

A Hyperbolic Fuzzy MCDM Framework Integrating LOPCOW, DEMATEL, and COPRAS for Enterprise Resource Planning System Selection

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ABSTRACT

Selecting the most suitable Enterprise Resource Planning (ERP) system is an important decision for organizations seeking to improve operational efficiency and competitiveness. This study proposes an integrated multi-criteria decision-making (MCDM) framework that combines the LOPCOW-DOBI method for expert weighting, hyperbolic fuzzy numbers to capture uncertainty in expert judgments, DEMATEL to examine cause-and-effect relationships among evaluation criteria, and COPRAS for the final ranking of ERP alternatives. Six evaluation criteria were identified: customization, support, implementation time, cost, ease of use, and integration. The DEMATEL analysis identified customization and support as the most influential criteria. Among the five ERP alternatives evaluated, ERP 2 emerged as the most suitable option. The proposed hybrid approach provides an effective mechanism for managing vagueness and subjectivity in expert judgments and supports more informed decision-making in the ERP selection process. The framework also has broader applicability and can be extended to other complex decision-making contexts involving interdependent criteria and uncertainty.

1. Introduction

1.1 Motivation and Challenges

Enterprise Resource Planning (ERP) systems are the cornerstone of modern organizations' technology infrastructure. They integrate various business processes and functions into a unified system, enhancing operational efficiency [1]. ERP systems are used for Information Integration and Process Automation. ERP systems collect and integrate data from various company functions, providing a comprehensive view of the organization and helping harmonize operations and procedures, mainly for manufacturing organizations [2, 3]. It also helps automate and standardize repetitive business processes. ERP reduces manual intervention, increases efficiency, and reduces errors [3, 4]. ERP enhances decision-making and performance by providing instant access to information. This results in better decision-making and improved overall performance [2, 5].

The ERP market is undoubtedly complex, with its plethora of versions, vendors, and its extremely non-transparent nature complicating the navigation of the market. Not only is it difficult to choose which ERP system is the 'best fit', but the unique potential selection criteria and requirements of each

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company will make this decision even harder [6]. Existing approaches to ERP Selection have tended to be designed to use qualitative analysis, which unfortunately will NOT represent a total assessment. Quantitative methods are more significant for evaluations, but again, often require a sophistication or understanding of technology and statistics that some enterprises may not possess [7]. Evaluation methods will often rely upon and work with a series of qualitative and quantitative criteria, and these evaluations do conflict with each other [8]. Tasking expert opinion is another new problem to solve, as traditionally, assessment always required engaging various experts in various areas of expertise, and went so far as to engage experts to a higher level of consensus reflectivity. This would require successful methods to group experts collectively and a synthesis of varied expert opinions. Variations found in expert instructions ultimately elude questions about 'vagueness' often found in expert opinions, uncertainty in judgments, and it's necessary to manage that inherent uncertainty in judgements, and it's necessary to manage inherent uncertainty require mathematical methods to best to lend, itself to better decision helping [9, 10].

Risks associated with poor ERP selection include implementation failure and organizational misalignment. Peculiarly, the most apparent problem in decision-making is uncertainty, particularly in real-world organizational situations that could potentially be complex. Hyperbolic fuzzy sets (HyFSs) are a more modern extension of the standard fuzzy set that can provide reasoning under ambiguous and uncertain conditions. It provides a high level of flexibility, and it also allows for a higher level of uncertainty than traditional fuzzy sets. This can be of use in the construction of decision matrices in MCDM, providing robustness for decision-making processes. MCDM methods are very useful when considering evaluating and prioritizing alternatives based on multiple criteria. MCDM is used in complex and highly uncertain situations [11]. Hyperbolic fuzzy logic and MCDM methods, especially when used together, use the ambiguity of fuzzy logic to combat uncertainty in decision-making and are a way to provide good utility for real-world decision-making.

1.2 Contribution of the present work

In this study, we contribute to ERP selection by proposing a new approach for combining the LOPCOW method with a Hyperbolic Fuzzy-DEMATEL-COPRAS framework. This approach utilizes the strengths of both methods in the decision-making process for the ERP selection. The proposed decision-making approach improves flexibility and credibility as it provides variability in assigning a degree of optimism and pessimism that fuzzy sets do not accommodate [12]. The use of HyFS improves the capability of dealing with a variety of expert hesitations and aggregating their opinions, thus solidifying the decision-making framework. We are unaware of any other work that has combined HyFS for expert opinion aggregation with LOPCOW for expert weighting in DEMATEL and COPRAS. Additionally, we are unaware of any other work that uses precisely measured factor ranking and weighting in the ordering of these factors, which is addressed with traditional fuzzy sets [12, 13].

It can manage complicated decision-making cases, such as ERP selection, by providing a systematic and flexible method to aggregate and weight uninformed opinions. Developing a hyperbolic decision matrix allows for a means of resolving subjectivity with the decision-making process and moving towards objectivity. By integrating hyperbolic functions along with the calculation of sophisticated scoring metrics, it increases the accuracy and reliability of fuzzy logic. The fuzzy DEMATEL method provides a clear description of the relationship of the criteria weights as a coefficient. In conjunction with fuzzy logic, it denotes a handle on the aspects necessary for the management of uncertainty and imprecision inherent in fuzzy, expert judgments, transforming those into actionable information. It can be used in countless contexts, from stakeholder analysis to performance assessment; its value across multi-criteria decision-making would be paramount [13]. LOPCOW (Logarithmic Percentage Change-driven Objective Weighting and COPRAS (Complex Proportional Assessment) are used to perform criteria weighting and alternatives ranking. It allows the scope for uncertain assessments while providing a well-rounded evaluation of alternatives, while enhancing LOPCOW and COPRAS' capacity to manage subjective judgement, minimising bias and dependencies between criteria, allows you to provide accurate findings on the decision [14].

2. Literature Review

2.1 Hyperbolic Fuzzy Set Review

Hyperbolic Fuzzy Sets(HFS) are a relatively new concept and provide a different perspective to deal with uncertainty and imprecision in decision-making processes than classical fuzzy sets, HFS's independent assignment of optimistic and pessimistic degrees allowed for greater flexibility and accuracy of representation of vague information and better representation of nuances of decision-maker preferences [15, 16]. Using HFS can lead to more precise decision-making outcomes, especially in complex and uncertain environments. ERP selection involves evaluating multiple criteria such as cost, functionality, vendor support, etc. Dutta and Borah [15] developed a hyperbolic fuzzy set framework that addresses the uncertainties in COVID-19-related problems and shows cases of the application across diverse scenarios. HFS are novel extensions of fuzzy sets where grades of membership and non-membership follow stipulations that the product of the optimistic and pessimistic degrees must be less than or equal to one, rather than their sum not exceeding one as in Intuitionistic Fuzzy sets. These concepts originate from hyperbola, providing extreme flexibility in imprecise information [15]. The sine hyperbolic q-rung ortho-pair fuzzy sets (sinh-qROFSs) and their associated Dombi operation laws(sinhDOLs) have been used to develop group decision-making approaches demonstrating the robustness of hyperbolic fuzzy models in handling multi-time process parameters [17]. It also has well-defined operational rules and aggregation operations that help in group and complex decision-making processes, thereby helping to maintain significant properties of HFS in practical applications. This is done by Operational Laws and Aggregation Operators [15]. A novel Hfs-based scoring function and the Minkowski distance measure have been introduced to construct a TOPSIS method for the MCDM problem [18]. Their applications in decision-making, particularly in medical and multi-criteria contexts, demonstrate their practical utility and effectiveness. Developing new operational laws, similarity measures, and aggregation operators further solidifies their role in advancing fuzzy set theory and its applications.

2.2 DEMATEL, COPRAS, and LOPCOW

DEMATEL(Decision-Making Trial and Evaluation Laboratory) is a method developed to examine and model the interdependencies between criteria within a complex system. DEMATEL uses the direct relation matrix to compute the total influence matrix by exponentiating the direct matrix until a sufficient level of convergence is observed, raising [19]. DEMATEL is also able to characterize influence among criteria and depict the result through an impact relationship diagram. To ensure the total influence matrix was correlatively acceptable, two types of special normalization methods were used, maximizing a matrix of values [19]. Modified Intuitionistic Fuzzy DEMATEL(IF-DEMATEL) was created for Subcontractor Selection by establishing cause-effect diagrams as a methodology for subcontractor selection and determining the critical criteria influencing the decision [20]. DEMATEL has also been modified for use in participatory processes(stakeholder analysis), demonstrating the application versatility of DEMATEL in other contexts [21]. DEMATEL - ANP was identified as a method of verifying, evaluating ERP Systems, which explores the interdependencies between criteria and develops decisions by converting cause-effect relationships into a visual model. DEMATEL is an effective tool within an MCDM system for understanding the interdependencies among the multiple criteria. The method is suited to a range of applications(ERP selection) and is largely combined with other methods to account for complexity in decision-making situations.

The COPRAS(complex proportional assessment) technique is a MCDM method to evaluate and rank alternatives based on their criteria. This technique has been used in various applications, such as the selection of ERP Organizations. Not only experience significant expenses in purchasing an ERP system, but it can also drastically reshape operations and competitive advantage. Fuzzy Analytical Hierarchy Process (F-AHP) with COPRAS-G for evaluating ERP consultants(for F-AHP considering comparative weights of selection criteria, and COPRAS-G for ranking the consultants based on utility degree). This combined decision process minimizes the rank reversal issue of MCDM, while providing an adaptable decision process [22]. Another study also proposed a Fuzzy-MOGA to weight and op-

timize ERP design (based on ISO25010 quality standards) and cost. This study facilitates a complex decision process and also ensures optimal selection [24]. Criteria such as system technologies and security, quality of information, system operations and processes, cost, and vendor reputation are also considered. The study provides a numerical example of the Indian industries using Fuzzy AHP and COPRAS-G in select ERP consultants, system process and operations, cost, and vendor reputation. This method facilitates complex decision-making and ensures optimal selection. The study shows a numerical example from Indian industries where Fuzzy AHP and COPRAS-G are used in selecting ERP consultants. This study suggests that integrating COPRAS with other MCDM techniques like Fuzzy AHP can mitigate problems such as rank reversal, which leads to a conclusion [22]. COPRAS assesses the alternatives by computing their degree of utility, which looks at how well the alternatives satisfy the selection criteria.

The Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) method is a multi-criteria decision-making (MCDM) technique used to determine the weights of criteria in various decision-making scenarios. This method demonstrates its versatility and effectiveness. LOPCOW eliminates biases by objectively determining the weights of criteria based on logarithmic percentage changes. The LOPCOW-DOBI multi-criteria sustainability performance assessment methodology, which is a novel objective weighting method designed to eliminate biases in the weighting process by addressing the size of the data and considering both positive and negative data, that ensuring generation of more reasonable weighting and enhance objectivity in decision making [23, 25]. This procedure is based on the components of two or more variables you are weighting and is designed to ensure that the size of a variable does not influence weightings. This method reduces the effect of size, especially if your data has a large size differential; it functions to eliminate these data size differentials as much as possible. The method will weight data as influenced by the positive and negative data, producing a more balanced weighting approach. This approach balances out more subjectivity manipulation and promotes more objectivity in the evaluation process. A different recent application reduces the subjective influence of the former methods by using logarithmic percentage changes. The main aim of this process is that it can be used in material selection and any MCDM context that requires consistent, unbiased weighting [23].

2.3 ERP Selection Through MCDM

The Multiple-Criteria Decision-Making (MCDM) methods provide a solid foundation for ERP selection issues while navigating the complexity and uncertainty associated with decision-making. Specifically, the Analytic Hierarchy Process (AHP) is the most commonly used approach for ERP selection problems to facilitate both qualitative and quantitative criteria. The AHP is mainly about hierarchically structuring the problem, comparing each criterion, and weighting them for ranking purposes. The AHP model seeks to prioritize a set of alternatives while considering the relative importance of the attributes involved in the multiple-criteria aspect of the decisions, as shown by reference [1, 5]. AHP, in conjunction with fuzzy logic, handles some of the ambiguities and vagueness with the criteria, allows for the most robust decisions, and provides strong associative work with other approaches like DEMATEL to help analyze criteria better using fuzzy set theory. However, it can be complicated and can be lengthy, particularly as the number of criteria grows. This method requires expertise in fuzzy logic, it can be computationally intensive. Among the MCDM methods, the Extended analysis method has been employed in many applications due to its computational simplicity, however, EAM has the problem of inconsistency rising as the number of criteria or alternatives increases [26].

3. Methodology and Preliminaries

3.1 Hyperbolic Fuzzy Sets (HyFS)

[18] proposed the concept of Hyperbolic Fuzzy Sets (HyFS) to overcome the limitations of Ordinary Fuzzy Sets (OFSs).

Definition 1. For a reference set X , a Hyperbolic Fuzzy Set (HyFS) is defined as:

$$H = \langle x, H^+(x), H^-(x) \rangle \quad \text{where} \quad H^+, H^- : X \rightarrow [0, 1] \quad (1)$$

Here, $H^+(x)$ and $H^-(x)$ denote the membership and non-membership degrees of the element $x \in X$, respectively.

Definition 2. The degree of indeterminacy is expressed as:

$$\pi_H(x) = 1 - H^+(x) - H^-(x) \quad (2)$$

Definition 3. To compare HyFSs, the following score and accuracy functions were introduced:

$$S(H) = 2H^+(x) - H^-(x) \quad (3)$$

$$A(H) = 2H^+(x) - H^-(x) \quad (4)$$

3.2 Decision-Making Trial and Evaluation Laboratory (DEMATEL)

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was initially developed by the Batelle Memorial Institute in the 1970s.

Definition 1 [27]: Consider a set of n factors. DEMATEL starts by constructing a direct relation matrix $A^{(k)} = [a_{ij}^{(k)}]$, where $a_{ij}^{(k)} \in \{0, 1, 2, 3, 4\}$ represents the degree of influence of factor i on factor j as assessed by the k -th expert. The average direct-relation matrix $Z = [z_{ij}]$ is computed as:

$$z_{ij} = \frac{1}{m} \sum_{k=1}^m a_{ij}^{(k)} \quad (5)$$

Definition 2 [27]: Matrix Z is normalized to obtain the normalized direct-relation matrix X :

$$s = \max \left(\max_{i,j} z_{ij}, \max_{j,i} z_{ji} \right) \quad (6)$$

$$X = \frac{Z}{s} \quad (7)$$

Definition 3 [27]: The total relation matrix T is calculated from the normalized matrix X , incorporating both direct and indirect effects:

$$T = X(I - X)^{-1} \quad (8)$$

where I is the identity matrix.

Definition 4 [27]: For each factor i , the row sum and column sum of T are computed as:

$$r_i = \sum_{j=1}^n t_{ij} \quad \text{and} \quad c_i = \sum_{j=1}^n t_{ji} \quad (9)$$

The prominence (importance) of factor i is given by $r_i + c_i$, while the relation (net influence) is $r_i - c_i$. If $r_i - c_i$ is positive, the factor is a *cause*; if negative, it is an *effect*.

Definition 5 [27]: The Influence Relation Map (INRM) is generated from the matrix T to visualize the causal and effect relationships among all factors.

3.3 Logarithmic Percentage-Change driven Objective Weighting (LOPCOW)

The LOPCOW method is an objective weighting technique used to determine the significance of evaluation criteria in multi-criteria decision-making (MCDM) problems. It combines linear normalization and dispersion-based statistics to generate data-driven weights.

Definition 1 [25]: Let m be the number of alternatives and n be the number of evaluation criteria. The decision-making environment is structured by an Initial Decision Matrix (IDM) $X = [x_{ij}]_{m \times n}$, where x_{ij} represents the performance score of alternative A_i with respect to criterion C_j :

$$X = [x_{ij}]_{m \times n} \quad (10)$$

Definition 2 [25]: To ensure comparability, the IDM is transformed into a Normalized Decision Matrix $R = [r_{ij}]_{m \times n}$ using linear max-min normalization:

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (\text{for benefit criteria}) \quad (11)$$

$$r_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (\text{for cost criteria}) \quad (12)$$

where $\max(x_j)$ and $\min(x_j)$ denote the maximum and minimum values of criterion C_j , respectively.

Definition 3 [25]: The percentage value (PV) of each criterion quantifies its normalized mean-square value relative to its standard deviation s_j , adjusting for scale differences:

$$PV_j = \frac{\sum_{i=1}^m r_{ij}^2}{s_j} \quad (13)$$

Definition 4 [25]: The objective weight w_j of criterion C_j is obtained by normalizing its percentage value. The weights satisfy $\sum_{j=1}^n w_j = 1$:

$$w_j = \frac{PV_j}{\sum_{j=1}^n PV_j} \quad (14)$$

These weights reflect the data-driven importance of each criterion and can be used for ranking in subsequent MCDM models.

3.4 Complex Proportional Assessment (COPRAS)

The Complex Proportional Assessment (COPRAS) method was initially proposed by Zavadskas *et al.* [28] and refined by Zavadskas and Kaklauskas [29] to solve multi-criteria decision-making (MCDM) problems involving both beneficial and non-beneficial criteria [28, 29]. The COPRAS-G method, an extension introduced by Zavadskas *et al.* [30], incorporates grey numbers from Grey System Theory to handle decision-making under partial uncertainty.

Definition 1 [31]: Let $A = \{A_1, A_2, \dots, A_m\}$ be a set of m alternatives evaluated over n criteria $C = \{C_1, C_2, \dots, C_n\}$. Let

$$x_{ij} = (x_{ij}^L, x_{ij}^U) \in G$$

denote the grey number representing the performance of alternative A_i under criterion C_j . The decision matrix X is expressed as:

$$X = \begin{bmatrix} (x_{11}^L, x_{11}^U) & \cdots & (x_{1n}^L, x_{1n}^U) \\ \vdots & \ddots & \vdots \\ (x_{m1}^L, x_{m1}^U) & \cdots & (x_{mn}^L, x_{mn}^U) \end{bmatrix} \quad (15)$$

Definition 2 [31]: The normalized decision matrix $X' = [x'_{ij}]$ is calculated differently for benefit and cost criteria as follows:

For **benefit criteria**:

$$x'_{ij} = \left(\frac{x_{ij}^L}{\sum_{i=1}^m x_{ij}^U}, \frac{x_{ij}^U}{\sum_{i=1}^m x_{ij}^L} \right) \quad (16)$$

For cost criteria:

$$x'_{ij} = \left(\frac{1/x_{ij}^U}{\sum_{i=1}^m 1/x_{ij}^L}, \frac{1/x_{ij}^L}{\sum_{i=1}^m 1/x_{ij}^U} \right) \quad (17)$$

Definition 3 [31]: Given the criterion weights w_j , the weighted normalized matrix $R = [r_{ij}]$ is:

$$r_{ij} = w_j \times x'_{ij} \quad (18)$$

Definition 4 [31]: Let J_b and J_c denote the index sets of benefit and cost criteria, respectively. The aggregated scores for each alternative A_i are:

$$S_i^+ = \sum_{j \in J_b} r_{ij} \quad (19)$$

$$S_i^- = \sum_{j \in J_c} r_{ij} \quad (20)$$

Definition 5 [31]: The relative significance (priority) of each alternative A_i is computed by:

$$Q_i = S_i^+ + \frac{\min_i S_i^- \times \sum_{i=1}^m S_i^-}{S_i^-} \quad (21)$$

where a higher Q_i indicates a better-performing alternative.

4. Case Example of ERP Selection

4.1 Background and Data collection

This study provides a systematic evaluation of five leading Enterprise Resource Planning (ERP) systems to identify the best solution specific to organizational needs. A multi-criteria decision-making (MCDM) process was applied, integrating Hyperbolic Fuzzy Sets, DEMATEL, LOPCOW, and COPRAS methods. The evaluation criteria are presented in Table 1.

Systems Evaluated

- SAP (ERP1)
- Sage (ERP2)
- Oracle Cloud (ERP3)
- Microsoft Dynamics 365 (ERP4)
- Infor (ERP5)

Evaluation Criteria

- Reputation and Experience (C1)
- Functionality (C2)
- Vendor Support (C3)
- Security (C4)
- Compatibility and Integration Capability (C5)
- Maintenance and Upgradation Cost (C6)

Data was collected from a structured evaluation conducted by three subject matter experts, each with more than 10 years of experience in ERP selection and process implementation. Pairwise comparison questionnaires were distributed using Google Forms and responses were collected using a 7-point Likert scale ranging from “Extremely Low” to “Extremely High.”

Table 1
Criteria for ERP Vendor Selection

Criteria	Description
Reputation and Experience	Brand name, market positioning, financials, certifications, and vendor experience
Functionality	Core features and functional fitness of the ERP system
Vendor Support	After-sales support for complex ERP applications
Security	Confidentiality, availability, authentication, integrity, non-repudiation
Compatibility and Integration Capability	Connecting/syncing ERP with other business applications
Maintenance and Upgradation Cost	Cost of hardware/software upkeep and system upgrades

Criteria	Citation
Reputation and Experience	[1, 10, 16]
Functionality	[1, 10, 16]
Vendor Support	[1, 7, 16]
Security	[1, 6, 10]
Compatibility and Integration Capability	[6, 10, 16]
Maintenance and Upgradation Cost	[1, 10, 16]

4.2 Steps for Ranking ERP Systems

i) Expert Weight Determination Using LOPCOW

The Logarithmic Percentage-Change Objective Weighting (LOPCOW) method was used to calculate expert weights based on expert consistency and accuracy when evaluating relative importance. The responses for each expert were measured using symbolic values which were then transformed into fuzzy values that indicated uncertainty and imprecision in their responses. After these fuzzy values were calculated, the accuracy matrices were derived from the fuzzy values using Equation (3) where each fuzzy value's membership degree u and its non-membership degree v were then used to measure the reliability of each response. These matrices provided the rationale for measuring the consistency of expert responses. The averages of the accuracy scores in each column were calculated, which provided an accuracy score across all criteria for each expert. These accuracy scores were then normalized to a single scale for proper comparison. The IDM is transformed into a Normalized Decision Matrix using linear max-min normalization. For benefit criteria and cost criteria we are having different normalization equation that is present in Equation (11) and (12) respectively. The Percentage Value (PV) was calculated using Equation (13) from the normalized scores and represents the relative importance of each expert considering their individual accuracy. The PV scores of the experts will be used to formally weight the experts in subsequent decision-making processes. The weights of experts are calculated using Equation (14) and were utilized in both DEMATEL and COPRAS approaches as presented in Table 2.

Table 2
Expert Weights Derived from LOPCOW and DEMATEL

Experts	LOPCOW weights	DEMATEL weights
Expert 1	0.258364	0.304021
Expert 2	0.347588	0.390844
Expert 3	0.394048	0.305134

ii) Critical Weight Determination Using DEMATEL

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was utilized to investigate the interconnections of the evaluation criteria. This process began with the formation of the 6×6 pairwise comparison matrices using the weighted data quantitatively given by the experts, reflecting the direct influence of one criterion to the other. To produce a uniform format based on expert responses, we had the experts transform their individual pairwise comparison matrices into a Simple Weighted Geometric Mean to produce one pairwise comparison matrix. The metric values of the pairwise comparison matrix were normalized to produce an unbounded normalized direct relation matrix using Equation (6) and (7). This matrix was converted to a total relation matrix **T** using Equation (8), the results of **T** calculate is presented in Table 3 reflecting both direct and indirect relationships of influence from other criteria is shown in Table 4. For each criterion the total influence on other criteria was represented by the sum of the values in each criterion's row, calculated by Equation (9). Conversely, the total relationship on other criteria was based on the sum of values in the column. These calculations were used to assess two primary indicators, which were prominence and relation. Competition from other criteria can be seen in the prominence numbers, which show the overall importance of that particular criterion within the system. In contrast, the relation value demonstrates whether the criterion is an influencer or a influenced. Finally the weights of the criteria as well as relationship is being shown Table 5.

Table 3
Total Relation Matrix (**T**)

Criteria	C1	C2	C3	C4	C5	C6
C1	0.241636	0.332432	0.433966	0.314976	0.366721	0.462450
C2	0.601748	0.521379	0.924043	0.672566	0.786782	0.751761
C3	0.502300	0.487657	0.495560	0.478923	0.553572	0.562532
C4	0.528190	0.627680	0.832073	0.457620	0.746554	0.746020
C5	0.531605	0.639415	0.735567	0.538067	0.527479	0.787834
C6	0.409591	0.411295	0.629407	0.422639	0.514803	0.417590

Table 4 presents the total influence given and received by each criterion.

Table 4
Total Influence Given and Total Influence Received

Criteria	C1	C2	C3	C4	C5	C6
Total influence given	2.1522	4.2588	3.0805	3.9381	3.7600	2.8053
Total influence received	2.8151	3.0199	4.0506	2.8848	3.4960	3.7282

Table 5 presents the criteria weights derived from DEMATEL.

Table 5
Criteria Weights Derived from DEMATEL in Relation

Criteria	Weights	Cause/Effect Relation
Reputation and Experience	0.1242	Effect
Functionality	0.1820	Cause
Vendor Support	0.1783	Effect
Security	0.1706	Cause
Compatibility and Integration	0.1814	Cause
Maintenance and Upgradation	0.1633	Effect

iii) ERP Ranking Using COPRAS

The ranking of Enterprise resource planning system was assessed through the COPRAS method that incorporated both benefits and cost criteria at once, the normalized decision matrix is calculated differently for benefit and cost criteria using Equation(16) and (17) respectively. In order to calculate values based on the criteria, the expert judgments given as Hyperbolic Fuzzy Data(HyFS) were de-fuzzified into crisp scores, Of the riskings criteria from COPRAS, the first five were identified as benefit criteria, while the last was identified as a cost criteria. With these criteria, to determine the first the benefit and cost values across several different values of q ranging from 0.1 to 0.9. The system rankings were calculated specifically for $q = 0.5$ and to get the final rankings those scores were aggregated employing the weights from LOPCOW. The final ranks of the ERP alternatives were based and developed from those scores. Final ranking result is presented in Table 6.

Table 6
Final Ranking of ERP

Rank	ERP System	Aggregate Score	Normalized Rank Score
1	ERP1	2.5297	1.0799
2	ERP2	2.7416	0.8680
3	ERP5	2.9071	0.7026
4	ERP4	3.2119	0.3977
5	ERP3	3.6096	0

4.3 Sensitivity Analysis

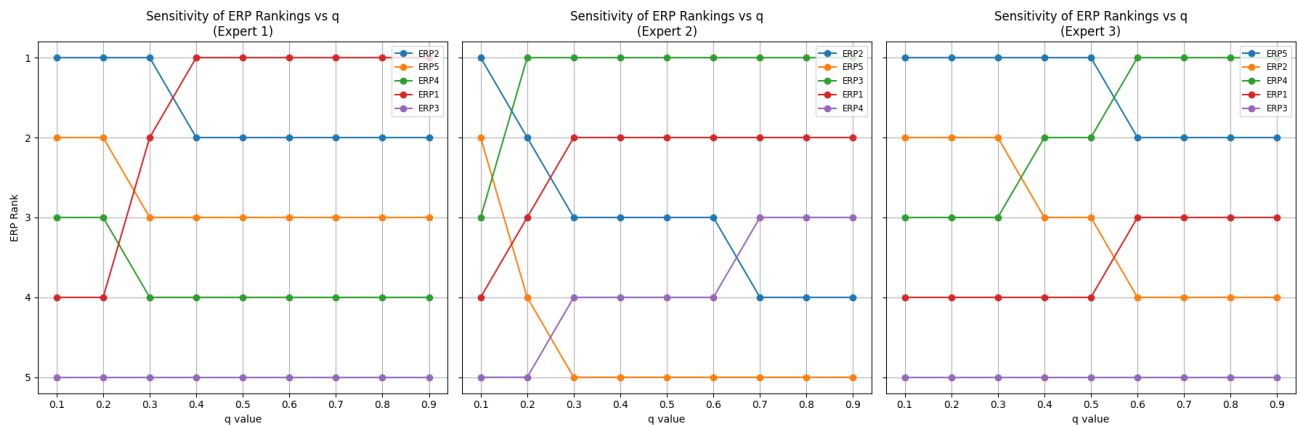
A sensitivity analysis was conducted by varying parameter q (0.1 to 0.9) to evaluate the robustness of the rankings in Table 7.

Table 7
Sensitivity Analysis Ranking Results for Each Expert at Different q Values

q -Value	Expert 1	Expert 2	Expert 3
0.1	1. ERP2	1. ERP2	1. ERP5
	2. ERP5	2. ERP5	2. ERP2
	3. ERP4	3. ERP3	3. ERP4
	4. ERP1	4. ERP1	4. ERP1
	5. ERP3	5. ERP4	5. ERP3
0.2	1. ERP2	1. ERP3	1. ERP5
	2. ERP5	2. ERP2	2. ERP2
	3. ERP4	3. ERP1	3. ERP4
	4. ERP1	4. ERP5	4. ERP1
	5. ERP3	5. ERP4	5. ERP3
0.3	1. ERP2	1. ERP3	1. ERP5
	2. ERP1	2. ERP1	2. ERP2
	3. ERP5	3. ERP2	3. ERP4
	4. ERP4	4. ERP4	4. ERP1
	5. ERP3	5. ERP5	5. ERP3
0.4	1. ERP1	1. ERP3	1. ERP5
	2. ERP2	2. ERP1	2. ERP4
	3. ERP5	3. ERP2	3. ERP2
	4. ERP4	4. ERP4	4. ERP1
	5. ERP3	5. ERP5	5. ERP3

Table 7Sensitivity Analysis Ranking Results for Each Expert at Different q Values (continued)

q -Value	Expert 1	Expert 2	Expert 3
0.5	1. ERP1	1. ERP3	1. ERP5
	2. ERP2	2. ERP1	2. ERP4
	3. ERP5	3. ERP2	3. ERP2
	4. ERP4	4. ERP4	4. ERP1
	5. ERP3	5. ERP5	5. ERP3
0.6	1. ERP1	1. ERP3	1. ERP4
	2. ERP2	2. ERP1	2. ERP5
	3. ERP5	3. ERP2	3. ERP1
	4. ERP4	4. ERP4	4. ERP2
	5. ERP3	5. ERP5	5. ERP3
0.7	1. ERP1	1. ERP3	1. ERP4
	2. ERP2	2. ERP1	2. ERP5
	3. ERP5	3. ERP4	3. ERP1
	4. ERP4	4. ERP2	4. ERP2
	5. ERP3	5. ERP5	5. ERP3
0.8	1. ERP1	1. ERP3	1. ERP4
	2. ERP2	2. ERP1	2. ERP5
	3. ERP5	3. ERP4	3. ERP1
	4. ERP4	4. ERP2	4. ERP2
	5. ERP3	5. ERP5	5. ERP3
0.9	1. ERP1	1. ERP3	1. ERP4
	2. ERP2	2. ERP1	2. ERP5
	3. ERP5	3. ERP4	3. ERP1
	4. ERP4	4. ERP2	4. ERP2
	5. ERP3	5. ERP5	5. ERP3

**Fig. 1.** Sensitivity of ERP Alternatives Rankings**Key Sensitivity Insights**

- Critical sensitivity zones were identified between $q = 0.3$ and $q = 0.6$.
- Significant inter-expert variability was observed, particularly concerning ERP3.
- ERP5 performed strongly at lower q values but its performance declined as benefit criteria gained predominance.
- No universally dominant alternative existed across all experts and q -values.

4.4 Comparative Analysis

The proposed hybrid model integrates multiple advanced decision-making techniques to address the limitations of traditional Multi-Criteria Decision-Making (MCDM) methods. Specifically, it employs Hyperbolic Fuzzy Logic to convert qualitative expert judgments into precise quantitative values, DEMATEL to evaluate interdependencies and determine criteria weights, LOPCOW for objective expert weighting, and COPRAS for the final ranking of alternatives.

A sensitivity analysis was conducted by varying parameter q (0.1 to 0.9) to evaluate the robustness of rankings. Figure 1 depicts the results.

A comparative evaluation has been conducted against other widely adopted models, including AHP-TOPSIS, Fuzzy DEMATEL-TOPSIS, and Standalone COPRAS. The comparison, as summarized in Table 8, spans key performance dimensions such as handling of fuzziness, dynamic expert weighting, treatment of interdependencies, ranking consistency, and computational complexity.

The analysis clearly shows that the proposed model outperforms conventional MCDM techniques on several fronts:

- **Enhanced Handling of Linguistic Uncertainty:** By integrating Hyperbolic Fuzzy Sets, the model captures the nuances of linguistic assessments with improved granularity, thereby preserving the semantic depth of expert opinions more effectively than linear fuzzy systems.
- **Incorporation of Inter-Criteria Relationships:** DEMATEL enables a structural understanding of causal relationships between criteria. This is especially valuable in ERP selection contexts, where interdependencies among factors such as cost, scalability, and usability can significantly influence outcomes.
- **Data-Driven Expert Weightings:** LOPCOW provides a systematic, quantifiable process of judging the relative importance of expert inputs. By moving away from traditional models that assume equal expertise, this functionality helps mitigate bias and improve the robustness of decision-making.
- **Transparent and Stable Ranking:** COPRAS, reinforced with both factor and expert weighting, produces rankings that are more stable and interpretable. Furthermore, the resulting stability and transparency contribute to informed decision-making in high-stakes, multi-stakeholder environments.

Table 8

Comparison of the Proposed Model with Other Models

Criteria/Method	AHP-TOPSIS	Fuzzy DEMATEL-TOPSIS
Handle categorical judgements	×	✓
Considers inter-factor influence	×	✓
Dynamic Expert weighting	×	×
Comprehensive ranking	✓	✓
Ranking stability	Medium	Medium
Computational complexity	Low	Medium
Suitability for ERP decision context	Moderate	Good

Criteria/Method	Standalone COPRAS	HyFz-DEMATEL-LOPCOW-COPRAS
Handle categorical judgements	×	✓ (Hyperbolic Fuzzy)
Considers inter-factor influence	×	✓ (DEMATEL)
Dynamic Expert weighting	×	✓ (LOPCOW)
Comprehensive ranking	✓	✓
Ranking stability	Low	High
Computational complexity	Low	Medium
Suitability for ERP decision context	Moderate	High

In conclusion, the proposed HyF-DEMATEL-COPRAS model exhibits superior performance in terms

of flexibility, realism, and analytical rigor. Its capacity to fuse fuzzy logic, causal mapping, and expert separation makes it particularly fit for convoluted and interdependent decision-making situations such as ERP system choice

5. Results, Discussion, and Implications

5.1 Summary of Key Findings

Choosing the right Enterprise Resource Planning (ERP) system is a critical strategic decision for an organization interested in becoming more operationally efficient. This study utilized an integrated MCDM approach employing Hyperbolic Fuzzy sets, DEMATEL, LOPCOW, and COPRAS to assess five prominent ERP systems against six key criteria. Results from the DEMATEL revealed that Functionality(C2) was determined to be the most significant criterion(weight: 0.1820), followed closely by Compatibility and Integration Capability(C5) at 0.1814 and Vendor Support(C3) at 0.1783; the criterion with the least importance was Reputation and Experience, with the lowest weight C1 at 0.1242. In addition, by cause-effect analysis, the Functionality (C2), Security(C4), and Compatibility(C5) criteria were classified as: “cause” criteria, whereas the Reputation(C1), Vendor Support(C3), and Cost(C6) criteria were determined to be “effect” criteria.

From the COPRAS results, a clear preference hierarchy emerged, with SAP(ERP1)being determined to be the best-performing solution, displaying a normalized score of 1.0799, followed by Sage(ERP2) with a score of 0.8680 and Infor (ERP5) with a score of 0.7026. The remaining ERP solutions, Microsoft Dynamics 365(ERP4) and Oracle Cloud (ERP3), ranked lower with scores of 0.3977 and 0, respectively.

5.2 Discussion of Results

SAP’s positioned ranking aligns with its market dominance as a firm-featured solution with high capability and integration. Its performance across the highest-weighted criteria(C2 and C5) reinforces the importance of technical characteristics in EPR selection and indicates that organizations prioritize operational capabilities over vendor reputation or cost considerations.

Sensitivity analysis identified a critical zone between q values of 0.3 and 0.6 where ranking fluctuations were most pronounced. This indicates a transitional phase where the balance between benefit and cost criteria significantly impacts outcomes. The analysis also revealed substantial inter-expert variability, particularly regarding Oracle Cloud(ERP3), highlighting the subjective nature of certain evaluation dimensions and the importance of incorporating multiple expert perspectives.

Infor performed strongly at lower q values, where cost criteria receive greater emphasis, suggesting value for budget-constrained organizations. However, its diminishing performance at higher q values indicates limitations in benefits-oriented criteria. The absence of a university-dominant alternative across all experts and parameter values confirms the inherent complexity of ERP selection decisions.

5.3 Implications

This research advances MCDM and ERP selection literature in three key areas. First, Hyperbolic Fuzzy Sets provide enhanced granularity in handling linguistic uncertainty compared to traditional fuzzy approaches. Second, the DEMATEL analysis suggests a critical degree of interdependent relations among criteria, questioning the traditional view of selection factors as independent dimensions. Third, LOPCOW presents objective validity for expert weightings and quantifies the reliability of the expert.

For organizations, the findings suggest that upon selecting between ERP alternatives, it is critical to evaluate functionality and integration. The wide and varied performance between different q values indicates that organizations need to be explicit about their priorities; namely, for example, benefit versus cost. Based on our analysis, there is evidence from the comparative sample results that confirms the decision makers that more reliable results are available from employing complete evaluation frameworks as opposed to simple evaluations that ignore dynamics in the decision context. For vendors, those same results suggest the need to have a clear strategic focus on functionality and integration in both product development and marketing. The fact that system performance within peer group-based rankings varied to enact expert evaluations further suggests that crafting value proposi-

tions across diverse organizational stakeholders presents immense challenges.

6. Conclusion and Future Research

6.1 Conclusion

This study tackles the important problem of ERP system selection by creating a new methodological framework that draws together Hyperbolic Fuzzy Sets, DEMATEL, LOPCOW, and COPRAS approaches. The resulting framework was able to adequately traverse the broad and complex shape of the decision environment that is always characterized by linguistic uncertainty, interdependent criteria, and, in some cases, expert judgment with variation.

There was useful and practical learning from the application of the framework, which delivered actionable, cognitive moments for the decision-makers in the organization, produced a clear preference ranking of a range of contemporary ERP solutions, and at the same time demonstrated how a variety of contextual factors can affect the potential best decision. The differences observed across all parameter values further reinforced the importance of an evaluation method that was organization-specific and that went beyond the generic 'selection' protocols.

Moreover, beyond its practical contributions, this study may add to the theoretical foundation of multi-criteria decision making in complex enterprise context - while it is demonstrated that the combination of more complex mathematical constructs in the evaluations forms even more robust evaluations with existing methods, it gives a way of thinking about incoming technological decisions similar to ones that face, separate from being regular or special cases because of multi-stakeholders, hypocritical objectives, risk of implementation.

6.2 Limitations and Future Research Directions

Notwithstanding its contributions, this study has identified certain shortcomings that could be explored in the future. First, while our framework incorporated six key evaluation criteria, future studies could expand this set to include emerging considerations such as cloud capabilities, mobile accessibility, artificial intelligence features, or sustainability aspects. Such extensions would enhance the comprehensiveness of the evaluation framework and better align it with evolving technological trends

Second, our case example involved three expert evaluators, which, while sufficient for demonstration purposes, could be expanded in future applications to incorporate more diverse stakeholders compositions that influence evaluation outcomes and whether certain expertise profiles yield more stable or accurate assessments.

Third, the present study focused on the selection phase of the ERP lifecycle. Future research could extend this framework to encompass implementation evaluation, creating a comprehensive decision support system spanning the entire ERP lifecycle. In turn, this may provide an organization with a framework of consistent methodological support throughout its ERP experience.

Fourth, while our sensitivity analysis offered some insight into how varying parameter values can impact ranking outcomes, subsequent research could offer more systematic robustness checks, incorporating alternate aggregation methods or appraising different fuzzy set theories (e.g., intuitionistic fuzzy sets or neutrosophic fuzzy sets).

Finally, with the advancement of artificial intelligence and machine learning, there may be opportunities to develop more interesting MCDM frameworks in the future, for instance to explore both how the model could be potentially changed to provide more dynamic weighting processes, or, how these technologies might be integrated into our model to support automated assessment evaluation for expert credibility or utilizing predictive analytics about implementation success based on selection decisions.

In conclusion, although this research advances both theory and practice in ERP selection, many opportunities exist for extension and improvement. The complexity of enterprise systems and rapid changes in technology are only increasing the difficulty of selecting an ERP system, so the decisions made in this domain will inevitably be challenging, and sophisticated analytics will always be required.

This framework is a contribution to overcoming this challenge - we remain excited about methodological development, providing ongoing innovation as the potential user organizations continue to alter their needs or the potential technologies continue to shift accordingly.

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Conflicts of Interest

The authors declare no conflicts of interest

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