Applying a linguistic MCDM method to handle the machinery purchase problem in the textile industry

DOI: 10.35530/IT.077.05.2025172

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ABSTRACT – REZUMAT

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Machinery investment decisions are complex, multi-criteria problems that require balancing cost, performance, and quality factors under uncertainty. This research introduces a linguistic multi-criteria decision-making (MCDM) method regarding machinery investments, integrating both qualitative and quantitative information in a structured computational framework. To ensure objectivity in the evaluation process, the entropy weighting method is employed to determine the criteria importance based on data dispersion. The proposed model enables experts' linguistic judgments to be transformed into comparable numerical scales, allowing seamless integration with quantitative data in a single decision matrix. An empirical application to the laser cutting machine investment issue in the textile sector demonstrates the method's effectiveness in ranking alternatives and reducing subjectivity in decision-making. Results show that the model provides transparent, reproducible, and computationally efficient evaluations. The study contributes to the broader industrial engineering literature by extending linguistic MCDM applications to machinery investment decisions, offering managers a systematic and data-driven tool for complex capital allocation problems.

Keywords: *investment selection, linguistic MCDM, machinery selection, management, textile companies*

Aplicarea unei metode lingvistice de luare a deciziilor multicriteriale (MCDM) pentru gestionarea problemei achiziționării de utilaje în industria textilă

Deciziile privind investițiile în utilaje reprezintă probleme complexe, multicriteriale, care necesită găsirea unui echilibru între factorii de cost, performanță și calitate în condiții de incertitudine. Acest studiu prezintă o metodă lingvistică de luare a deciziilor multicriteriale (MCDM) aplicabilă investițiilor în utilaje, care integrează atât informații calitative, cât și cantitative într-un cadru computațional structurat. Pentru a asigura obiectivitatea procesului de evaluare, se utilizează metoda ponderării prin entropie pentru determinarea importanței criteriilor în funcție de dispersia datelor. Modelul propus permite transformarea deciziilor lingvistice ale experților în scale numerice comparabile, facilitând integrarea fără probleme cu datele cantitative într-o singură matrice decizională. O aplicație empirică care vizează problema investiției într-o mașină de tăiat cu laser în sectorul textil demonstrează eficacitatea metodei în ierarhizarea alternativelor și reducerea subiectivității în procesul decizional. Rezultatele arată că modelul oferă evaluări transparente, reproductibile și eficiente din punct de vedere computațional. Studiul contribuie la literatura de specialitate din domeniul ingineriei industriale prin extinderea aplicațiilor MCDM lingvistice la deciziile privind investițiile în utilaje, oferind managerilor un instrument sistematic și bazat pe date pentru gestionarea problemelor complexe de alocare a capitalului.

Cuvinte-cheie*: selectarea investițiilor, MCDM lingvistic, selectarea utilajelor, management, companii din industria textilă*

INTRODUCTION

Machinery investment decisions are crucial to sustaining the competitiveness and operational efficiency of manufacturing firms. These decisions are typically capital-intensive and influence key performance outcomes such as product quality, productivity, and flexibility. Selecting the most appropriate machinery alternative, therefore, represents a complicated MCDM problem that needs the simultaneous evaluation of both quantitative and qualitative factors. A suboptimal investment may lead to inefficiencies, unnecessary capital expenditure, and reduced long-term competitiveness.

The decision environment in machinery selection is inherently uncertain, as many evaluation criteria, such as usability, precision, or aesthetic design, are linguistic or qualitative in nature. Experts often express their assessments through linguistic terms rather than precise numerical values, which complicates aggregation and comparison. To address this, linguistic MCDM methods provide a robust computational mechanism for modelling human judgment and transforming qualitative evaluations into quantifiable forms. These methods enable decision makers to integrate both linguistic and numerical data consistently within a unified framework.

Previous research has successfully applied MCDM approaches such as AHP, TOPSIS, and VIKOR in areas including equipment selection, supplier evaluation, and personnel recruitment. For example,

Štirbanović et al. [1] used TOPSIS and VIKOR methods to deal with the flotation machine selection and compared the results. Thasni et al. [2] employed the fuzzy TOPSIS method for evaluation of cloud service providers. Chen and Hung [3] used a two-phase MCDM method for the personnel recruitment problem. Uddin et al. [4] used an integrated model by combining the analytic hierarchy process (AHP) with the technique for order of preference by similarity to ideal solution (TOPSIS) for enterprise resource planning (ERP) system selection in Bangladesh. While AHP was used for computing the criteria weights, TOPSIS was employed to determine the ranking order of alternatives.

As stated above, MCDM methods are widely used in almost all aspects of business decisions. However, MCDM studies addressing issues in the textile or clothing industry are quite limited. For example, Yayla et al. [5] used the Fuzzy TOPSIS method for supplier selection in the garment industry. Aydın et al. [6] evaluated the performance attributes of retailers using a supply chain operation reference model and the analytical hierarchy process in the clothing industry. Onden and Eldemir [7] used a combination of geographic information systems and fuzzy analytic hierarchy process (fuzzy AHP) to evaluate the textile manufacturing facility location alternatives.

Karabasevic et al. [8] employed SWARA and EDAS methods to evaluate websites in the textile industry. Bathrinath et al. [9] conducted a risk analysis in the textile industry using a hybrid MCDM method. Ulutaş and Karakuş [10] used an integrated MCDM method to select the location for a textile manufacturing facility.

Although the existing MCDM studies have made important contributions to decision-making problems in manufacturing and the textile industry, there are some limitations in the existing literature. Many studies use quantitative data. This may not be sufficient to understand the subjective nature of expert judgements. In addition, criteria weights are often calculated using subjective methods such as AHP [4, 9] or expert scoring. This may be biased and reduce reproducibility. Few studies provide an integrated computational framework that simultaneously combines linguistic evaluations and objective weighting mechanisms within a single decision matrix. There is a need for decision makers to combine linguistic information with data-driven weighting techniques to increase objectivity and transparency in decision-making problems.

Therefore, the main aim of this study is to develop and apply a computational linguistic MCDM framework for machinery investment selection in the textile industry, where decision-making involves both quantitative data and qualitative expert judgments under uncertainty. To achieve this aim, the study pursues the following specific objectives: (i) to integrate linguistic expert evaluations and quantitative performance indicators within a unified decision matrix; (ii) to determine criterion weights objectively using the entropy weighting method; (iii) to rank alternative machinery investment options using a distance-based evaluation mechanism; and (iv) to demonstrate the applicability of the proposed framework through a real-world case study involving advanced textile machinery.

This study makes three contributions. First, it introduces a data-driven and computationally efficient linguistic MCDM framework that integrates expert knowledge with quantitative measures. Second, it extends the use of entropy-based weighting in linguistic environments, ensuring greater objectivity in industrial decision-making. Third, it provides a replicable decision-support tool that can be adapted to other machinery selection and capital investment problems beyond the textile sector.

The following sections are as follows. The theoretical foundation and methodology of the suggested approach are explained in the 2nd and 3rd sections. An empirical application for laser cutting machine selection is outlined in the 4th section. The 5th section presents the conclusion and addresses implications, limitations, and suggestions for further study.

PRELIMINARIES

Definition 1. Linguistic term set $L = \{L_0^t, L_1^t, ..., L_{t-1}^t\}$ is the group which includes t kinds of linguistic variables. Each linguistic variable can be represented as a triangular fuzzy number [11].

Definition 2. Suppose that Θ is the linguistic transfer function. This function will transfer a linguistic variable into a crisp value n ($n \in [0,1]$) as follows [11].

$$\Theta(L_b^t) = n \tag{1}$$

where $n = \frac{b}{t-1}$.

Definition 3. Suppose that Θ^{-1} is the linguistic transfer inverse function. This function can transfer crisp value n ($n \in [0,1]$) into a linguistic variable as follows [11].

$$\Theta^{-1}(n) = L_{n*(t-1)}^t \tag{2}$$

Definition 4. Suppose that Θ and Θ^{-1} are the linguistic transfer function and the linguistic transfer inverse function, respectively. Let $G_1, G_2, \ldots, G_k$ be the linguistic opinions of k experts. The collective opinion of experts (G^{int}) will be integrated as follows [11].

$$G^{int} = \Theta^{-1}\left(\frac{\sum_{h=1}^{k}\Theta(G_h)}{k}\right) \tag{3}$$

PROPOSED METHOD

Machinery investment selection can be considered as an MCDM issue. It can be formulated by the following notation.

(1) Expert set $E = \{E_1, E_2, \ldots, E_k\}$. k means the number of experts.

(2) Investment target set $I = \{I_1, I_2, \ldots, I_m\}$. m means the number of investment targets.

(3) Criteria set $C = \{C_1, C_2, \ldots, C_b, C_{b+1}, \ldots, C_n\}$. n means the total number of criteria. Criteria C_1 to C_b are quantitative criteria. Criteria C_{b+1} to C_n are qualitative criteria.

(4) A decision matrix X can be described as follows.

$$X = \begin{array}{c} \\ I_1 \\ I_2 \\ \cdots \\ I_m \end{array} \begin{array}{c} \begin{array}{ccccccccc} C_1 & C_2 & \cdots & C_b & C_{b+1} & C_{b+2} & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,b} & \tilde{x}_{1,b+1} & \tilde{x}_{1,b+2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,b} & \tilde{x}_{2,b+1} & \tilde{x}_{2,b+2} & \cdots & x_{2,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,b} & \tilde{x}_{m,b+1} & \tilde{x}_{m,b+2} & \cdots & x_{m,n} \end{bmatrix} \end{array} \quad (4)$$

where x_{ij} is the rating of investment target i with respect to criterion j.

The proposed linguistic MCDM algorithm proceeds through the following computational stages (figure 1 for a schematic flowchart):

Step 1. Define investment targets. In the beginning, an investor must choose an investment field. In this investment field, some high-quality machinery investment targets can be chosen.

Step 2. Design criteria. A panel of experts collaboratively defines the most relevant cost and performance criteria for assessing alternatives.

Step 3. Collect experts' opinions and quantitative information for each machine investment target.

Afterwards, quantitative information of each machine investment target should be collected. Let x_{ij}^{qn} be the crisp performance of machinery investment target i with respect to quantitative criterion j.

Following this, experts will express their opinions about the performance of those machine investment targets with respect to qualitative criteria. Let $\tilde{x}_{ijk}$ be the linguistic opinion of expert k about the performance of machine investment target i with respect to qualitative criterion j. The aggregated opinion can be computed by the following formula [12, 13]:

$$\tilde{x}_{ij} = \triangle^{-1}\left(\frac{\sum_{k=1}^{K}\triangle(\tilde{x}_{ijk})}{K}\right) \quad (5)$$

Step 4. Transforming experts' opinions and quantitative information. To integrate the entire information reasonably, the performance of machine investment targets with respect to all criteria should be transformed.

(1) The transformed method for benefit qualitative criterion can be computed as

$$t_{ij} = \triangle^{-1}(\tilde{x}_{ij}) \quad (6)$$

(2) The transformed method for the benefit quantitative criterion can be computed as

$$t_{ij} = \frac{x_{ij}^{qn}}{\max_i\{x_{ij}^{qn}\}} \quad (7)$$

(3) The transformed method for the cost qualitative criterion can be computed as

$$t_{ij} = 1 - \triangle^{-1}(\tilde{x}_{ij}) \quad (8)$$

(4) The transformed method for the cost quantitative criterion can be computed as

$$t_{ij} = \frac{\min_i\{x_{ij}^{qn}\}}{x_{ij}^{qn}} \quad (9)$$

Step 5. Construct the normalised decision matrix as $D = [x_{ij}]_{m\times n}$, where $x_{ij} = \dfrac{t_{ij}}{\sum_{i=1}^{m} t_{ij}}$.

Step 6. Calculate the weight of each criterion.

The decision-making evaluation process is often biased by the subjective judgement of the evaluator if the weights are set based only on the subjective opinion of the decision maker or expert. Therefore, it is more objective to evaluate the importance of criteria by considering the distribution of data. 'Entropy' is a thermodynamic concept that describes the degree of confusion in a thermodynamic system. The entropy weight method is mainly used to calculate the entropy value and relative weight of each criterion by taking advantage of the distribution of data in the decision matrix. The greater the data dispersion of the criterion, the lower the entropy value and the higher the entropy weight, i.e. the higher the importance of the criterion [14].

Calculate the entropy value (E_j) of criterion (C_j) as follows:

$$E_j = -k\sum_{i=1}^{m} x_{ij} \ln x_{ij} \quad (10)$$

where $k = \dfrac{1}{\ln m}$ and $0 \le E_j \le 1$.

Calculate the dispersion (d_j) of criterion (C_j) and the weight (w_j) of criterion (C_j) as follows:

$$d_j = 1 - E_j \quad (11)$$

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (12)$$

Step 7. Construct the weighted decision-making matrix V as follows:

$$V = [v_{ij}]_{m\times n} \quad (13)$$

where $v_{ij} = x_{ij} * wj$.

Step 8. Based on the weighted decision-making matrix, determine the positive ideal solution (A^+) and negative ideal solution (A^-) as follows [14, 15]:

$$A^+ = \{v_1^+, v_2^+, \ldots, v_n^+\} \quad (14)$$

$$A^- = \{v_1^-, v_2^-, \ldots, v_n^-\} \quad (15)$$

where $v_j^+ = \max\limits_j v_{ij}$, $v_j^- = \min\limits_j v_{ij}$.

Step 9. Calculate the distance (S_i^+) between investment target (I_i) and positive ideal solution (A^+), the distance (S_i^-) between investment target (I_i) and negative ideal solution (A^-) as follows:

$$S_i^+ = \left[\frac{1}{n}\sum_{j=1}^{n}(v_{ij} - v_j^+)^2\right]^{1/2} \quad (16)$$

$$S_i^- = \left[\frac{1}{n}\sum_{j=1}^{n}(v_{ij} - v_j^-)^2\right]^{1/2} \quad (17)$$

Step 10. Calculate the closeness coefficient (CC_i) of investment target (I_i) as follows:

$$CC_i = \frac{S_i^-}{S_i^- + S_i^+} \quad (18)$$

Step 11. According to the closeness coefficients, we can determine the ranking order of all investment targets. If $CC_i > CC_j$, then investment target I_i is better than target I_j.

To provide a clear overview of the procedure, the entire process of the proposed linguistic MCDM method is illustrated in figure 1. The flowchart summarises the sequential steps, starting from the

definition of investment targets and criteria, followed by the collection and transformation of quantitative and qualitative data, calculation of criteria weights, and the determination of closeness coefficients for ranking the alternatives. This visual representation helps readers quickly grasp the logical structure and steps of the methodology.

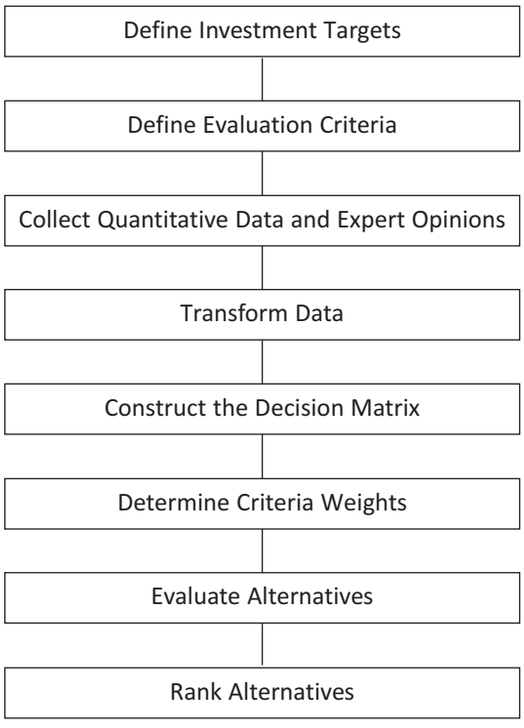


Fig. 1. Workflow diagram of the proposed linguistic MCDM method for machinery selection

EXAMPLE

Data analysis

The proposed linguistic MCDM framework was applied to a real-world laser cutting machine selection issue in the textile sector. The objective was to demonstrate how the model integrates qualitative expert judgments and quantitative data within a unified computational system. The steps are the execution process.

Step 1. Define the investment target. In the textile industry, many laser cutting machine types can be selected, such as alternative 1 (I_1), alternative 2 (I_2) and alternative 3 (I_3).

Step 2. Design criteria. Six criteria should be considered in selecting a suitable machine, such as cost (C_1), machinery appearance (C_2), engraving speed (C_3), cutting speed (C_4), resolution ratio (C_5) and resetting positioning accuracy (C_6). The criteria, cost (C_1), is a quantitative criterion, while the others are qualitative.

Step 3. Collect quantitative information of each machine investment target with respect to the criteria as seen in table 1. For the qualitative criterion, three experts use seven scale linguistic variables (very poor, poor, medium poor, fair, medium good, good and very good) to evaluate the performance of each machine investment target with respect to the criteria, as seen in table 2. We use formula 5 to integrate the opinions of experts.

Step 4. Transforming quantitative and qualitative performances of each machine investment target with respect to the criteria as given in table 3. Cost (C_1) is a cost quantitative criterion. Machinery appearance (C_2), engraving speed (C_3), cutting speed (C_4), resolution ratio (C_5) and resetting positioning accuracy (C_6) are benefit qualitative criteria.

Step 5. The normalised decision matrix can be shown in table 4.

Step 6. Calculate the weights of all criteria as seen in table 5.

Step 7. The weighted decision matrix can be shown as given in table 6.

Step 8. Determine the positive and negative ideal solutions as seen in table 7.

Step 9 and Step 10. Calculate the distances and closeness coefficients of all targets as seen in table 8.

Step 11. Based on the closeness coefficients, the ranking order of the three machine investment targets is $I_3 > I_1 > I_2$.

Table 1 presents the quantitative performance data of the three laser cutting machine alternatives with respect to the cost criterion (C1). Lower values correspond to lower investment costs, which are preferable since cost is a minimisation (cost-type) criterion. This variable provides a baseline for comparing the economic efficiency of each alternative in subsequent computational steps.

Table 2 reports the linguistic evaluations of three alternatives across five qualitative criteria (C2–C6), as assessed by three domain experts (E1–E3). Experts used a seven-point linguistic scale ranging from “very poor” to “very good”. These linguistic inputs serve as the foundation for the subsequent transformation process, where qualitative assessments are mapped into comparable crisp numerical values.

In table 3, the linguistic evaluations have been converted into numerical values using the linguistic transformation function, and the quantitative data have been normalised to a comparable scale. These

Table 1

QUANTITATIVE PERFORMANCE RATINGS			
Criterion	**Alternative 1 (I1)**	**Alternative 2 (I2)**	**Alternative 3 (I3)**
cost (C1)	7280	9380	4880

Table 2

LINGUISTIC PERFORMANCE RATINGS			
E1	**Alternative 1 (I1)**	**Alternative 2 (I2)**	**Alternative 3 (I3)**
C2	very good	medium good	good
C3	good	good	good
C4	good	good	good
C5	medium good	medium good	medium good
C6	good	good	good
E2	**Alternative 1 (I1)**	**Alternative 2 (I2)**	**Alternative 3 (I3)**
C2	good	poor	medium good
C3	good	good	fair
C4	good	medium good	medium good
C5	fair	good	fair
C6	good	good	medium good
E3	**Alternative 1 (I1)**	**Alternative 2 (I2)**	**Alternative 3 (I3)**
C2	good	fair	medium good
C3	medium good	medium good	medium good
C4	medium good	fair	fair
C5	medium good	good	good
C6	very good	very good	good

Table 3

TRANSFORMED DATA OF ALL TARGETS			
Criterion	**Alternative 1 (I1)**	**Alternative 2 (I2)**	**Alternative 3 (I3)**
C1	0.6703	0.5203	1.0000
C2	0.8889	0.4444	0.7222
C3	0.7778	0.7778	0.6667
C4	0.7778	0.6667	0.6667
C5	0.6111	0.7778	0.6667
C6	0.8889	0.8889	0.7778

Table 4

NORMALISED DATA OF ALL TARGETS			
Criterion	**Alternative 1 (I1)**	**Alternative 2 (I2)**	**Alternative 3 (I3)**
C1	0.3060	0.2375	0.4565
C2	0.4324	0.2162	0.3514
C3	0.3500	0.3500	0.3000
C4	0.3684	0.3158	0.3158
C5	0.2973	0.3784	0.3243
C6	0.3478	0.3478	0.3044

transformed values are used to construct the decision matrix.

Table 4 displays the normalised decision matrix, which ensures that all criteria are dimensionless and comparable.

Table 5 presents the criterion weights derived using the entropy method. The highest weight corresponds to machinery appearance (C2 = 0.4371), reflecting the criterion's high variability across alternatives and thus greater decision influence. Conversely, resetting positioning accuracy (C6 = 0.0226) shows minimal

Table 5

THE WEIGHTS OF ALL CRITERIA	
Criterion	**Weights**
C1	0.4246
C2	0.4371
C3	0.0298
C4	0.0319
C5	0.0588
C6	0.0226

Table 6

THE WEIGHTED DECISION MATRIX			
Criterion	**Alternative 1 (I1)**	**Alternative 2 (I2)**	**Alternative 3 (I3)**
C1	0.1299	0.1008	0.1938
C2	0.1867	0.0933	0.1517
C3	0.0104	0.0104	0.0089
C4	0.0118	0.0101	0.0101
C5	0.0175	0.0222	0.0191
C6	0.0079	0.0079	0.0069

differentiation, contributing less to the overall ranking. The entropy weighting technique objectively quantifies importance without relying on subjective input from experts.

Table 6 shows the weighted decision matrix. This matrix reflects the combined impact of each alternative's performance and the relative importance of each criterion.

Table 7 identifies the positive ($A+$) and negative ($A-$) ideal solutions for each criterion. These reference points are essential for measuring each alternative's Euclidean distance to the ideal condition, a core principle in the TOPSIS-based component of the proposed method.

Table 7

THE POSITIVE AND NEGATIVE IDEAL SOLUTIONS		
Criterion	**A^+**	**A^-**
C1	0.1938	0.1008
C2	0.1867	0.0933
C3	0.0104	0.0089
C4	0.0118	0.0101
C5	0.0222	0.0175
C6	0.0079	0.0069

Table 8 summarises the computed distances of each alternative to the positive and negative ideal solutions and their resulting closeness coefficients (CCi). The alternative with the highest CCi is considered the optimal choice. Here, Alternative 3 (CC3 = 0.7571) ranks highest, followed by Alternative 1 (CC1 = 0.6044), while Alternative 2 (CC2 = 0.0371) performs worst.

Comparison and explanations

The simple weighting method is one of the most employed multi-criteria decision-making approaches. Based on the data in table 6, the performance values calculated for the three alternatives using this method are 0.364 (alternative 1), 0.2447 (alternative 2), and 0.3905 (alternative 3). The ranking of the three alternatives aligns with the methodology proposed in this study. If the decision-maker were to employ subjective preferences, an optimistic decision-maker would base judgements on maximum values, yielding performance values of 0.1867 (alternative 1), 0.1008 (alternative 2), and 0.1938 (alternative 3). In contrast, a pessimistic decision-maker would base judgements on the minimum values, yielding performance scores of 0.0079 (alternative 1), 0.0079 (alternative 2), and 0.0069 (alternative 3). This demonstrates that the three scenarios produce unstable ranking outcomes due to decision-makers' subjective preferences. In fact, the simple weighted method merely calculates each alternative's performance value using a linear model for ranking. However, the ranking method proposed in this study simultaneously considers each alternative's distance from the positive ideal solution and its distance from the negative ideal solution across six criteria. Utilising these two distances to compute a closeness coefficient yields a value that enables more objective and stable alternative ranking. This study employs the entropy method to calculate criterion weights primarily based on the degree of data dispersion for each alternative across each criterion. In other words, when all alternatives exhibit identical data for a given criterion, it signifies that criterion holds no distinction among the alternatives and is therefore deemed insignificant. This approach enables a more objective calculation of criterion weights and mitigates bias arising from evaluators' subjective judgements. Typically, qualitative criteria often require input from evaluators. Consequently, when the number of evaluators is small, their opinions may be more concentrated, potentially leading to smaller assigned weights.

Table 8

THE DISTANCES AND CLOSENESS COEFFICIENTS OF ALL TARGETS			
Alternative	**Alternative 1 (I1)**	**Alternative 2 (I2)**	**Alternative 3 (I3)**
S_i^+	0.0261	0.0538	0.0144
S_i^-	0.0399	0.0021	0.0448
CC_i	0.6044	0.0371	0.7571

In the example presented in this paper, the three experts exhibited considerable divergence in their assessments of the three proposals under the criterion 'machinery appearance'. Conversely, their evaluations under the criterion 'resetting positioning accuracy' demonstrated greater consistency.
Consequently, when comparing the merits of the three alternatives, the criterion 'resetting positioning accuracy' exerted a relatively minor influence due to the proximity of the assessment values, resulting in a low weighting value. Conversely, the assessment opinions for the criterion 'machinery appearance' were more divergent, thus carrying greater influence and consequently a higher weighting value.
In summary, the main contributions of this paper comprise: (1) This study employs an entropy method to calculate criterion weights, enabling a more objective weighting process while mitigating bias arising from evaluators' subjective judgements. (2) The proposed ranking method simultaneously considers each alternative's distance from the positive ideal solution and its distance from the negative ideal solution across six criteria. By calculating closeness coefficients based on these dual distances, the resulting values enable more objective and stable alternative ranking.

CONCLUSIONS

This study presented a computational linguistic MCDM framework for machinery investment selection, addressing the challenges of combining qualitative and quantitative information in industrial decision environments. The proposed model integrates linguistic expert evaluations with quantitative performance data and employs the entropy weighting method to derive objective criterion weights. This hybrid structure ensures a transparent and reproducible evaluation process, reducing reliance on purely subjective expert judgments.
An empirical application to laser cutting machine selection in the textile industry verified the practicality of the proposed model. The results demonstrated that Alternative 3 achieved the highest performance score, primarily due to its low cost and strong qualitative evaluations in key criteria. These findings confirm the method's capacity to process hybrid data effectively and generate rational, data-driven investment decisions.
From a managerial perspective, the proposed framework provides a systematic decision support tool that can help managers make well-informed investment choices under uncertainty. It facilitates the integration of expert knowledge and measurable data within a unified computational system, enabling more consistent, evidence-based, and auditable decisions.
Despite these contributions, this study has several limitations. The application was limited to a single case study and involved a small group of experts, potentially limiting the generalizability of the findings. Future research should expand the empirical scope by applying the proposed framework to other industrial sectors.
Overall, this research contributes to the industrial engineering and computational decision-making literature by demonstrating how linguistic MCDM can be operationalised as a data-driven, objective, and replicable computational tool. The model not only extends the methodological frontier of MCDM applications but also provides industrial practitioners with a reliable and scalable framework for complex machinery and capital investment decisions.

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