Prioritizing Matcha Green Tea Production Criteria by Logarithmic Fuzzy FUCOM with Z-Numbers

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ABSTRACT

The rapid growth of the global matcha market requires manufacturers to develop systematic tools for production planning under uncertainty. Matcha manufacturing involves multiple interdependent criteria, including cost, tea raw material quality, physicochemical properties, sensory attributes, and dissolvability, each contributing differently to overall product performance and consumer acceptance. Experts' opinions are not only vague but also differ in reliability, which limits the effectiveness of conventional Multi-Criteria Decision-Making (MADM) methods that treat all expert opinions equally. To address this limitation, this paper presents the Logarithmic Fuzzy Full Consistency Method with Z-numbers (LF-Z-FUCOM), which integrates fuzzy sets, logarithmic preference programming, and Z-numbers into a unified weighting framework. The proposed method allows both the importance of criteria and the confidence level of expert assessments to be incorporated directly into the weight estimation process. A real-world case study was conducted on matcha green tea production in Thailand. The results are compared with those obtained from the conventional FUCOM and Fuzzy FUCOM methods. The findings demonstrate that LF-Z-FUCOM provides more discriminative and reliability-consistent criterion weights, clearly identifying cost (0.3208) and tea raw material quality (0.2829) as the dominant factors, whereas FUCOM and Fuzzy FUCOM fail to sufficiently separate closely ranked criteria. The proposed method improves decision transparency, consistency, and managerial interpretability in uncertain multi-criteria environments.

Keywords-LF-Z-FUCOM; Multi-Criteria Decision-Making (MCDM); Z-numbers; matcha production; fuzzy evaluation

I. INTRODUCTION

In recent years, matcha green tea has become famous around the world. In Thailand, matcha now appears in drinks and sweets as a fashionable item. Therefore, companies must list and rank the standards that define top-grade matcha so that factories can check each step against market demand and keep clients satisfied. Many factors influence matcha quality, including its aroma, taste, and appearance [1, 2]. Each step alters the final product, and every production stage requires close control to maintain quality. Much recent work examines how agriculture and processing affect the quality and chemistry of matcha [3-5]. However, these studies are primarily experimental or analytical in nature and do not provide a structured framework for prioritizing production criteria when trade-offs exist among economic, sensory, and functional objectives.

Production managers or Decision-Makers (DMs) must judge the value of each criterion. Their deep know-how and grasp of the situation let them weigh company goals against what buyers want. When they rank key points, factories fix production rules that properly deploy resources, sharpen product edges, and increase buyer satisfaction. However, such decisions are typically based on expert knowledge, which is inherently imprecise and characterized by varying levels of confidence. Conventional decision-making approaches, including many fuzzy MCDM methods, represent linguistic uncertainty but implicitly assume that all expert judgments are equally reliable. This assumption is unrealistic in practice, particularly in complex food manufacturing systems where experts differ in experience, specialization, and confidence.

Although fuzzy MCDM methods such as the Fuzzy Analytic Hierarchy Process (Fuzzy AHP), the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS), and the Fuzzy Full Consistency Method (Fuzzy FUCOM) have been widely used, their inability to explicitly model the reliability of expert judgments remains a critical limitation. Z-numbers were introduced to address this issue by representing each assessment as a pair consisting of a fuzzy value and its associated reliability [6]. However, existing Z-number-based MCDM models do not incorporate full consistency conditions, which are essential for generating logically coherent and stable weights.

To address this gap, this study presents the newly developed Logarithmic Fuzzy Full Consistency Method with Z-numbers (LF-Z-FUCOM) to ascertain the relative weights of the essential criteria influencing matcha green tea production in a case study factory in Thailand. The proposed method integrates fuzzy sets, Z-numbers, and logarithmic preference programming into the FUCOM framework, enabling the simultaneous treatment of uncertainty, reliability, and consistency. This makes the approach suitable for modern decision-making problems characterized by ambiguous data and heterogeneous expert confidence.

Unlike Fuzzy FUCOM, which assumes equal reliability of all expert judgments, LF-Z-FUCOM embeds reliability as a second-order uncertainty. This makes the method applicable to modern decision problems characterized by inconsistent experts, incomplete data, and volatile environments, such as food production, supply chains, and sustainability planning. The main contributions of this study are:

- Development of LF-Z-FUCOM by integrating logarithmic FUCOM with Z-number reliability modeling.
- Provides a reliability-aware weighting framework that improves discrimination among closely ranked criteria for food production.
- Demonstrates, via a real matcha case study, that LF-Z-FUCOM outperforms FUCOM and Fuzzy FUCOM in discriminating closely ranked criteria.

II. BACKGROUND

A. *Evaluation of Interrelated Production Factors*

Numerous factors have been associated with the production of matcha green tea [7-9]. Its main features, for instance, production costs, leaf quality, physicochemical properties, sensory attributes, and processing conditions, are not from a single source but are interrelated in complex, dynamic, and mutual ways. In fact, by improving leaf quality or increasing the level of amino acids and chlorophyll, the food product can taste better [7, 10-13]. Nevertheless, it may make the production process more expensive or less efficient. Therefore, understanding how these factors interact is a prerequisite for planning that optimally balances the economic and qualitative aspects of manufacturing. To properly assess these interrelated factors, producers need an analytical framework that enables them to identify the optimal balance between production costs, product quality, nutritional content, and processing efficiency [9, 14]. Using such a strategy, Thai matcha companies can use data-driven insights to adapt their production methods to customer preferences. Through economic and technical assessments, companies can better position themselves to align their market growth with the growing demand for high-quality, health-oriented products.

B. *Multi-Criteria Decision-Making (MCDM) Approaches*

During matcha production, multiple criteria that interact in complex ways must be evaluated. The assessment of various factors cannot be performed using traditional single-objective decision-making methods that consider only cost or quality. MCDM frameworks enable DMs to evaluate complex scenarios using structured methods that integrate quantitative data with qualitative expert assessments [15-17]. Such evaluation methods would allow DMs to determine criterion rankings and weights, which, in turn, would lead to manufacturing decisions that result in better balance and transparency. Recent studies have employed fuzzy MCDM methods to evaluate complex systems under uncertainty, demonstrating their flexibility and effectiveness in real-world applications [12]. However, despite their broad applicability, these fuzzy MCDM models treat all expert inputs equally, which limits their use in environments where some experts are more experienced or confident than others.

C. *Z-Number-Based and Recent Fuzzy MCDM Developments*

Z-numbers were introduced to overcome the limitation of conventional fuzzy MCDM methods, which represent uncertainty in expert judgments but do not account for the reliability of judgments. A Z-number consists of a fuzzy restriction and a fuzzy measure of confidence, allowing both the value of an assessment and its reliability to be explicitly modeled, enhancing decision robustness in uncertain environments [18]. Growing research has applied Z-number MCDM to enhance classical ranking methods such as TOPSIS, AHP, and fuzzy EDAS (Evaluation based on Distance from Average Solution) [6, 19]. These models demonstrate that explicitly modeling reliability can improve stability and reduce misleading rankings under high uncertainty. However, many approaches still convert Z-numbers into ordinary fuzzy numbers, which can dilute their reliability information.

Recent (2024–2026) methodological advances further extend the Z-number framework. For example, spherical fuzzy Z-numbers have been proposed to represent higher-order uncertainty and enhanced membership flexibility, and have been applied to municipal waste management problems using ARAS (Additive Ratio Assessment) combined with TODIM (Tomada de Decisao Iterativa Multicriterio) and CRITIC (Criteria Importance Through Intercriteria Correlation) techniques, showing improved treatment of stakeholder vagueness and imprecision [20]. Meanwhile, new combination weighting methods using Z-numbers integrate subjective and objective weighting processes, explicitly incorporating both expert evaluations and confidence levels into a unified criteria weighting framework [21]. In [22], a novel hybrid decision-making framework integrated complex fuzzy sets with Z-number reliability into both the Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) and Weighted Aggregate Sum Product Assessment (WASPAS) MCDM methods to evaluate alternatives in Augmented Reality (AR) decision environments. This approach extends traditional MARCOS and WASPAS models by using complex fuzzy membership values combined with Z-numbers to capture both the uncertainty and confidence of expert judgments in AR system selection problems.

D. Gap Identification and Positioning

Although the literature shows a clear trend toward integrating Z-numbers with diverse MCDM techniques, few studies explicitly incorporate full consistency mechanisms, such as FUCOM, into Z-number environments for criterion weighting. Existing Z-number methods either convert Z-numbers into regular fuzzy numbers (potentially leading to information loss) or perform direct computations without consistency optimization, which may reduce the reliability of the derived weights. Furthermore, recent developments focus more on methodological extensions to ranking algorithms and domain-specific applications, with fewer contributions addressing the core issue of reliably and consistently weighting criteria under uncertainty and heterogeneous expert confidence.

In summary, the current literature confirms that while Z-number-based MCDM methods are increasingly studied, there remains a methodological gap in developing full-consistency, reliability-aware weighting frameworks that produce weights that are both discriminative and robust to expert reliability variability. This gap motivated the development of the LF-Z-FUCOM model, which integrates Z-number reliability and logarithmic FUCOM optimization to enhance applicability and interpretability in complex problems.

III. METHODOLOGIES

A. Multi-Attribute Decision Making: Logarithmic Fuzzy Full Consistency Method with Z-Numbers (LF-Z-FUCOM)

FUCOM provides a systematic method to evaluate multiple decision criteria while maintaining logical consistency. The method produces weight coefficients that satisfy both proportionality and transitivity requirements. Later, the Fuzzy FUCOM model was developed to handle uncertainty in human judgment using a fuzzy linguistic variable to represent expert evaluation.

This study developed a fuzzy-based hierarchical framework that incorporates the Z-number concept into the fuzzy logarithmic preference structure of the FUCOM method, called LF-Z-FUCOM. Such an improvement implies a new calculation that merges fuzzy significance values with their respective reliability evaluations. Although a standard Fuzzy FUCOM works with fuzzy linguistic judgments only, the LF-Z-FUCOM changes each expert evaluation into a reliability-weighted fuzzy ratio. In this way, the pairwise significance between criteria not only shows the subjective importance of each criterion but also the level of confidence in each judgment. As a result, the method provides more accurate comparisons, thereby improving the consistency of the weighting process. The procedures of the model are as follows:

1) Step 1

Defining a set of evaluation criteria represented by a set $C = \{C_1, C_2, \ldots, C_n\}$.

2) Step 2

The MCDM model requires evaluating criteria by their importance, followed by ranking them according to their projected influence on the choice. The ranking process starts with the criterion with the highest weight coefficients, then proceeds with those with successively lower predicted weight coefficients, until the last, as shown in the following list.

$$C_{j(1)} > C_{j(2)} > \cdots > C_{j(k)} \quad (1)$$

3) Step 3

Triangular Fuzzy Numbers (TFNs) are employed to compare criteria that are based on subjective assessments. The fuzzy criterion significance ($\varpi C_{j(k)}$) is obtained for each criterion ranked in Step 2 and used for comparison with the first-ranked criterion. They need to be compared n times, since the top-ranked criterion is evaluated against both itself and the subsequent criteria.

4) Step 4

Pairwise comparisons are conducted between the base criterion and each remaining criterion. Reliability parameters are included within the Z-number framework, as illustrated in Table I, to indicate the degree of confidence for each assessment. The Z-number representing the DMs' preferences is obtained by merging the TFNs, which correspond to linguistic importance levels, with their respective reliability values. The mathematical expression for determining Z-number values is given in (2). Meanwhile, equation (3) specifies the vector of the pairwise comparisons between the reference criterion and the other criteria in Z-number terms. The reliability coefficient (α) is therefore a result of changing the second component of the Z-number into a crisp value, as explained in (4), which presents a new ratio-based calculation. This new formulation ensures that the resulting reliability measure reflects a proportional comparison structure consistent with the LF-Z-FUCOM framework.

TABLE I. LINGUISTIC VARIABLES OF RELIABILITY

Linguistic variables	TFNs
Very low	(0, 0, 0.3)
Low	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
High	(0.5, 0.7, 0.9)
Very high	(0.7, 1.0, 1.0)

$$Z - number\left(l_{Z(ij)}, m_{Z(ij)}, u_{Z(ij)}\right) = \left(l_j \times \alpha_n, m_j \times \alpha_n, u_j \times \alpha_n\right) \quad (2)$$

$$\tilde{A}_B = \left(l_{Z(B1)}, m_{Z(B1)}, u_{Z(B1)}\right), \left(l_{Z(B2)}, m_{Z(B2)}, u_{Z(B2)}\right), \dots, \left(l_{Z(Bn)}, m_{Z(Bn)}, u_{Z(Bn)}\right) \quad (3)$$

where $\left(l_{Z(Bn)}, m_{Z(Bn)}, u_{Z(Bn)}\right)$ represent the relative importance of the base criterion to the n criteria, employing Z-numbers.

$$\alpha_n = \sqrt{\alpha_{B1}/\alpha_{Bn}} \quad (4)$$

The assignment of relative importance values for pairwise comparisons should follow the guidelines outlined in:

$$\left(l_{ij}, m_{ij}, u_{ij}\right) = \frac{(l_{Bj}, m_{Bj}, u_{Bj})}{(l_{Bi}, m_{Bi}, u_{Bi})} \quad (5)$$

Next, based on the given importance, the following equation is used to determine the fuzzy comparative significance $\varphi_{k/(k+1)}$:

$$\varphi_{\frac{k}{k+1}} = \varpi C_{j(k+1)}/\varpi C_{j(k)} = \left(\varpi^l_{j(k+1)}, \varpi^m_{j(k+1)}, \varpi^u_{j(k+1)}\right)/\left(\varpi^l_{j(k)}, \varpi^m_{j(k)}, \varpi^u_{j(k)}\right) \quad (6)$$

The fuzzy vector of the comparative importance of the evaluation criteria is provided by:

$$\Phi = \left(\varphi_{1/2}, \varphi_{2/3}, \dots, \varphi_{k/(k+1)}\right) \quad (7)$$

where $\varphi_{k/(k+1)}$ denotes the relevance of the $C_{j(k)}$ rank concerning the $C_{j(k+1)}$ rank.

5) Step 5

To obtain the optimal fuzzy weight, the final value of the fuzzy weight coefficients $(w_1, w_2, \dots, w_n,)^T$ are obtained. There are two conditions that the final weight coefficient must satisfy.

Condition 1:

$$w_k/w_{k+1} = \varphi_{k/(k+1)} \quad (8)$$

Condition 2:

$$w_k/w_{k+2} = \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \quad (9)$$

The final nonlinear model for calculating the ideal fuzzy values of the weight coefficients for all criteria is built using the two previously stated conditions.

$$Minimize\ J = (1-\lambda)^2 + M \cdot \left(\sum_{k=1}^{n} \delta^2_{k/k+1} + \eta^2_{k/k+1}\right)$$

$$S.t. \begin{cases} x_k - x_{(k+1)} - \lambda\, ln\left(\varphi^m_{\frac{k}{k+1}}/\varphi^l_{\frac{k}{k+1}}\right) + \delta_{\frac{k}{k+1}} \geq ln\,\varphi^l_{\frac{k}{k+1}} \\ -x_k + x_{(k+1)} - \lambda\, ln\left(\varphi^u_{\frac{k}{k+1}}/\varphi^m_{\frac{k}{k+1}}\right) + \eta_{\frac{k}{k+1}} \geq -ln\varphi^u_{\frac{k}{k+1}} \\ \lambda, x_k, x_{(k+1)} \geq 0 \\ \delta_{\frac{k}{k+1}}, \eta_{\frac{k}{k+1}} \geq 0 \\ k = 1, \dots, n. \end{cases} \quad (10)$$

Let k denote the criterion's rank, $\varphi_{k/(k+1)} = \left(\varphi^l_{k/(k+1)}, \varphi^m_{k/(k+1)}, \varphi^u_{k/(k+1)}\right)$, $x_k = \ln w_k$ for $k = 1, \dots, n$, and $w_k = \left(w^l_k, w^m_k, w^u_k\right)$, x^*_k is an optimal solution. M represents a huge constant value (10^3), λ is the membership degree, and $\delta_{k/(k+1)}, \eta_{k/(k+1)}$ are nonnegative deviation variables for $k = 1, \dots, n$. The value of x^*_k is normalized, and the fuzzy pairwise comparison matrices are sorted using:

$$w^*_k = exp\, x^*_k / \textstyle\sum_{j=1}^{n} exp(x^*_k)\ , k = 1, \dots, n. \quad (11)$$

where exp () is the exponential function for which the computation is $\exp(x^*_k) = e^{x^*_k}$, for $k = 1, \dots, n$, and w^*_k is the weight of each criterion for $k = 1, \dots, n$.

6) Step 6

A consistency test is conducted. If an inconsistency is discovered, it must be investigated until the condition listed below is met.

In general, a positive optimum value is preferred. However, if its ideal value is $\lambda^* = 0$, it indicates a notable inconsistency among fuzzy decisions unless $\sum_{k=1}^{n}(\delta^2_{k/k+1} + \eta^2_{k/k+1}) = 0$. The larger the value of δ^*, the more inconsistent the fuzzy judgments. Consequently, the value of δ^* in the fuzzy pairwise comparison matrices is a measure of inconsistency.

IV. CASE STUDY

To ensure that the production processes meet both industry standards and customer expectations, it is essential to identify and evaluate the most important criteria that have a big effect on production outcomes. From a thorough review of the literature, significant factors highlighted in previous research on tea manufacturing, food processing, and quality assessment are grouped into five main categories: economic, material, chemical, sensory, and functional.

- Cost (C_1): The cost criterion concerns the monetary aspects of matcha production, including the cost of selecting raw materials, managing the growing process, and running the factory. The production processes of harvesting, withering, steaming, grinding, and drying are not free, and each of these processes requires proper planning and the use of funds [7, 8].
- Tea Raw Material (C_2): The quality of tea raw materials determines how matcha will taste and smell, what color it will be, and what nutrients it will contain. The selection of tea cultivars, growing conditions, and harvest timing determine the quality of matcha [12].
- Physicochemical properties (C_3): matcha's internal structure and its operational characteristics are primarily influenced by its physicochemical properties. These properties mainly

refer to the content of caffeine, polyphenols, and amino acids, which are closely related to nutritional and health-related factors of matcha [23].

- Sensory quality (C_4): Sensory characteristics are the overall perception of matcha through taste, smell, color, and texture. The intensity of the taste and the freshness, along with the product's appearance, are primarily determined by the accuracy of the production process and, therefore, by the tea grade and storage conditions [10, 24].
- Dissolvability (C_5): Dissolvability refers to the ability of matcha powder to disperse and dissolve uniformly in water during preparation. This factor affects not only the appearance and texture of the beverage but also the efficiency of nutrient extraction [25, 26].

The assessment was conducted by a group of key stakeholders comprising senior-level process engineers, production control managers, and executive personnel responsible for overseeing quality and operational planning. The panel consisted of two senior production engineers (over 15 years of experience), two quality control managers, two supply-chain planners, and one factory director. Their insights were essential for ensuring that the comparative judgments accurately reflected the operational priorities and constraints of the production system.

To obtain a representative consensus judgment while minimizing individual bias, the linguistic evaluations from the seven experts were first aggregated using the geometric mean, yielding the results presented in Table II. These aggregated values were subsequently processed within the Z-number framework, allowing both the importance ratings and their associated confidence levels to be incorporated into the calculation. Table III summarizes the resulting reliability-adjusted assessments.

TABLE II. FUZZY PAIRWISE COMPARISONS WITH RELIABILITY ASSESSMENTS FOR EACH CRITERION

criteria	C_1	C_2	C_3	C_4	C_5
l	0.9437	0.9437	1.3359	0.8052	2.1605
m	1.0000	1.0000	1.8114	1.1699	2.6718
u	1.0596	1.0596	2.3241	1.6930	3.1792
Reliability	(0.7,1.0, 1.0)	(0.5,0.7, 0.9)	(0.3,0.5, 0.7)	(0.1,0.3, 0.5)	(0.5,0.7, 0.9)
alpha	0.9	0.7	0.5	0.3	0.7

TABLE III. LINGUISTIC VARIABLES CONVERTED TO FUZZY Z-NUMBERS

$l_{z(11)}, m_{z(11)}, u_{z(11)}$	$l_{z(12)}, m_{z(12)}, u_{z(12)}$	$l_{z(13)}, m_{z(13)}, u_{z(13)}$	$l_{z(14)}, m_{z(14)}, u_{z(14)}$	$l_{z(15)}, m_{z(15)}, u_{z(15)}$
0.9437, 1.0000, 1.0596	1.0701, 1.1339, 1.2015	1.7923, 2.4303, 3.1181	1.3947, 2.0264, 2.9324	2.4498, 3.0296, 3.6049

A numerical example of the Z-number, with reliability assessment for C_1, is illustrated as follows.

$$Z-number\left(l_{Z(11)}, m_{Z(11)}, u_{Z(11)}\right) = (l_1 \times \alpha_1, m_1 \times \alpha_1, u_1 \times \alpha_1)$$

$$Z-number\left(0.9737\text{x}\sqrt{\frac{0.9}{0.9}}, 1.0000\text{x}\sqrt{\frac{0.9}{0.9}}, 1.0596\text{x}\sqrt{\frac{0.9}{0.9}}\right) = (0.9437, 1, 1.0596)$$

Based on the ranked importance of the criteria, equations (6) and (7) were applied to compute the fuzzy comparative significance values $\varphi_{k/(k+1)}$ and construct the corresponding fuzzy comparative vector Φ. The resulting comparative significance values obtained from these equations are summarized in Table IV. An example of the computation of φ_{12} is shown as follows.

$$\varphi_{12} = \varpi C_{12}/\varpi C_{11} = (\varpi_{12}^l, \varpi_{12}^m, \varpi_{12}^u)/(\varpi_{11}^l, \varpi_{11}^m, \varpi_{11}^u)$$

$$\varphi_{12} = \frac{(1.0701, 1.1339, 1.2015)}{(0.9437, 1, 1.0596)} =$$

$$(1.0099, 1.1339, 1.2732)$$

TABLE IV. FUZZY COMPARATIVE SIGNIFICANCE VALUES

$\varphi_{12}^l, \varphi_{12}^m, \varphi_{12}^u$	$\varphi_{24}^l, \varphi_{24}^m, \varphi_{24}^u$	$\varphi_{43}^l, \varphi_{43}^m, \varphi_{43}^u$	$\varphi_{35}^l, \varphi_{35}^m, \varphi_{35}^u$
1.0099 1.1339 1.2732	1.1608 1.7871 2.7403	0.6112 1.1993 2.2357	0.7857 1.2466 2.0113
$\varphi_{14}^l, \varphi_{14}^m, \varphi_{14}^u$	**$\varphi_{23}^l, \varphi_{23}^m, \varphi_{23}^u$**	**$\varphi_{45}^l, \varphi_{45}^m, \varphi_{45}^u$**	
1.1722 2.0264 3.4889	0.7095 2.1433 6.1265	0.4802 1.4951 4.4966	

Afterward, the local priority vectors were determined using (10) and (11), and the corresponding optimization problem was solved. Subsequently, the weight coefficients were calculated by (10) using LINGO 20. The resulting weights represent the consistency-adjusted importance of each criterion under the integrated fuzzy and reliability framework as shown in Figure 1. To confirm the resilience of the proposed approach, the LF-Z-FUCOM weights were also compared with those obtained from the traditional FUCOM and Fuzzy FUCOM [27] as shown in Table V. This comparison provides insight into the effect of including Z-number reliability on the final weight distribution across the criteria.

TABLE V. CRITERIA WEIGHTS

Rank	**FUCOM Weights**		**Fuzzy FUCOM Weights**		**LF-Z-FUCOM Weights**	
1	W_2	0.2645	W_2	0.2693	W_1	0.3208
2	W_1	0.2645	W_1	0.2310	W_2	0.2829
3	W_4	0.2261	W_4	0.2309	W_4	0.1583
4	W_3	0.1460	W_3	0.1503	W_3	0.1320
5	W_5	0.0990	W_5	0.1185	W_5	0.1059

V. SUPERIORITY ANALYSIS

The weight coefficients in Table V highlight a notable limitation of the conventional FUCOM and Fuzzy FUCOM approach. In the case of FUCOM, identical weights are assigned to criteria C_1 and C_2, indicating a weak discriminative capability. For Fuzzy FUCOM, although the expert team (DM group) provided average judgments, indicating that Cost (C_1) and Tea raw material (C_2) hold the highest and nearly equal levels of importance, the Fuzzy FUCOM results do not accurately reflect this consensus. The technique in question allocates the first rank to Tea raw material (C_2). On the other hand, Cost (C_1) and Sensory (C_4) are very close. The problem with this result is that Cost (C_1) and Sensory (C_4) should receive the same managerial consideration, even though the DMs have explicitly shown the opposite. Inconsistencies in these issues indicate that Fuzzy FUCOM might not be sufficient to capture subtle differences in expert judgments when vagueness and reliability variation are involved.

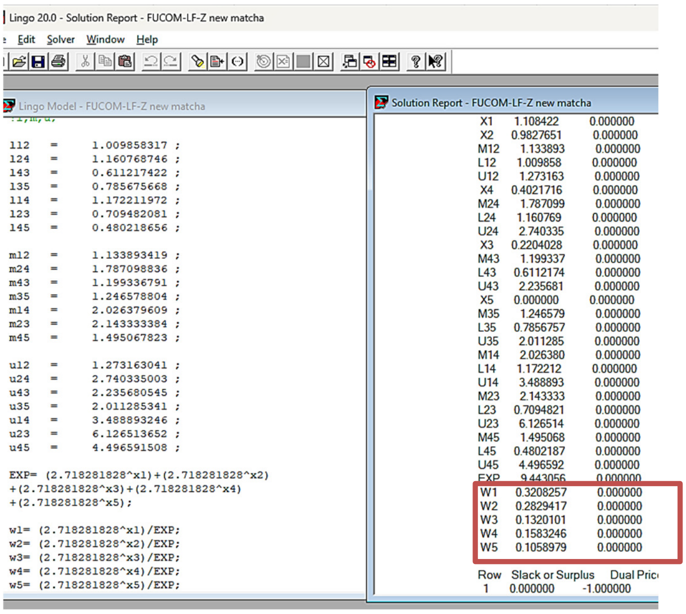

Fig. 1. Results of weights from LINGO.

On the other hand, the LF-Z-FUCOM model yields a more definite and easily understandable criteria hierarchy. By embedding the reliability of each expert judgment into the weighting procedure, LF-Z-FUCOM can distinguish differences in the relative importance of criteria that were treated as equal under the conventional fuzzy approach. The method ranks Cost (C_1) as the most crucial criterion and Tea raw material (C_2) as the next, which is consistent with the combined expert evaluations. Besides that, Sensory (C_4) is clearly in third place, thus eliminating the uncertainty as the Fuzzy FUCOM result. This improved discriminative power exemplifies the benefit of combining Z-numbers and logarithmic functions with the FUCOM approach, therefore providing more robust, consistent, and decision-aligned weighting results for complex decision problems.

The ranking of the criteria achieved by the LF-Z-FUCOM model is $C_1 > C_2 > C_4 > C_3 > C_5$, reflecting a clear prioritization of factors affecting matcha green tea production.

C_1(Cost) is the dominant factor; consequently, production expenses—that is, the costs of labor, materials, and others—are the main contributors to economic feasibility and price competitiveness. The result is consistent with the reality of operations in the matcha production industry, where cost efficiency is the primary concern for producers seeking to balance quality and market expectations.

C_2 (Tea raw material) is the next-highest criterion, highlighting good-quality tea leaves as the primary source of fresh matcha flavor, vibrant green color, and health-beneficial properties, since the quality of the raw material is the primary factor in determining product features and consumer perception.

C_4 (Sensory) ranked third, signifying the importance of taste, aroma, and appearance in determining consumer acceptance. Even though sensory features are essential for the product's attractiveness, they rely heavily on upstream factors, such as raw material quality and processing conditions, which is why they carry slightly lower weight.

C_3 (Physicochemical properties) ranked fourth, showing that chemical composition—for instance, amino acids, caffeine, and polyphenols—is essential for nutrition and functional properties, but might be considered by DMs as having less influence than the cost and sensory attributes in daily production decision-making.

C_5 (Dissolvability) is the last criterion, with the lowest weight, implying that, even if it is a factor that makes the product usable and pleasant to the consumer, it is relatively less critical than the other criteria for determining overall production priorities.

VI. DISCUSSION

The findings of this study provide important insights into both the methodological contributions of the LF-Z-FUCOM approach and the practical implications of the resulting criterion weights for matcha production.

A. Validation of the Weighting Results

The LF-Z-FUCOM model produces a fully consistent and stable set of criterion weights for the matcha production problem. The full consistency condition of FUCOM is satisfied, confirming that the logarithmic Z-number formulation preserves the ordinal and ratio relationships provided by the experts while incorporating uncertainty and reliability. The resulting weights indicate that Cost (C_1) and Tea raw material quality (C_1) are the two most influential factors, followed by Sensory quality (C_3) and Physicochemical properties (C_4). This ranking aligns with practical knowledge in food and beverage production, where raw material quality and cost structure largely determine product competitiveness. The consistency between the model outputs and expert expectations demonstrates that LF-Z-FUCOM yields realistic, interpretable results rather than purely mathematical outputs.

B. Managerial Interpretation of the Results

The obtained criterion weights provide direct decision support to matcha production managers and policymakers. The dominance of Cost (C_1) and Tea raw material (C_2) implies that strategic efforts should focus primarily on supplier selection, procurement planning, and raw material quality control. Improvements in these areas are likely to yield greater performance gains than adjustments in downstream processing alone. Managers should therefore allocate budgets primarily to leaf sourcing and cost control rather than downstream processing.

The substantial weight of Sensory quality (C_3) reflects the importance of taste, color, and aroma in premium matcha markets, where consumer perception strongly influences market value. Meanwhile, Physicochemical properties (C_4) play a supporting role by ensuring product stability and compliance with quality standards. Therefore, the LF-Z-FUCOM results translate expert judgments into actionable priorities that can guide investment, quality management, and production planning.

C. Ablation and State of the Art Comparison

An ablation analysis was conducted using three FUCOM-based weighting schemes: classical FUCOM, Fuzzy FUCOM, and the proposed LF-Z-FUCOM. These represent deterministic, fuzzy, and reliability-aware fuzzy decision environments, respectively. Table VI presents a comparative summary of FUCOM-based weighting methods.

TABLE VI. COMPARISON OF FUCOM-BASED WEIGHTING METHODS

Method	Handles uncertainty	Consistency	Reliability of experts
FUCOM	×	×	×
Fuzzy FUCOM	✓	×	×
LF-Z-FUCOM (proposed)	✓✓	✓✓	✓✓

✓ = supported, ✓✓ = explicitly and systematically addressed

Traditional FUCOM is primarily concerned with logical consistency and does not account for uncertainty or experts' reliability. Fuzzy FUCOM changes the method by adding fuzzy logic to address vagueness, but it still, by implication, assumes that all experts are equally reliable. The new LF-Z-FUCOM removes these restrictions by not only incorporating expert reliability via Z-numbers but also combining it with a logarithmic-ratio-based structure for better discrimination and more stable weight estimation.

Moreover, the logarithmic representation does not allow defuzzification; thus, the information's fuzziness is preserved throughout the optimization process. For this reason, the weight coefficients from an internal perspective are more stable and consistent. The model deals with the Fuzzy FUCOM standard, which is characterized by very low sensitivity to slight changes in expert assessments. The problem of Fuzzy FUCOM is solved by the LF-Z-FUCOM method through the introduction of reliability as an additional discriminator, thus providing more explicit and interpretable results.

As shown in Table V, FUCOM obtains identical weights of Cost (C_1) and Tea raw material (C_2). Fuzzy FUCOM produces ambiguous rankings between closely related criteria, particularly Cost (C_1) and Sensory attributes (C_3). LF-Z-FUCOM resolves this ambiguity and clearly identifies Cost (C_1) and Tea raw material (C_2) as the dominant criteria, consistent with expert consensus.

VII. CONCLUSION

This paper proposes a new decision-making framework, LF-Z-FUCOM, for ranking under uncertainty that incorporates expert reliability. Unlike conventional FUCOM and Fuzzy FUCOM, which either ignore uncertainty or assume equal reliability among experts, the proposed method integrates fuzzy evaluations with Z-number-based reliability and logarithmic preference programming into a unified consistency-driven optimization model. As a result, LF-Z-FUCOM provides a more realistic and discriminative capability for human judgment in complex decision environments. The problem of prioritizing interdependent production requirements in the production of matcha green tea was a primary concern. Five key production criteria were evaluated by seven experts, and the resulting weights revealed that cost and tea raw material quality are the most critical factors, followed by sensory attributes, physicochemical properties, and dissolvability. Compared with FUCOM and Fuzzy FUCOM, LF-Z-FUCOM produced a clearer and more consistent hierarchy, resolving ambiguities caused by ignoring the reliability of expert assessments. These results offer practical guidance to managers, indicating that strategic investments should primarily focus on raw material sourcing and cost control while maintaining appropriate sensory and functional quality levels.

Despite its advantages, the proposed model has certain limitations. The case study was based on a single production facility and a limited number of criteria, which may restrict the generalizability of the numerical results. In addition, the computational complexity of LF-Z-FUCOM is higher than FUCOM and Fuzzy FUCOM due to the inclusion of fuzzy and reliability-based optimization.

Future research may extend the proposed framework by integrating LF-Z-FUCOM with ranking methods such as MARCOS, WASPAS, or VIKOR to support full alternative evaluation. The model could also be applied to broader problems in which uncertainty and heterogeneous expert reliability play a crucial role.

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