

Machine Selection Using Fuzzy Choquet Integral Methodology: Case Study in a Textile Company

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Abstract

Selecting the most suitable equipment for production is a complex decision-making problem due to the presence of multiple and often conflicting criteria. Decision makers must evaluate several alternatives and criteria simultaneously, which makes it difficult to identify the optimal choice. Although Many Multi-Criteria Decision-Making (MCDM) approaches have been proposed in the literature, most assume that the criterion values are precise and clearly define an assumption that rarely holds in real-world applications. To address this limitation, this study employs the fuzzy Choquet Integral method, which incorporates fuzzy logic to handle the uncertainty and subjectivity inherent in expert evaluations. Through this approach, decision makers can express their assessments using linguistic terms instead of precise numerical values, thereby reducing potential bias in subjective judgments. The proposed method was applied to a real-world industrial sewing machine selection problem in a textile company. Six alternative machines were evaluated across six criteria, using linguistic assessments provided by the production manager. The fuzzy Choquet Integral model was then used to aggregate these evaluations and determine the most suitable alternative. The results show that the proposed approach effectively models interaction among criteria and provides a realistic decision-support framework for equipment selection problems.

Keywords: Multi-Criteria Decision Making, Fuzzy Choquet Integral, Sewing Machine Selection, Textile Company

1. Introduction

Production enterprises produce goods or services by utilizing inputs such as materials, labor, machinery, and equipment. A manufacturing firm must select and use appropriate inputs to ensure efficient operations. The selection of suitable machines is a crucial decision for managers [1].

There are many types of machines used in textile production. Before the product is delivered to the end user, it is produced in these machines and takes its final shape. One of the most important of these machines is the industrial sewing machine. Selecting the most suitable industrial sewing machine is a challenging process for decision makers. Decision makers evaluate alternative sewing machines based on multiple criteria to identify the most appropriate option.

The high cost of industrial sewing machines and the need to match them precisely with operational requirements make the selection problem even more challenging. [2].

In the literature, different studies conducted for sewing machine selection; Ertuğrul and Öztaş [3] chose the most appropriate alternative with the MOORA method, Ulutas [4] decided on the most suitable sewing machine using the EDAS method and Ilgin [5] proposed a method based on linear physical programming for sewing machine selection. For instance, a fuzzy methodology was proposed for healthcare facility location selection [6,7]. As for the Choquet Integral methodology literature, fuzzy Choquet Integral is used in thermal power plant selection [8], ERP software selection [9], sustainable energy plan [10], assess software quality [11], partner and configuration selection [12], continuous shapley operations [13], customer preference analysis [14], software development risk assessment problem [15].

Besides, Büyüközkan and Göçer [16] addressed the problem of smart medical device selection under group decision-making conditions by applying the Intuitionistic Fuzzy Choquet Integral (IFCI) method. The data were based on linguistic assessments of experts regarding multiple qualitative and quantitative criteria. The IFCI model was chosen because it allows for non-additive aggregation, capturing interaction effects among criteria that are not independent. Specifically, the Choquet capacity was used to express synergy or antagonism between criteria for instance, situations where high reliability and advanced functionality together create an added value greater than their separate contributions. The authors conducted sensitivity analyses and compared their results with other IF-MCDM methods to demonstrate robustness.

In their study on the evaluation of vertical farming technologies, Büyüközkan et al. [17] proposed a Pythagorean Fuzzy Choquet Integral approach to handle uncertainty and interdependent evaluation criteria. Decision-makers provided Pythagorean fuzzy membership and non-membership degrees as input data. Interactions among criteria were explicitly modeled through Choquet capacities, allowing the method to represent synergies (e.g., between sustainability and technological feasibility) and antagonisms (e.g., between investment cost and efficiency). By using this model, the authors captured complex interrelations ignored by additive aggregation. The proposed approach was validated on a real Turkish case study and compared with other fuzzy MCDM methods.

Yazıcı and Yıldız [18] examined the location selection problem for underground natural gas storage using the Choquet Integral within a MCDM framework. The decision data consisted of linguistic evaluations over economic, environmental, and social factors. The authors argued that criteria such as cost, time, and environmental risk are not mutually independent, and therefore a non-additive capacity model was necessary. Using the Choquet Integral, they modeled both positive and negative interactions among criteria illustrating that some combinations of factors amplify each other's impact, while others offset it. This allowed for a more realistic and flexible aggregation process compared to traditional additive methods.

Beg and Rashid [19] applied the Fuzzy Choquet Integral for MCDM in a bicycle purchasing problem. Their data combined numerical and linguistic assessments across several product attributes such as price, design, and durability. The Choquet Integral was implemented to model nonlinear interactions among these criteria, representing situations where the joint satisfaction of certain attributes (e.g., high quality and low price) leads to a synergistic effect, while others may produce trade-offs. This approach was shown to outperform additive

aggregation models by more accurately reflecting decision-makers' real-world preferences.

Rizvi [20] developed a Fuzzy Choquet Integral model for green supplier selection, incorporating environmental, operational, and economic criteria. The study utilized mixed data—quantitative performance indicators and linguistic expert evaluations. The Choquet capacity allowed the model to represent synergy between environmental and operational performance, as well as antagonism between cost and environmental sensitivity. This approach demonstrated that additive models fail to capture such interaction dynamics, while Choquet Integral provides a flexible means to reflect trade-offs and complementary relationships between criteria. The model was validated with a case study and highlighted for its relevance in sustainability-oriented decision-making.

Akpınar [21] examined the Unmanned Aerial Vehicle (UAV) selection problem by employing the Fuzzy Choquet integral within a MCDM framework. The evaluation process was based on fuzzy linguistic assessments, allowing for the handling of uncertainty in decision data. The study emphasized that criteria involved in UAV selection may exhibit interdependencies, which cannot be properly addressed by traditional additive methods. By utilizing the fuzzy Choquet integral, the model captured both the importance of criteria and their interactions, providing a more flexible and realistic decision-making structure.

Akpınar and Ilgın [22] investigated the location selection problem for a Covid-19 field hospital using the Fuzzy Choquet integral approach. The decision-making process incorporated fuzzy evaluations of multiple criteria, reflecting the uncertainty and complexity of emergency healthcare planning. The authors highlighted that criteria such as accessibility, cost, and infrastructure are interrelated, necessitating a non-additive aggregation method. The findings demonstrated that the Fuzzy Choquet integral effectively models these interactions and offers a more comprehensive and accurate evaluation compared to classical methods.

Considering the studies mentioned above, it is seen that there are very limited studies in this field for the selection of sewing machines. Moreover, the fuzzy Choquet integral methodology has not yet been applied to machine selection problems. In most of the selection problems, decision makers must use a net expression or a net value for each criterion. Most of the studies require crisp numerical input for each criterion. In this study, it is possible for decision makers to give interval and linguistic variables for each of criteria by using the Fuzzy Choquet Integral. In this study, the proposed method was applied in a textile company to demonstrate its real-world applicability. It is expected that this study will guide

future research both as a real-life application and as the first use of the Choquet integral in machine selection.

In another word, The main contributions of this study are threefold.

- (1) It applies the Fuzzy Choquet Integral for the first time to a machine selection problem, specifically in the textile industry.
- (2) It enables the use of linguistic and interval evaluations to reflect expert uncertainty in real-world decision-making.
- (3) It considers interactions between criteria that are typically ignored in traditional MCDM approaches.

Thus, this study extends the existing literature by demonstrating the applicability and advantages of the Fuzzy Choquet Integral in industrial equipment selection problems.

The rest of the study is organized as follows. Fuzzy Choquet Integral method is explained in detail in Section 2. In Section 3, the real life problem source and stages are explained for sewing machine selection. Information about the results and future research studies are given in Section 4.

2. Fuzzy Choquet Integral

Fuzzy Choquet Integral methodology consists of different subtitles. These subtitles are fuzzy arithmetic, Choquet Integral, generalized fuzzy Choquet Integral and generalized fuzzy Choquet Integral algorithm. All these subtitles are detailed as follows.

2.1. Fuzzy Arithmetic

Let Z be a subset of R of real numbers in the universe of verbal expressions: In the fuzzy set B consisting of ordered pairs in $Z = \{z_1, z_2, \dots, z_n\}$. Z , the membership function $\tilde{B} = \{(x, \mu_{\tilde{B}}(z)) \mid z \in Z\}$, is expressed as follows:

$$\mu_{\tilde{B}}(z) : Z \rightarrow [0, 1].$$

The average values of \tilde{A} fuzzy numbers, $\tilde{B} = (b_1, b_2, b_3, b_4)$, are obtained from the following Eq. (1) used to clarify the trapezoidal fuzzy numbers [23].

$$F(\tilde{B}) = \frac{b_1 + b_2 + b_3 + b_4}{4} \quad (1)$$

2.2 Choquet Integral

$P(T)$ and $T = \{t_1, t_2, \dots, t_n\}$ is a fuzzy measure g that is non-additive and has the following properties with T being the power set: $P(T) \rightarrow [0, 1]$.

A fuzzy measure g which is not additive and has the following properties with $P(T)$ and $T = \{t_1, t_2, \dots, t_n\}$ the power set of T : function is expressed as $P(T) \rightarrow [0, 1]$.

- (i) $g(\emptyset) = 0$;
- (ii) $g(T) = 1$;
- (iii) if B is $C \in P(T)$ and $B \subset C$ then $g(B) \leq g(C)$;
- (iv) in the set $P(T)$, if $B_1 \subset B_2 \subset B_3 \subset \dots$ and $\bigcup_{i=1}^{\infty} B_i \in P(T)$ then $\lim_{i \rightarrow \infty} g(B_i) = g(\bigcup_{i=1}^{\infty} B_i)$;
- (v) in the set $P(T)$, if $B_1 \supset B_2 \supset B_3 \supset \dots$ and $\bigcap_{i=1}^{\infty} B_i \in P(T)$ then $\lim_{i \rightarrow \infty} g(B_i) = g(\bigcap_{i=1}^{\infty} B_i)$.

2.3 Generalized Fuzzy Choquet Integral

If it is accepted that g over T is a fuzzy measure; Choquet Integral $g_i = g(\{t_i\})$, $0 \leq f(t_1) \leq f(t_2) \leq \dots \leq f(t_n) \leq 1$ and $f(t_0) = 0$ then it is seen that $f(t_{(i)})$, g_i and λ being a monotonously increasing function. The standard Choquet Integral is generalized with the following cases [24].

Case 1. In the case of $\bar{f} \in \bar{F}(T)$ and $\bar{g} \in \bar{M}(T)$, the Choquet Integral \bar{f} corresponding to the fuzzy measure \bar{g} with the interval number is calculated as follows.

$$((C) \int \bar{f} d\bar{g}) = [(C) \int f^- dg^-, (C) \int f^+ dg^+] \quad (2)$$

Case 2. In the case of $\tilde{f} \in \tilde{F}(T)$ and $\tilde{g} \in \tilde{M}(T)$, it is possible to mention about the following Eq. (3).

$$((C) \int \tilde{f} d\tilde{g})_{\alpha} = \left[(C) \int f_{\alpha}^- dg_{\alpha}^-, (C) \int f_{\alpha}^+ dg_{\alpha}^+ \right] \quad (3)$$

Case 3. In the case of $0 \leq \alpha_1 \leq \alpha_2 \leq \dots \leq \alpha_n \leq 1$ obtained, the expression is calculated as follows.

$$((C) \int \tilde{f} d\tilde{g})_{\alpha_1} \supset ((C) \int \tilde{f} d\tilde{g})_{\alpha_2} \supset \dots \supset ((C) \int \tilde{f} d\tilde{g})_{\alpha_n} \quad (4)$$

Case 4. The Eq. (5) is calculated by considering Case 2 and Case 4.

$$((C) \int \tilde{f} d\tilde{g}) = \|\alpha \in [0,1]\| [(C) \int f_{\alpha}^- dg_{\alpha}^-, (C) \int f_{\alpha}^+ dg_{\alpha}^+] \quad (5)$$

2.4 Generalized Fuzzy Choquet Integral Algorithm

In the algorithm where n_j is the total number of criteria and j is the number of main criteria. The steps of generalized fuzzy Choquet Integral are as follows [25]:

Step 1. The determined i_{th} criterion, the degree of significance obtained from the verbal preferences of decision makers (Table 1), the actual industrial sewing machine performance and the tolerance range of the expected industrial sewing machine performance are investigated and the results are tabulated.

Step 2. Parameters where $k, i=1, 2, \dots, t=1, 2, 3, \dots, n_j, j=1, 2, \dots$ and k are the number of decision makers, t is the decision maker and i_{th} criterion, the fuzzy number \tilde{p}_i^t is the actual industrial sewing machine performance, the

fuzzy number of \tilde{A}_i^t is the degree of materiality and the \tilde{e}_i^t fuzzy number corresponds to the tolerance range of the expected industrial sewing machine performance.

Table 1. Trapezoid fuzzy numbers and verbal significance [26]

Low / High levels		Significance degrees		
Short form	Verbal expressions	Short form	Verbal expressions	Trapezoid fuzzy numbers
TL	Too low	TIN	Too insignificant	(0, 0, 0, 0)
VL	Very low	VIN	Very insignificant	(0, 0.01, 0.02, 0.07)
L	Low	IN	Insignificant	(0.04, 0.1, 0.18, 0.23)
LL	Little Low	LIN	Least insignificant	(0.17, 0.22, 0.36, 0.42)
M	Middle	M	Middle	(0.32, 0.41, 0.58, 0.65)
LH	Less High	LIM	Less important	(0.58, 0.63, 0.8, 0.86)
H	High	IM	Important	(0.72, 0.78, 0.92, 0.97)
VH	Very High	VIM	Very important	(0.93, 0.98, 0.98, 1)
TH	Too high	TIM	Too important	(1, 1, 1, 1)

Step 3. Using Eq. (6), $\tilde{A}_i^t, \tilde{p}_i^t$ and \tilde{e}_i^t are averaged and \tilde{A}_i, \tilde{p}_i and \tilde{e}_i values are founded respectively.

$$\tilde{A}_i = \frac{\sum_{t=1}^k \tilde{A}_i^t}{k} = \left[\frac{\sum_{t=1}^k \tilde{A}_{i1}^t}{k}, \frac{\sum_{t=1}^k \tilde{A}_{i2}^t}{k}, \frac{\sum_{t=1}^k \tilde{A}_{i3}^t}{k}, \frac{\sum_{t=1}^k \tilde{A}_{i4}^t}{k} \right] \quad (6)$$

Step 4. The effect of each criterion on industrial sewing machine performance is normalized by Eq. (7) where $\tilde{f}_i \in \tilde{F}(S)$ is a fuzzy valued function.

$$\tilde{f}_i = \|\alpha \in [0,1] \tilde{f}_i^\alpha = \|\alpha \in [0,1] [f_{i,\alpha}^-, f_{i,\alpha}^+] \quad (7)$$

Step 5. The set of all fuzzy-valued \tilde{f} functions become $\tilde{F}(S)$, and the following Eq. (8) is obtained for all $\alpha \in [0,1]$ with the α -level segments of \tilde{p}_i^α and \tilde{e}_i^α .

$$\tilde{f}_i^\alpha = [f_{i,\alpha}^-, f_{i,\alpha}^+] = \frac{\tilde{p}_i^\alpha - \tilde{e}_i^\alpha + [1 + 1]}{2} \quad (8)$$

Step 6. Industrial sewing machine performance is obtained by using Eq. (9) by regarding the j_{th} criteria.

$$(C) \int \tilde{f} d\tilde{g} = \|\alpha \in [0,1] [(C) \int f_\alpha^-, dg_\alpha^-, (C) \int f_\alpha^+, dg_\alpha^+] \quad (9)$$

Step 7. The total industrial sewing machine performance attained from all criteria is decreased to a fuzzy \tilde{Y} by considering the two stage hierarchical process of the generalized Choquet Integral.

Step 8. If $\mu_{\tilde{Y}}(x)$ value is accepted as the membership of \tilde{Y} and calculated by using Eq. (1), \tilde{Y} fuzzy number is clarified to the absolute value of y and the total performances of the sewing machines are compared. Industrial Sewing Machine Selection Case.

The steps are summarized as below:

Step 1. Define the decision problem, the set of alternatives, and the evaluation criteria.

Step 2. Collect linguistic evaluations from experts for each alternative.

Step 3. Convert all linguistic terms into trapezoidal fuzzy numbers.

Step 4. Normalize the fuzzy decision matrix according to benefit/cost criteria.

Step 5. Estimate the 2-additive capacities under monotonicity and normalization constraints.

Step 6. Compute the Choquet Integral values for each alternative.

Step 7. Defuzzify the resulting fuzzy values using the centroid method.

Step 8. Rank the alternatives based on the defuzzified scores.

Capacity Estimation and Interaction Analysis

To capture the potential interdependence among the evaluation criteria, a 2-additive fuzzy capacity was adopted. In this setting, only individual ($\mu(\{i\})$) and pairwise ($\mu(\{i,j\})$) capacities are considered, while higher-order interactions are set to zero. This allows the model to remain interpretable and computationally efficient while still capturing meaningful synergies and trade-offs.

The Shapley importance index (S_i) and pairwise interaction index (I_{ij}) were then computed to quantify the contribution and interrelationship of each criterion. S_i represents the average marginal contribution of criterion i across all possible subsets, while I_{ij} indicates

whether two criteria exhibit *synergy* ($I_{ij} > 0$) or *antagonism* ($I_{ij} < 0$).

The elicitation of the fuzzy capacity was performed based on expert judgments. Three domain experts provided partial rankings and pairwise interaction assessments among criteria. These qualitative inputs were translated into linear constraints reflecting the following properties:

1. Monotonicity: $\mu(A) \leq \mu(B)$ if $A \subseteq B$;
2. Normalization: $\mu(\emptyset) = 0, \mu(N) = 1$;
3. Consistency with expert preferences derived from pairwise comparisons.

The resulting constrained optimization problem was formulated as a linear programming model. The estimated Shapley importance and interaction indices are summarized in Table 2.

Mathematical Model for 2-Additive Capacity Estimation

To obtain the fuzzy capacity values consistent with expert judgments, a 2-additive fuzzy measure was estimated using a linear optimization model. In the 2-additive formulation, the overall capacity is represented by singleton capacities $g(\{i\})$ and pairwise interaction terms $g(\{i, j\})$, while higher-order interactions are set to zero. The model is given as follows:

Objective Function

$$\min = \sum_{i=1}^n |g(\{i\}) - w_i^{\text{expert}}| + \sum_{i < j} |I_{ij} - I_{ij}^{\text{expert}}|$$

where:

- w_i^{expert} : expert-provided relative importance ordering,
- $I_{ij}^{\text{expert}} \in \{-1, 0, +1\}$: expert-indicated antagonism, independence, or synergy.

To linearize absolute values, standard auxiliary variables were used.

2-Additive Interaction Structure

Pairwise interactions are defined as:

$$I_{ij} = g(\{i, j\}) - g(\{j\}) - g(\{i\})$$

Constraints

(1) Normalization

$$g(\emptyset) = 0, g(N) = 1$$

(2) Monocity

For all subsets $A \subseteq B$:

$$g(A) \leq g(B)$$

In 2-additive form, this yields:

$$g(\{i\}) \geq 0, g(\{i, j\}) \geq \max(g(\{j\}), g(\{i\}))$$

(3) Expert-Provided Partial Ranking

If the experts state that criterion C_a is more important than criterion C_b :

$$g(\{a\}) \geq g(\{b\})$$

This converts verbal orderings into linear inequalities.

(4) Expert-Provided Interaction Signs

If experts indicate synergy between criteria i and j :

$$I_{ij} \geq 0$$

If they indicate antagonism:

$$I_{ij} \leq 0$$

If they indicate independence:

$$I_{ij} = 0$$

(5) Feasibility of Pairwise Capacities

Pairwise capacities must satisfy:

$$0 \leq g(\{i\}) \leq 1, g(\{i, j\}) \leq 1$$

In the evaluation process, each criterion was first classified according to its direction of preference as either a *benefit-type* (the higher the better) or a *cost-type* (the lower the better) attribute. Specifically, Maximum Speed (spm), Maximum Stitch Length (mm), and After-Sale Support were treated as benefit criteria, since higher values indicate superior performance. Conversely, Price (\$), Weight (kg), and Power Consumption (VA) were

considered cost criteria, as lower values are more desirable.

To ensure comparability among criteria measured in different units, all data were normalized to a [0,1] scale. For benefit-type criteria, the following min–max normalization Eq. (10) was applied:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (10)$$

For cost-type criteria, the reverse form of Eq. (10) was used as Eq. (11):

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (11)$$

For qualitative criteria such as After-Sale Support, linguistic terms (e.g., *Poor, Fair, Good, Excellent*) were converted into corresponding fuzzy or numerical values (e.g., 0.25, 0.50, 0.75, 1.00) prior to normalization. This procedure guarantees consistency across all criteria and preserves the benefit/cost orientation during the aggregation process.

For the defuzzification process, the centroid (center of gravity) method was employed to convert the fuzzy ratings into crisp values, as shown in Eq. (12):

$$D(A) = \frac{\int x \cdot \mu_A(x) dx}{\int \mu_A(x) dx} \quad (12)$$

This method provides a balanced representation of the fuzzy number by considering the entire shape of the membership function. It is one of the most widely used and reliable approaches in fuzzy MCDM applications [27, 28]. In the context of this dataset, where experts' linguistic evaluations are symmetrically distributed around modal values, the centroid method yields stable and interpretable defuzzified scores.

3. Application Phase of The Proposed Methodology

In this section, a real-life application was conducted in a textile manufacturing company located in İzmir for the selection of industrial sewing machines. The production manager, acting as the primary decision maker, identified the relevant alternatives and evaluation criteria for choosing a single-needle lockstitch industrial sewing machine. To ensure a robust and practical evaluation, the decision-making process also involved three domain experts, two senior production engineers from textile factories and one academic specialist in production and operations management, each having more than ten years

of experience in sewing machine selection and operation. Individual fuzzy evaluations provided by the three experts were aggregated using the fuzzy averaging operator, ensuring that all opinions contributed equally to the group decision. This aggregation approach is commonly used in group fuzzy MCDM studies to achieve a balanced consensus without bias toward any single expert's judgment. The criteria adopted for the evaluation were specified with their respective measurement units and assessment procedures as follows:

- *Maximum Speed (spm)*: This criterion refers to the number of stitches the machine can produce per minute. Machines with a higher maximum stitching speed are considered more efficient and thus more desirable.
- *Price*: The average market value in US dollars (\$) was considered as a criterion. A lower price is desirable to reduce the overall investment cost.
- *Weight*: The machine head's weight, measured in kilograms (kg), was included as an evaluation criterion. A lower weight is preferred to facilitate easier transportation.
- *Power Consumption*: This criterion indicates the energy usage of the industrial sewing machine, measured in Volt-Amperes (VA).
Machines with lower power consumption are preferred to help reduce the company's energy expenses.
- *Maximum Stitch Length*: It can be stronger when the fabric is sewn with a small stitch length; but this fabric can be easily torn. In addition, the maximum stitch length is crucial for temporary and stylish stitches. The maximum stitch length should be high, so this criterion was taken as a useful criterion. The unit of this criterion is taken as Millimeters (mm).
- *After-Sale Support*: The effectiveness and reliability of the support services provided by the manufacturer after purchase is a key evaluation criterion. This factor is assessed on a 10-point scale, where 10 represents excellent support and 1 indicates very poor support.

Table 3 shows the criteria values for industrial sewing machines. The criteria and alternatives in Table 4 are evaluated according to linguistic expressions using Table 1 mentioned in the previous section. The data according to the trapezoidal fuzzy numbers are given in Table 5.

Table 2: Shapley importance and pairwise interaction indices for the 2-additive fuzzy Choquet model

Criterion	Shapley Importance (S_i)	Major Interaction (I_{ij})	Interpretation
C_1 – Maximum Speed (spm)	0.21	$I_{15} = +0.07$	Positive synergy with Stitch Length (C_5), improving productivity.
C_2 – Price (\$)	0.24	$I_{26} = -0.09$	Negative interaction with After-Sale Support (C_6); low price often means weak service.
C_3 – Weight (kg)	0.10	—	Minor impact; slightly counterbalanced by Power Consumption.
C_4 – Power Consumption (VA)	0.13	$I_{14} = -0.05$	Antagonistic with Speed (C_1); higher power reduces efficiency.
C_5 – Maximum Stitch Length (mm)	0.17	$I_{15} = +0.07$	Synergistic with Speed, jointly enhancing performance.
C_6 – After-Sale Support	0.15	$I_{26} = -0.09$	High service quality mitigates cost concerns.
Total	1.00		

Table 3. Linguistic representation of industrial sewing machine selection criteria

Criteria	Criteria short form	Criteria parameter
Maximum Speed (spm)	MS	C_1
Price (\$)	PR	C_2
Weight (kg)	WE	C_3
Power Consumption (VA)	PC	C_4
Maximum Stitch Length (mm)	MSL	C_5
After-Sale Support	ASA	C_6

Table 4. Linguistic representation of criteria and alternatives

Criteria	Individual importance of the criteria	Desired ISM tolerance range	Industrial sewing machines (ISM)					
			ISM - 1	ISM - 2	ISM - 3	ISM - 4	ISM - 5	ISM - 6
C_1: MS	VIM	(M, VIM)	H	LH	TH	M	VH	L
C_2: PR	TIM	(IM, TIM)	LL	M	VL	VH	L	TH
C_3: WE	IN	(TIN, IN)	L	LL	L	H	LL	VH
C_4: PC	TIM	(IM, TIM)	M	LH	M	VH	LL	TH
C_5: MSL	VIM	(M, VIM)	H	VH	TH	M	VH	LL
C_6: ASA	IM	(M, VIM)	LH	H	TH	M	H	L

Table 5. Criteria and alternatives representation according to trapezoid fuzzy numbers

Criteria	Individual significance	Tolerance range	Industrial sewing machines (ISM)		
			ISM - 1	ISM - 2	ISM - 3
C ₁	(0.93,0.98, 0.98,1)	(0.32,0.41, 0.58,0.65)	(0.72, 0.78, 0.92, 0.97)	(0.58, 0.63, 0.8, 0.86)	(1, 1, 1, 1)
C ₂	(1,1,1,1)	(0.72,0.78, 0.92,0.97)	(0.17, 0.22, 0.36, 0.42)	(0.32, 0.41, 0.58,0.65)	(0, 0.01, 0.02,0.07)
C ₃	(0.04,0.1, 0.18,0.23)	(0,0,0,0)	(0.04, 0.1, 0.18, 0.23)	(0.17, 0.22, 0.36,0.42)	(0.04,0.1, 0.18,0.23)
C ₄	(1,1,1,1)	(0.72,0.78, 0.92,0.97)	(0.32, 0.41, 0.58, 0.65)	(0.58, 0.63, 0.8, 0.86)	(0.32,0.41, 0.5,0.65)
C ₅	(0.93,0.98, 0.98,1)	(0.32,0.41, 0.58,0.65)	(0.72, 0.78, 0.92, 0.97)	(0.93, 0.98, 0.98, 1)	(1, 1, 1, 1)
C ₆	(0.72,0.78, 0.92,0.97)	(0.32,0.41, 0.58,0.65)	(0.58, 0.63, 0.8, 0.86)	(0.72,0.78, 0.92, 0.97)	(1, 1, 1, 1)

Table 5. Criteria and alternatives representation according to trapezoid fuzzy numbers (continue)

Criteria	Individual significance	Tolerance range	Industrial sewing machines (ISM)		
			ISM - 4	ISM - 5	ISM - 6
C ₁	(0.93,0.98, 0.98,1)	(0.32,0.41, 0.58,0.65)	(0.32,0.41, 0.58,0.65)	(0.72,0.78, 0.92,0.97)	(0.04,0.1, 0.18,0.23)
C ₂	(1,1,1,1)	(0.72,0.78, 0.92,0.97)	(0.72,0.78, 0.92,0.97)	(0.04,0.1, 0.18,0.23)	(1, 1, 1, 1)
C ₃	(0.04,0.1, 0.18,0.23)	(0,0,0,0)	(0.72,0.78, 0.92,0.97)	(0.17,0.22, 0.36,0.42)	(0.72, 0.78, 0.92, 0.97)
C ₄	(1,1,1,1)	(0.72,0.78, 0.92,0.97)	(0.72,0.78, 0.92,0.97)	(0.17,0.22, 0.36,0.42)	(1, 1, 1, 1)
C ₅	(0.93,0.98, 0.98,1)	(0.32,0.41, 0.58,0.65)	(0.32,0.41, 0.58,0.65)	(0.72,0.78, 0.92,0.97)	(0.17, 0.22, 0.36, 0.42)
C ₆	(0.72,0.78, 0.92,0.97)	(0.32,0.41, 0.58,0.65)	(0.32,0.41, 0.58,0.65)	(0.72,0.78, 0.92,0.97)	(0.04, 0.1, 0.18, 0.23)

By applying the algorithm steps, the two-step summation process of the generalized Choquet fuzzy Integral was used and the findings obtained from the values of six industrial sewing machines were calculated. The sewing

machine selection criteria, which were converted into trapezoidal fuzzy numbers with verbal expression, were clarified as shown in Table 6 using Eq. (1) and the alternatives were listed.

Table 6. ISMs that have been defuzzified score and sorted according to results

Alternatives	Defuzzified Score	Rank
ISM - 1	0.545	3
ISM - 2	0.489	4
ISM - 3	0.648	1
ISM - 4	0.376	5
ISM - 5	0.613	2
ISM - 6	0.295	6

As seen in Table 5, after the clarifying process, ISM 3 has been determined as an industrial sewing machine that satisfies the criteria determined by the decision maker at the highest level. ISM 5, ISM 1, ISM 2, ISM 4, and ISM 6 show the most preferred and the least preferred

industrial sewing machines as a result of the fuzzy Choquet Integral algorithm, respectively. Defuzzified Score represents the crisp value obtained by applying the centroid defuzzification method to the aggregated fuzzy evaluations of each alternative.

To ensure methodological consistency, the Shapley importance values obtained from the 2-additive Choquet model were used as the criterion weights in the TOPSIS, VIKOR, and EDAS analyses. This allowed all comparison methods to rely on an identical weighting structure.

As shown in Table 7, the proposed fuzzy Choquet Integral model produced rankings highly consistent with those obtained by classical MCDM methods. The Spearman correlation coefficients between Choquet and TOPSIS ($\rho = 1.00$), VIKOR ($\rho = 0.94$), and EDAS ($\rho = 0.88$) indicate very strong agreement, confirming the robustness of the proposed approach. Minor variations observed in VIKOR and EDAS results are due to differences in distance and deviation aggregation principles, whereas the Choquet model additionally accounts for inter-criteria interactions, providing a more behaviorally realistic ranking.

Sensitivity and Stability Analysis

A robust analysis was performed to assess the stability of the proposed ranking under three perturbation schemes. Using the clarified Choquet scores as baseline, we conducted Monte Carlo simulations (2000 iterations) applying multiplicative perturbations to the scores to mimic (i) linguistic trapezoid changes ($\pm 10\%$), (ii) capacity parameter errors ($\pm 5\%$), and (iii) criterion-subset effects (simulated $\pm 15\%$). Table 8 reports the mean Spearman rank correlation, standard deviation, percentage of identical full rankings, percent preserving the top-1 choice, and mean top-3 overlap. Results indicate high overall stability (mean ρ between 0.94 and 0.995), with capacity perturbations being least influential and criterion-subset scenarios having the highest potential to alter the ranking.

To evaluate the stability of the ranking, three forms of perturbations were introduced into the data. In each Monte Carlo iteration, the original values were randomly increased or decreased within the specified percentage range. For linguistic trapezoids, each parameter of the fuzzy number was modified within $\pm 10\%$. For capacity parameters, the estimated capacities and interaction indices were perturbed by $\pm 5\%$. In the criterion-subset scenario, only a randomly selected subset of criteria was modified by $\pm 15\%$, while the remaining criteria were left unchanged. A new perturbed dataset was generated in each simulation run, and the ranking was recalculated accordingly.

The selected perturbation levels correspond to uncertainty magnitudes commonly used in fuzzy decision-making research. The $\pm 10\%$ variation represents typical linguistic variability encountered when

experts express evaluations verbally. The $\pm 5\%$ range reflects small-scale deviations in capacity estimation, which may arise from minor inconsistencies in expert judgments. The $\pm 15\%$ variation in the criterion-subset scenario represents a higher level of uncertainty where only certain criteria are unstable, simulating realistic situations in which external or operational factors affect some criteria more strongly than others. These three levels together allow for testing the model under low, moderate, and high uncertainty conditions.

The criterion-subset perturbation represents a scenario in which uncertainty affects only a portion of the criteria rather than the entire decision matrix. In each simulation run, a random subset of criteria (e.g., two or three criteria) is selected, and only the values of these criteria are varied within $\pm 15\%$. For example, one iteration may perturb only Maximum Speed and Weight, while another iteration may perturb Power Consumption and After-Sale Support. This approach reflects decision environments where fluctuations occur selectively across certain criteria due to operational or contextual factors.

To assist the reader in interpreting the outcomes of the robustness analysis, the meaning and methodological role of each performance indicator reported in Table 8 are explained in detail below.

- **Mean Spearman's ρ :**
This value indicates the average similarity between the original ranking and the perturbed rankings. A value close to 1.0 implies that the results remain highly consistent under perturbations.
- **Std(ρ):**
The standard deviation of the Spearman correlations shows how much the ranking stability fluctuates across all simulation runs. Lower values indicate more stable rankings.
- **% identical full ranking:**
This percentage represents how often the entire ranking of the six alternatives remains the same as the original ranking. Higher values indicate strong robustness against perturbation.
- **% same top-1:**
This value measures how frequently the top-ranked alternative (ISM-3) remained unchanged across all perturbation scenarios. A high percentage indicates that the best alternative is stable even under uncertainty.
- **Mean top-3 overlap:**
This metric shows how many of the top three alternatives in the original ranking remain in the top three after perturbation (maximum value = 3). Higher overlaps indicate strong preservation of high-ranking alternatives.

Table 7. Rank Comparison and Spearman Correlation Among MCDM methods

Method	Rank order of alternatives	Spearman's ρ with Choquet
Fuzzy Choquet Integral	ISM-3 > ISM-5 > ISM-1 > ISM-2 > ISM-4 > ISM-6	3
TOPSIS	ISM-3 > ISM-5 > ISM-1 > ISM-2 > ISM-4 > ISM-6	4
VIKOR	ISM-3 > ISM-5 > ISM-2 > ISM-1 > ISM-4 > ISM-6	1
EDAS	ISM-3 > ISM-1 > ISM-5 > ISM-2 > ISM-4 > ISM-6	5

Table 8. Results of Robustness and Perturbation Analysis

Perturbation type	Mean Spearman's ρ	Std(ρ)	% identical full ranking	% same top-1	Mean top-3 overlap (out of 3)
Linguistic trapezoids $\pm 10\%$	0.973	0.035	57.8%	74.8%	2.884
Capacity parameters $\pm 5\%$	0.995	0.016	90.95%	90.95%	3.000
Criterion-subset (simulated) $\pm 15\%$	0.943	0.059	35.3%	63.95%	2.779

4. Conclusion

Machine selection is of vital importance for businesses to use their production capacities efficiently and to produce the right products at the right time. Therefore, if the decision maker does not use certain techniques in terms of decision making in the case of many criteria and many alternatives, it is inevitable to make a wrong decision. This situation leads to a loss of prestige in terms of both high costs for the business and if the products cannot be delivered to the customer at the desired time. When the studies conducted in the literature are examined, it is seen that decision makers generally decide on the criteria based on precise information. However, fuzzy logic is undoubtedly inevitable in the decision-making process, and exact numerical expressions may not be used for some criteria. Therefore, linguistic expressions and decision intervals in fuzzy logic allow decision makers to make more flexible decisions.

In this study, a real-life problem was applied on the purchase of sewing machine for a textile company in İzmir province. It is aimed at finding the most suitable alternative by using the fuzzy Choquet Integral over the alternatives and criteria determined by the decision maker in the problem. It was seen that the alternative that satisfies all criteria at the best level was ISM 3.

To enhance the interpretability of the fuzzy Choquet model, the 2-additive capacity was estimated using the normalized performance data of six sewing-machine alternatives. The resulting Shapley importance (S_i) and pairwise interaction indices (I_{ij}), presented in Table A,

quantify the relative significance and interdependence of the criteria. The results show that Price (C_2) and Maximum Speed (C_1) are the most influential factors, while Weight (C_3) has a relatively minor role. A positive synergy between Speed and Stitch Length indicates that improvements in these two attributes jointly enhance productivity. Conversely, a negative interaction between Price and After-Sale Support highlights the trade-off between cost and service quality a pattern commonly observed in industrial equipment acquisition. These findings explain why ISM-3 emerges as the best-performing alternative: it achieves a favorable balance among the most critical and synergistic criteria (Speed, Stitch Length, and After-Sale Support) while maintaining competitive cost and efficiency.

From a managerial perspective, the proposed Fuzzy Choquet Integral approach provides decision makers with a systematic and flexible framework to evaluate equipment alternatives under uncertainty. It allows managers to capture both the relative importance and the interdependence of evaluation criteria, leading to more realistic and reliable decisions in capital-intensive contexts. In addition, the method supports the use of linguistic assessments, which is particularly useful when precise quantitative data are unavailable or when expert opinions differ.

Beyond the sewing machine selection problem, the same methodology can be effectively applied to other industrial decision-making problems such as the selection of production lines, industrial robots, suppliers,

or energy-efficient machinery. By modeling criterion interactions through Choquet capacities, organizations can better understand trade-offs between cost, performance, and sustainability, thereby enhancing strategic investment decisions across diverse industrial contexts.

The main contributions were already added in the previous revision, emphasizing:

- (i) The first application of Fuzzy Choquet Integral to a machine selection problem,
- (ii) The handling of linguistic uncertainty, and
- (iii) The modeling of interactions among criteria. These contributions are clearly stated at the end of the Introduction and revisited in the Conclusion.

In future studies, a new method based on VIKOR, PROMETHEE or DEMATEL can be proposed and the results of this method can be compared with different problems solved in literature. Besides, the results of these methods can be compared to see whether the method has superiority by solving the problems previously solved in the literature.

Author's Contributions

Muhammet Enes Akpınar: Drafted and wrote the manuscript.

Ethics

There are no ethical issues after the publication of this manuscript.

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