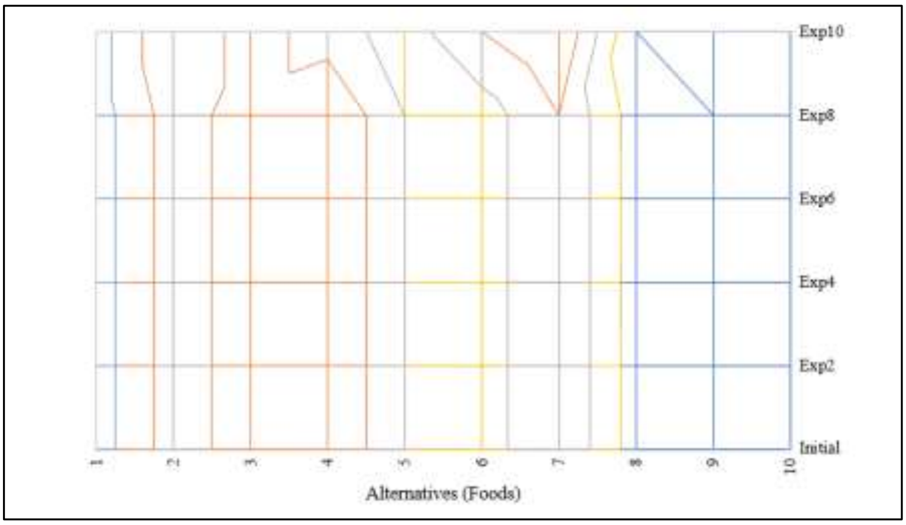

Figure 2: Result of sensitivity analysis

From the sensitivity analysis, it is evident that except experiment 10, for all other cases the alternatives maintain their initial positions. Moreover, under experiment 10, there is not much significant deviation noticed for the alternatives except F4 (that changed its initial position from 2nd to 5th). Overall, the top and bottom performers remain to their list despite changes in the external conditions. Therefore, it may be contended that there is a stability in the outcome. The change in the criteria weight is a representative of the variations in the consumer preferences. From that perspective the result of the sensitivity analysis shows that overall preferential order of the organic foods under comparison does not suffer from substantial vulnerabilities.

5.2. Comparison with other MCDM models

The reliability of the outcomes acquired from MCDM model hinges on several fundamental assumptions like criteria decision and their interrelationship, possibility of the algorithm specified the context and its capability to depict the actual scenario, dissimilarities in the criteria weights, variation in the alternative and criteria etc. Hence, it is essential to perform the validation test for confirming the robustness and stability in the final model. We check the validity in the following ways.

a) Comparing the outcomes acquired from the technique with that resulting using other established algorithms
b) Then Spearman's correlation test is performed

In the paper, the comparative analysis of the organic foods is done using TOPSIS and COPRAS method. Table 18 displays that there are hardly any variations in the comparative ranking of the alternatives. Figure 3 reflects the results. Table 19 exhibits Spearman's Rank Correlation test, which suggest that the method is comparable with other popular widely used method. So, it can be stated that the solution obtained is quite reliable in nature.

Table 18: Result of comparative analysis of MCDM models

Model	Food	Method		
		EDAS	COPRAS	TOPSIS
F1	Vegetables and Fruits	1	1	2
F2	Milk and Dairy Products	5	4	4
F3	Cereals and Grains Products	3	3	3
F4	Eggs and Poultry	2	2	1
F5	Meats (excluding Poultry)	6	6	5
F6	Condiments and Seasonings	7	7	7
F7	Snack Foods	4	5	6
F8	Baby Foods	9	9	10
F9	Non-alcoholic Beverages (excluding milk and dairy)	10	10	9
F10	Alcoholic Beverages	8	8	8

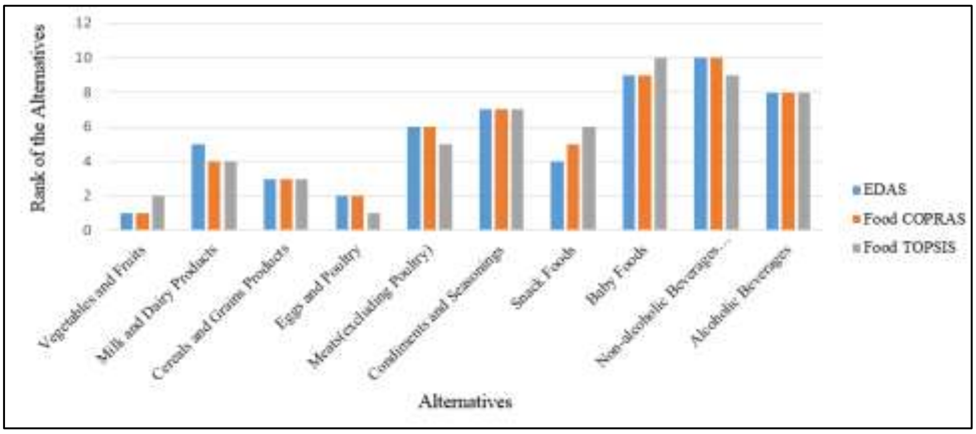

Figure 3: Result of comparative analysis of MCDM models

Table 19: Result of Spearman's rank correlation test

Correlation Coefficient	Method	COPRAS	TOPSIS
Spearman's rho	EDAS	.988**	.939**
Sig. (2-tailed)		0.000	0.000
** Correlation is significant at the 0.01 level (2-tailed).			

6. DISCUSSION

The consumer black box model is a combination of sociology, economics, and psychology. Its goal is to comprehend how buyers make decisions, both individually and collectively. It aims to understand people's demands by studying consumer characteristics, including demographics and behavioral variables. Additionally, it makes an effort to evaluate the impact of various social groupings, including the consumer's family, friends, reference group, and society at large. The interactions between stimuli, customer traits, the decision-making process, and consumer reactions are illustrated by the black box model.

This model suggests that customers have specific reactions to various stimuli after they have mentally "processed" them. More specifically, the model proposes that, although things outside, i.e., product, price, information, availability, and word-of-mouth (WOM), will serve as a stimulus for customer behavior, the consumer's own traits and decision-making process, like trust, curiosity, and perceived risks, will combine with the stimulus to produce a unique behavioral response.

From the analysis it can be notified that while purchasing organic food, the customers give priorities to the criteria like the price, perceived risks, curiosity, trust, trendy, information, WOM, better taste, more nutritious, easy availability etc. The top five criteria, the customers look for while buying organic food are price, perceived risks, curiosity, trust and trendy. Organic food products are usually high priced because of the additional production costs [51]. This is one of challenge of organic food consumption as suggested by earlier research [109]. One study revealed that consumers' trust in organic labels can motivate them to deliver higher propensity to buy organic food [110]. Former studies also have suggested that the customers are sensitive to the price and ready to go for premium price for it [111]. This study highlights fact that Indian consumers still judge the product based on its value for money. The results of this paper highlight the fact the recent raising of greenwashing is impacting the consumers' trust and enhancing the perceived risks towards it. This paper also identified that there is an intention-behavior gap. The recent age customers are more conscious in understanding the greenness of the product. They are hesitant in paying high-price for organic food considering the fact of food scandals. Food scandals have triggered their concerns towards the quality of food products [51]. This makes the customers believe that organic foods are not free from chemical. Thus, the customers are focusing on price and perceived risks while selecting for organic food. It is quite evident that enhanced greenwashing lead to risk perception along with reduction of consumer satisfaction [112].

It is highly impactful to diminish the risks of eco-opportunism in order successfully combat greenwashing [113]. It is evident in the literature that the customers perceived value in terms of health, hedonic and social can influence customers buying intentions specially towards organic fruits and vegetables [114]. The customers buy organic food based on the values and opinions related to environmental issues [115] as well as trustworthiness [2]. These types of products are perceived as healthier and nutritious than traditional ones [116], so nutrition and taste are not coming as the leading criteria for food selection. The same conclusion is drawn by another study within Chinese consumers, who are also not considering the taste of it superior [2]. When the customers purchase organic food, they believe that they are getting highest value out of it. The people of doing organic food consumption because of marketing hype, social pressure and the desire for superior social upright [2]. Likewise, social ambiances and peer opinions make the customers curious about in organic buying [117]. On the other way, availability of organic food is least important factor while selecting it, which support the previous study too [31]. In terms of organic food inclination, vegetables and fruits, eggs and poultry, cereals and grains products, snack foods, milk and dairy products are top five preferred organic food. Past literature had also supported the fact that in India, fruits and vegetables have the utmost demand in organic food consumption [47].

The present paper has opted for IFS based analysis for a number of reasons such as a) offsetting the subjective bias in the opinions; b) consideration of both membership and non-membership degrees by IFS; c) simplicity in conceptualization and application as compared with the other variants of fuzzy. However, IFS also has limitations. The notable limitation is that the sum of membership and non-membership degrees should be less than or equal to 1. To give more flexibility to the decision makers and to carry out a granular analysis (while trading off with computational complexity), the present work can also employ the approaches followed in past studies (that used other versions of fuzzy numbers and rough/grey number based analysis and multi-objective optimization models) (for instance, [118-124]) among others.

7. CONCLUSION

This study has made a different attempt in order to identify the critical factors prompting the organic food selection. The business-units can augment, the curiosity level of the customers by implementing the ambush marketing. In this marketing strategy, the advertisements can be placed in such spaces, where the customers neither do not believe to see them nor can readily avoid them. Since most of the priorities of selecting organic food are extrinsic in nature, so due to the absence of the satisfactory involvement with it, the customers frequently assess the quality of it based on the external cues, which are not intrinsic properties in the product. So, the experiential marketing can be executed to engage and interact with the organic food in sensory way to create trust and reduce the effect of perceived risks. This is also because organic food is connected with well-being (Rana and Paul, 2019) of the customers with a emotion of consuming healthy nutrients.

The markets must able deliver added total customer benefit, which is the combination of product benefit, image benefit, personnel benefit etc., then the total customer cost, which bundles the monetary cost, time cost, energy cost, psychological cost etc. The firms can enhance the total customer benefit by focusing on product benefit, functional benefit or emotional benefit rather than any other cost. It is also important to provide customer multiple cues to stimulate them towards organic food familiarity like reappearance of the advertisement, noticeable sponsorship along with some peripheral cues like celebrity endorsement, noticeable packing, branding, attractive promotion etc. Greenwashing need to reduce in order to increase the green trust and lessening the green gap. In order to increase the curiosity among the new customers, marketers can apply various marketing communication mix like sales promotions, events, contests, seminars, speeches etc. The application of online (e.g. blogs, search ads, display ads) and social media marketing platforms (e.g. Facebook, Twitter etc.) can speed up acceptance ratio, particularly amongst tech-savvy consumers like youth [125]. From the technical aspects, this study provides a reliable and stable output. Hence, the current model can be applied in future difficult circumstances.

8. LIMITATION AND FUTURE SCOPE

The research has few limitations which generate some future scopes. This study is mainly conducted in the urban areas, where the relative awareness of organic products is more. In contrast, the future study can be conducted in rural or semi-rural areas specific focus on low-income consumers to understand the consumers perception towards it. Thus, one of the acknowledged limitations of this research is restricted sample size in one geographic zone. Consequently, future research can focus on extended geographic region to check the validity of the output. To broaden the scope, the comparative analysis can be done between the organic and non-organic users to understand the diversity in customer segmentation. Future researchers can include other factors like-advertisement, government regulations, certifications etc. or negative variables such as green consumer skepticism also to understand intention behavior gaps. Future research can analyze various types of perceived risks in organic food choice. Furthermore, the research can be studied in other brand categories like-clothing, cosmetics, furniture to intensification the generalizability of the results.

In this work we have not considered a mixed theoretic lens using other theories like VBN or uses-gratification or SOR which may be thought of in a future study. The sample units considered in this work are heterogenous in nature that posits limitation for optimizing the price. Hence, a potential work may be carried out to compare organic foods intra and inter-segment wise. From the technical point of view the methodology used in this paper may be further explored for other complex selection problems and optimization purpose. As a matter of fact, the methodology used in this paper can be supplemented by application of machine learning models like natural language processing and sentiment analysis. The sentiments regarding the organic foods may be captured and analyzed by our used framework. Also, the present framework shall be extended with using rough sets, fuzzy rough numbers, other variants of fuzzy with the possibility of having a granular analysis. Nevertheless, the future scope cannot undermine the usefulness and novelty of the ongoing work as it provides an analytical framework not only to the researchers but also to the strategic decision makers.

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APPENDIX

Table A1: Rating of the alternatives by respondent 1 (R1)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	3	3	3	3	3	3	3	3	3	3
F2	3	3	3	3	3	3	3	3	3	3
F3	3	3	3	3	3	3	3	3	3	3
F4	3	3	3	3	3	3	3	3	3	3
F5	3	3	3	3	3	3	3	3	3	3
F6	3	3	3	3	3	3	3	3	3	3
F7	3	3	3	3	3	3	3	2	3	3
F8	3	3	3	1	1	1	1	1	1	1
F9	3	3	3	1	1	1	1	1	1	1
F10	3	3	3	1	1	1	1	1	1	1

Table A2: Rating of the alternatives by respondent 1 (R2)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	2	3	4	3	2	1	4	2	4	3
F2	4	5	4	2	2	1	4	2	5	3
F3	3	4	5	2	2	1	4	2	5	3
F4	4	5	5	2	2	1	4	2	5	3
F5	4	5	5	2	2	1	4	2	5	3
F6	3	3	3	3	4	1	4	5	4	3
F7	4	4	3	5	5	1	4	5	3	3
F8	1	1	1	1	2	1	4	1	1	3
F9	4	4	5	1	4	1	4	4	4	3
F10	1	1	1	1	5	1	4	5	1	3

Table A3: Rating of the alternatives by respondent 1 (R3)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	4	4	4	4	4	4	4	4	4	4
F2	3	3	4	4	4	4	4	3	3	3
F3	3	4	4	2	2	4	4	4	2	2
F4	2	4	4	3	3	3	3	3	3	2
F5	4	2	3	3	3	2	2	2	4	3
F6	3	4	4	2	2	3	4	3	3	4
F7	4	4	4	3	3	3	4	4	2	4
F8	1	4	3	2	2	2	4	3	2	3
F9	4	2	2	2	3	3	3	2	2	2
F10	4	2	2	2	2	2	3	3	3	2

Table A4: Rating of the alternatives by respondent 1 (R4)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	4	2	2	3	3	3	3	4	3	3
F2	2	2	2	4	2	2	4	2	2	2
F3	3	3	3	3	3	3	3	3	3	4
F4	4	2	2	4	4	4	3	2	4	3
F5	3	2	2	3	3	3	2	3	3	3
F6	3	2	2	2	3	2	3	4	2	2
F7	4	2	2	3	2	3	3	3	3	3
F8	4	5	5	3	3	4	3	4	4	4
F9	4	4	4	4	2	3	4	2	3	3
F10	3	4	4	3	3	3	2	3	2	3

Table A5: Rating of the alternatives by respondent 1 (R5)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	4	3	3	3	3	3	4	4	4	3
F2	3	2	2	2	4	4	2	2	4	2
F3	4	3	4	3	2	2	2	3	2	3
F4	4	4	3	4	3	2	3	3	3	4
F5	4	2	2	4	2	2	4	2	2	3
F6	3	2	3	3	3	4	2	3	3	2
F7	4	3	4	2	4	3	3	3	3	3
F8	3	4	3	3	3	3	3	4	4	2
F9	4	3	3	3	4	4	4	2	4	4
F10	3	3	4	3	3	2	3	3	3	3

Table A6: Rating of the alternatives by respondent 1 (R6)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	5	3	5	4	3	3	4	1	5	4
F2	4	3	5	5	3	3	4	1	4	3
F3	4	4	4	3	4	4	5	2	4	3
F4	3	4	4	5	3	3	5	2	4	4
F5	3	4	4	5	3	3	5	2	4	3
F6	2	3	3	3	5	2	3	4	1	2
F7	1	5	5	4	5	2	5	5	2	3
F8	3	4	3	4	4	3	3	4	4	4
F9	3	5	3	5	4	2	5	5	1	3
F10	1	5	4	2	5	2	5	5	1	1

Table A7: Rating of the alternatives by respondent 1 (R7)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	3	1	3	2	3	1	2	2	3	1
F2	3	2	3	2	3	1	2	2	3	2
F3	3	2	2	2	2	1	2	2	2	2
F4	3	3	3	3	3	1	2	2	3	3
F5	3	3	3	3	3	3	2	2	3	3
F6	1	1	1	1	2	2	3	3	1	2
F7	1	2	1	3	2	2	2	2	1	2
F8	3	3	3	1	2	3	2	2	3	2
F9	2	2	3	2	2	2	3	2	2	2
F10	3	3	2	2	3	3	2	2	3	2

Table A8: Rating of the alternatives by respondent 1 (R8)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	1	2	2	3	2	2	2	3	3	2
F2	1	2	2	3	2	2	2	3	3	2
F3	3	1	2	2	2	2	2	3	2	2
F4	2	2	2	3	2	2	2	3	2	2
F5	1	2	2	2	2	2	2	3	2	2
F6	1	2	2	3	2	2	2	3	1	2
F7	1	1	2	3	2	2	2	3	1	2
F8	3	2	2	3	2	2	2	3	3	2
F9	3	2	2	3	2	2	2	3	1	2
F10	3	2	2	3	2	2	2	3	1	2

Table A9: Rating of the alternatives by respondent 1 (R9)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	1	3	3	3	2	2	2	2	3	2
F2	1	3	3	3	2	2	2	2	3	2
F3	1	3	3	3	2	2	2	2	3	2
F4	2	2	3	3	2	2	2	2	3	2
F5	2	2	3	3	2	2	2	2	2	2
F6	1	3	2	2	2	2	2	2	2	2
F7	1	3	3	2	2	2	2	2	1	2
F8	1	3	2	2	2	2	2	2	2	2
F9	2	2	3	2	2	2	2	2	1	2
F10	2	2	2	2	2	2	2	2	2	2

Table A10: Rating of the alternatives by respondent 1 (R10)

Food	UA1	UA2	UA3	UA4	UA5	UA6	UA7	UA8	UA9	UA10
F1	1	2	1	3	3	3	2	4	4	3
F2	3	2	2	3	3	4	2	3	3	3
F3	3	2	2	2	2	2	2	4	2	3
F4	3	2	3	3	3	2	2	3	3	3
F5	2	2	3	2	3	2	2	2	4	3
F6	2	2	2	3	2	4	2	3	3	3
F7	2	2	2	3	2	3	2	4	2	3
F8	2	2	2	3	2	3	2	3	2	1
F9	3	2	2	3	2	4	2	2	2	1
F10	2	2	2	3	3	2	2	3	3	1