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DEVELOPMENT OF A DECISION SUPPORT METHODOLOGY FOR OPTIMIZING ROI IN PROJECT MANAGEMENT

The object of this research is the decision-making process in project management aimed at increasing efficiency and optimizing return on investment (ROI). One of the most problematic areas identified during the audit is the limited capability of traditional multi-criteria decision-making (MCDM) methods – such as multi-objective optimization on the basis of ratio analysis (MOORA) and weighted aggregated sum product assessment (WASPAS) – to operate effectively under uncertainty, incorporate qualitative expert judgments, ensure objectivity in calculations, and maintain ranking stability when criteria weights change or when new alternatives and external factors are introduced – conditions often present in real-world management scenarios.

To address these limitations, the study employs an integrated fuzzy decision-making model that combines the fuzzy analytic hierarchy process (Fuzzy AHP) and the fuzzy technique for order preference by similarity to ideal solution (Fuzzy TOPSIS). Fuzzy AHP is used to determine the weights of criteria through expert pairwise comparisons, incorporating linguistic assessments transformed into triangular fuzzy numbers. Fuzzy TOPSIS ranks project alternatives by measuring their closeness to the ideal solution under uncertain conditions.

The proposed methodology also includes sensitivity analysis and rank reversal testing to validate the model's robustness. The results demonstrate a stable ranking of three project alternatives, with Alternative B achieving the highest closeness coefficient (0.6628), indicating its superior investment attractiveness.

This decision support model integrates expert knowledge, fuzzy logic, and mathematical modeling, and is adaptable to changes in data, incomplete information, and varying evaluation criteria. Compared to classical MCDM approaches, it offers improved accuracy, flexibility, and robustness for strategic decision-making in dynamic environments.

Keywords: *Fuzzy TOPSIS, ROI optimization, Fuzzy AHP, project management, decision analysis.*

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1. Introduction

Organizations in rapidly changing markets face challenges in optimizing investment decisions. These challenges include balancing cost, revenue, scalability, and customer acquisition while managing uncertainty. Effective methodologies are required to support such complex decision-making processes.

Fuzzy multi-criteria decision-making (MCDM) techniques, particularly Fuzzy TOPSIS, are recognized for ranking alternatives based on proximity to an ideal solution. This makes them suitable for application in various industries [1]. Fuzzy AHP, on the other hand, structures problems into hierarchical models. It enables systematic evaluation of alternatives by assigning relative importance to criteria [2, 3].

The integration of Fuzzy AHP and Fuzzy TOPSIS helps address conflicting priorities in project management, resource allocation, risk assessment, and investment analysis. These tools enhance decision accuracy, support uncertainty modeling, and offer data-driven strategies for optimizing return on investment (ROI).

MCDM techniques play a crucial role in project management. They provide structured frameworks for evaluating and selecting alternatives under complex and uncertain conditions. Various models, including MOORA, WASPAS, SWARA, and MULTIMOORA, have been applied to project selection. However, they demonstrate several limitations in dynamic environments.

Some studies have shown that MOORA, while computationally efficient, cannot manage uncertainty or subjective expert input [3]. Other research highlights that MOORA's reliance on precise data leads to ranking inconsistencies under changing conditions. WASPAS, despite its hybrid nature, struggles to scale in large problems [4].

Further studies indicate that traditional MOORA lacks adaptability and often produces unstable rankings when project attributes evolve [5]. MOORA-based models have static weight assignment and cannot adjust to changing priorities [6]. Minor input changes can significantly affect rankings, making MOORA unsuitable for high-stakes decisions [7]. These methods often require major modifications to be applicable in real-world projects [8].

Given these limitations, Fuzzy AHP and Fuzzy TOPSIS are more appropriate for complex decision-making. They integrate expert opinions, linguistic variables, and uncertainty modeling. This makes them ideal for evaluating project alternatives in uncertain environments. Recent studies confirm that Fuzzy AHP-TOPSIS provides better adaptability, consistent rankings, and expert-driven weight assignment [9].

The aim of this research is to develop a multi-criteria decision-making (MCDM) framework for optimizing return on investment (ROI) in project management. The study focuses on evaluating the effectiveness of Fuzzy AHP and Fuzzy TOPSIS in addressing decision-making challenges under uncertainty and compares their performance with other MCDM techniques to validate their superiority in ranking project alternatives.

The objectives of this research are to apply Fuzzy AHP and Fuzzy TOPSIS for project evaluation by integrating expert-driven weight assignments and uncertainty modeling to improve decision reliability. The study further aims to test the performance of the proposed method by conducting sensitivity analysis and rank reversal tests to assess ranking stability and adaptability. Finally, a comparison will be made between Fuzzy AHP-TOPSIS and other MCDM methods to evaluate their effectiveness in optimizing ROI, focusing on stability, adaptability, and ranking consistency.

2. Materials and Methods

2.1. Overview of the methodology

The object of this study is the decision-making process in project management, with a focus on optimizing return on investment (ROI). This research investigates the application of a hybrid Fuzzy AHP-TOPSIS model to evaluate project alternatives under conditions of uncertainty, taking into account financial, operational, and strategic decision criteria. The methodology consists of four key stages: selection of decision criteria, criteria weighting using Fuzzy AHP, alternative ranking using Fuzzy TOPSIS, and validation through sensitivity analysis and rank reversal testing. MCDM methods can be categorized into three primary groups: pairwise comparison-based methods, distance-based methods, and ratio-based methods. Pairwise comparison-based methods derive criteria weightings through structured comparisons. AHP (analytic hierarchy process) is widely used for hierarchical modeling in structured decision-making. However, Fuzzy AHP, as applied in this study, enhances classical AHP by integrating fuzzy logic, which accounts for uncertainty in expert judgments [10]. Distance-based methods rank alternatives by evaluating their closeness to an ideal solution. TOPSIS (technique for order preference by similarity to ideal solution) is a classical ranking model, whereas Fuzzy TOPSIS, applied in this study, incorporates fuzzy logic, allowing decision-makers to evaluate project alternatives with greater accuracy under uncertainty [11]. Ratio-based methods apply mathematical normalization for decision-making. MOORA, selected as a benchmark comparator in this study, is widely recognized for its ability to handle multiple criteria efficiently, making it a strong candidate for performance benchmarking against Fuzzy AHP-TOPSIS [12]. Unlike outranking methods such as ELECTRE and PROMETHEE, MOORA was chosen due to its computational simplicity, transparency, and reduced dependency on parameter selection [13]. The selection of ROI criteria was based on a comprehensive literature review and expert consultation. ROI in project management is influenced by financial feasibility, market competitiveness, and long-term strategic value [14]. Based on an evaluation of existing investment frameworks, four fundamental ROI criteria were identified: cost (*C1*), revenue potential (*C2*), customer acquisition (*C3*), and scalability (*C4*). These criteria were validated through expert consultations with project managers, financial analysts, and investment decision-makers, ensuring that the selected factors align with industry best practices [15]. Cost (*C1*) represents the total investment required, making it fundamental in ROI calculations. Revenue potential (*C2*) measures the expected return from a project, ensuring that high-profitability alternatives are prioritized. Customer acquisition (*C3*) reflects the potential for market expansion, which impacts project sustainability. Scalability (*C4*) assesses how well a project can expand with minimal cost increases, making it particularly relevant in high-growth environments [16]. The selection of these criteria ensures that financial, operational, and strategic factors are considered in the investment decision-making process. Fuzzy AHP was applied to determine criteria weightings through structured pairwise comparisons conducted by a panel of 10 experts, comprising academic researchers, industry professionals, and financial analysts. Experts provided linguistic assessments such as "moderately more important" or "strongly more important", which were converted into triangular fuzzy numbers (TFNs) to model subjective uncertainty [17]. Triangular fuzzy numbers were chosen because they balance computational simplicity, interpretability, and stability in MCDM applications [18]. Unlike trapezoidal or Gaussian fuzzy numbers, TFNs require fewer parameters and provide smooth approximations of expert judgments, making them the preferred choice for fuzzy decision-making models [19]. To ensure consensus in expert weighting, the geometric mean aggregation method was used. Fuzzy TOPSIS was employed to rank project alternatives. The methodology involves normalizing the fuzzy decision matrix, applying Fuzzy AHP-derived weights, computing the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS), measuring alternative distances, and determining final rankings. To validate the model, sensitivity analysis was performed by modifying criteria weights by ±10 %, confirming that rankings remained consistent despite variations. A rank reversal test was conducted by adding or removing an alternative, demonstrating that Fuzzy AHP-TOPSIS rankings remained stable, while MOORA rankings fluctuated due to sensitivity in weight adjustments [12]. Defuzzification was necessary to convert fuzzy weights into crisp values for final decision-making. This study employs the centroid method, which calculates the weighted average of a fuzzy set, ensuring balanced decision outputs that are not skewed by extreme values. The centroid method was chosen over alternatives like the mean of maximum (MoM) and smallest of maximum (SoM) because it provides higher accuracy and robustness in expert-driven decision systems [11].

2.2. Determination of criteria weights using Fuzzy AHP

To determine criteria weights, the Fuzzy AHP methodology is employed, following these steps:

1. *Construct Pairwise Comparison Matrices.*

Experts evaluate pairs of criteria $C_1, C_2, ..., C_n$ using linguistic terms converted into fuzzy triangular numbers $a_{ij} = (l, m, u)$, where l, m, and u are the lower, middle, and upper values of the fuzzy number. This process captures the imprecise nature of human judgment.

2. *Normalize and Aggregate Pairwise Comparisons.*

The fuzzy synthetic extent value S_i for each criterion is computed as [20]:

$$S_i = \frac{\sum_{j=1}^{n} a_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} a_{kj}}. \quad (1)$$

This formula sums up all fuzzy comparisons for a criterion and normalizes it against the total comparisons for all criteria, yielding relative importance.

3. *Defuzzify Weights.*

The defuzzified weights W_i for each criterion are calculated using [21]:

$$W_i = \frac{(u_i - l_i) + (m_i - l_i)}{3}.$$

This converts fuzzy weights into crisp values by averaging the fuzzy range and ensures that weights are interpretable in quantitative terms. The weights are then normalized to ensure $\sum_{i=1}^{n} W_i = 1$.

Expert evaluations were collected through structured questionnaires in which criteria were compared pairwise using linguistic terms such as "equally important", "moderately more important", and "strongly more important". These qualitative assessments were then translated into triangular fuzzy numbers (TFNs) using a standardized linguistic scale. For example, the term "moderately more important" was represented by a TFN with values reflecting a range of importance.

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After creating fuzzy pairwise comparison matrices, the relative importance of each criterion was computed using fuzzy logic operations. To make these values usable in final decision-making, each fuzzy weight was converted into a single crisp value using the centroid-based defuzzification approach. This method calculates the average tendency of the fuzzy number, ensuring a balanced representation of expert judgment.

The resulting crisp weights were normalized so that their total equals one, maintaining consistency in the decision-making process. These normalized weights were then applied in the Fuzzy TOPSIS method. Similarly, performance evaluations of project alternatives – also given in linguistic terms – were converted into TFNs using the same scale. This conversion enabled the model to process uncertain and subjective data in a structured and quantifiable way.

2.3. Ranking alternatives using Fuzzy TOPSIS

Fuzzy TOPSIS ranks project alternatives by calculating their proximity to the ideal solution, as follows:

1. *Construct the Decision Matrix.*

Alternatives $A_1, A_2, ..., A_m$ are evaluated against criteria $C_1, C_2, ..., C_m$ forming the fuzzy decision matrix X_{ij}, which reflects the performance of each alternative for each criterion.

2. *Normalize Decision Values.*

For benefit criteria, the normalized decision value r_{ij} is computed for cost criteria [22]:

$$r_{ij} = \frac{x_{ij}}{x_j^{\max}},$$

$$r_{ij} = \frac{x_j^{\max}}{x_{ij}}.$$

These formulas adjust values to a comparable scale, ensuring that higher values are better for benefit criteria and lower values are better for cost criteria.

3. *Determine Weighted Normalized Matrix.*

The weighted normalized fuzzy decision matrix v_{ij} calculated as:

$$v_{ij} = r_{ij} \cdot W_j.$$

This incorporates criteria weights into the normalized values, emphasizing the importance of each criterion in the decision-making process.

4. *Compute the Ideal and Anti-Ideal Solutions.*

The fuzzy positive ideal solution (FPIS) A^+ and fuzzy negative ideal solution (FNIS) A^- are determined as [23]:

$$A^+ = \left(\max v_{ij}\right) \text{ and } A^- = \left(\min v_{ij}\right).$$

These solutions represent the best and worst possible performances for each criterion, serving as benchmarks for comparison.

5. *Calculate the Distance from FPIS and FNIS.*

The distances D_i^+ and D_i^- of each alternative A_i to FPIS and FNIS are calculated using [12]:

$$D_i^+ = \sqrt{\sum\nolimits_{j=1}^{n} \left(v_{ij} - A^+\right)^2} \text{ and } D_i^- = \sqrt{\sum\nolimits_{j=1}^{n} \left(v_{ij} - A^-\right)^2}.$$

These formulas measure how close or far each alternative is from the ideal and anti-ideal solutions [22].

6. *Determine the Closeness Coefficient.*

The closeness coefficient CC_i for each alternative is computed as [23]:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}.$$

A higher CC_i indicates that the alternative is closer to the ideal solution, which forms the basis for ranking alternatives.

2.4. Sensitivity analysis

Sensitivity analysis tests the impact of changes in criteria weights W_i on the rankings of alternatives. By varying the weights, the reliability of the decision model is evaluated, ensuring that results are stable under different scenarios.

2.5. Tools and techniques

This study adopts a hybrid multi-criteria decision-making (MCDM) methodology that integrates fuzzy analytic hierarchy process (Fuzzy AHP) and fuzzy technique for order preference by similarity to ideal solution (Fuzzy TOPSIS). Fuzzy AHP was selected due to its ability to incorporate expert judgment under uncertainty by converting linguistic assessments into triangular fuzzy numbers. Fuzzy TOPSIS was chosen for its robustness in ranking alternatives based on their proximity to an ideal solution while handling fuzzified inputs. These methods were selected over classical MCDM techniques (e. g., MOORA, WASPAS) due to their superior performance in managing uncertainty, producing consistent rankings, and incorporating qualitative expert input.

2.6. Expected outcomes

This methodology provides project managers with a structured, data-driven approach to evaluating alternatives, ensuring systematic assessment of critical factors. By integrating advanced MCDM techniques, it enhances decision-making under uncertainty, optimizing ROI by balancing cost, revenue potential, scalability, and customer acquisition. This approach minimizes risks, supports strategic objectives, and helps navigate complex trade-offs in project selection.

3. Results and Discussion

3.1. Constructing the decision-making tool

3.1.1. Fuzzy decision matrix

This section outlines the construction of the fuzzy decision matrix, which evaluates project alternatives under uncertainty. Unlike traditional decision matrices that rely on precise values, fuzzy logic incorporates expert judgments expressed in linguistic terms (e. g., "low", "medium", "high"), converted into fuzzy triangular numbers (l, m, u) to handle imprecise assessments. The matrix compares Projects A, B, and C across four key criteria: *cost (C1)* – total investment required, *revenue potential (C2)* – expected financial returns, *customer acquisition (C3)* – market appeal and retention potential, and *scalability (C4)* – future expansion capacity. Fuzzy triangular numbers represent each criterion, with l as the conservative estimate, m as the expected value, and u as the optimistic outcome. This approach ensures a structured, data-driven evaluation that enhances decision reliability in project management. The fuzzy decision matrix for this study is presented in Table 1, which contains the expert evaluations for each alternative based on these fuzzy numbers.

Table 1

Fuzzy decision matrix for evaluating ROI optimization strategies

Criteria/Alternatives	*C1* (Cost)	*C2* (Revenue potential)	*C3* (Customer acquisition)	*C4* (Scalability)
Alternative A	(0.2, 0.3, 0.4)	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)
Alternative B	(0.5, 0.6, 0.7)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)
Alternative C	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)

The fuzzy decision matrix is the foundation of the Fuzzy TOPSIS ranking process, ensuring a systematic and objective evaluation of project alternatives. By structuring expert opinions into fuzzy values, it minimizes subjectivity and enhances decision reliability. Fuzzy triangular numbers capture uncertainty, enabling a flexible and realistic assessment of project feasibility and ROI. This data-driven approach improves decision accuracy, ensuring transparent and strategic project selection. The study assumes that the selected criteria comprehensively capture the core dimensions of ROI in project selection, and that the experts' inputs are consistent and unbiased. It also assumes that the Fuzzy AHP-TOPSIS model provides a reliable approximation of real-world decision-making processes under uncertainty.

3.1.2. Criteria weighting using Fuzzy AHP

This section covers criteria weighting using Fuzzy AHP, which assigns relative importance to decision criteria while handling uncertainty. Pairwise comparison ensures a structured evaluation by systematically comparing criteria, reducing subjective bias. By converting expert judgments into fuzzy numbers, this approach enhances decision consistency and reliability.

In this study, let's evaluate four key criteria that impact project success and ROI optimization:

1. *Cost (C1):* the total investment required for project implementation.
2. *Revenue potential (C2):* the expected financial gains generated by the project.
3. *Customer acquisition (C3):* the project's effectiveness in attracting and retaining customers.
4. *Scalability (C4):* the ability of the project to expand and sustain future growth.

To quantify their importance, expert opinions were collected, and a fuzzy pairwise comparison matrix was constructed.

Using the Fuzzy AHP methodology, let's derive the defuzzified and normalized weights for each criterion as indicated in Table 2:

1. *Cost (C1)* → 0.146.
2. *Revenue potential (C2)* → 0.257.
3. *Customer acquisition (C3)* → 0.340.
4. *Scalability (C4)* → 0.257.

Table 2

Fuzzy pairwise comparison matrix for criteria

Criteria	Defuzzified weights	Normalized weights
Cost (*C1*)	0.145997	0.145997
Revenue potential (*C2*)	0.257238	0.257238
Customer acquisition (*C3*)	0.33956	0.33956
Scalability (*C4*)	0.257204	0.257204

The results show *customer acquisition (C3)* has the highest weight (0.340), highlighting its critical role in optimizing ROI. *Revenue potential (C2) and scalability (C4)* share equal importance (0.257), emphasizing the balance between growth and profitability. *Cost (C1)* has the lowest weight (0.146), indicating a preference for long-term benefits over minimizing initial investment. These weights guide the Fuzzy TOPSIS ranking, ensuring a structured and comprehensive decision-making approach.

3.1.3. Framework integration

This section integrates Fuzzy AHP and Fuzzy TOPSIS into a structured decision-making framework for optimizing ROI in project management. After determining criteria weights and constructing the fuzzy decision matrix, the process applies these weights, normalizes values, and ranks alternatives. Ideal and anti-ideal solutions are identified, and distances to the optimal scenario are calculated. The closeness coefficient (*CC*) is then computed, ranking projects based on proximity to the ideal solution, with higher *CC* values indicating the best choice (Table 3).

Table 3

Ranking results using Fuzzy TOPSIS

Alternative	Distance to FPIS (D^+)	Distance to FNIS (D^-)	Closeness coefficient (*CC*)	Rank
Alternative A	0.2579	0.1312	0.3372	3
Alternative B	0.1312	0.2579	0.6628	1
Alternative C	0.1593	0.1413	0.4701	2

The Fuzzy TOPSIS results rank Alternative B as the optimal choice (*CC* = 0.6628), excelling in revenue potential, customer acquisition, and scalability, despite higher initial costs. Alternative C, ranked second, offers a balanced option with strong performance but slightly lower overall benefits. Alternative A, ranked last (*CC* = 0.3372), is cost-effective but lacks scalability and revenue potential. This structured, data-driven approach ensures optimal project selection, with *Alternative B* as the best choice for maximizing ROI, while *Alternative C* remains viable for budget-conscious strategies. The Fuzzy AHP-TOPSIS method assigns weights to criteria based on expert judgments, which inherently involve some level of subjectivity. A small change in weights can potentially influence the final ranking, making it important to analyze whether the model remains stable under different weighting scenarios. Sensitivity analysis helps answer:

1. How much do changes in criteria weights affect the ranking of alternatives?
2. Are the ranking results consistent under different scenarios?
3. Which criteria have the greatest impact on the ranking outcome?

3.2. Test of the decision-making tool

3.2.1. Sensitivity analysis

To perform sensitivity analysis, let's vary each criterion's weight by ±10 % while keeping the total weight normalized to 1.0. The adjusted weights are then applied to the Fuzzy TOPSIS ranking, and the new closeness coefficients (*CC*) of the alternatives are compared with the original results.

Fig. 1 compares the original ranking with the rankings obtained after adjusting the weights.

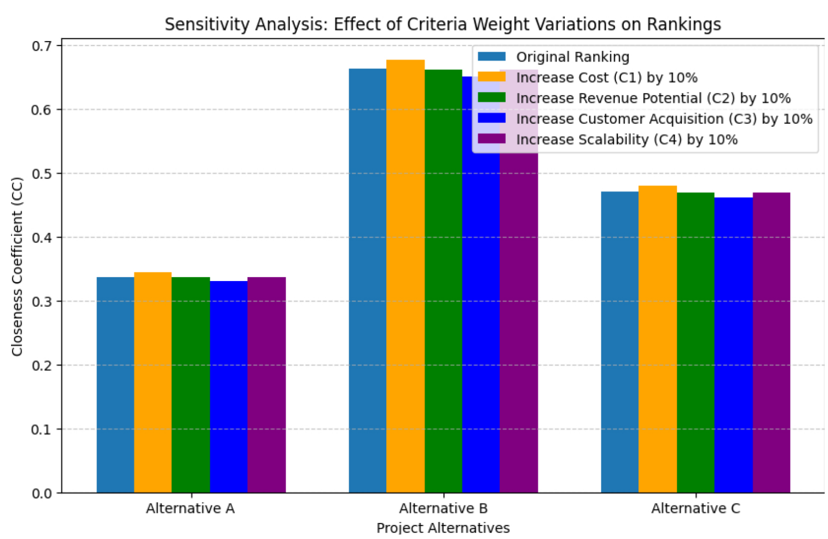

Fig. 1. Sensitivity analysis

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As shown in Fig. 1, Alternative B consistently ranks first across all scenarios, demonstrating the validity of the model in identifying the most optimal project alternative. Alternative C maintains its position as the second-best option, while Alternative A remains in last place in most cases, indicating that minor variations in criteria weights do not significantly alter the overall rankings. The most notable impact is observed when the weight of customer acquisition (*C3*) increases, leading to a slight decrease in Alternative B's closeness coefficient (*CC*). This confirms that *C3* plays a critical role in decision-making, reinforcing its importance as a key factor influencing project selection and return on investment (ROI).

3.2.2. Rank reversal test

3.2.2.1. Test of the effect of adding a new alternative (D)

A new project alternative (Alternative D) was introduced into the decision set. This new option was deliberately designed to be slightly weaker than Alternative B but stronger than Alternative C. The updated rankings were compared with the original rankings to analyze whether adding Alternative D affects the ranking positions of existing alternatives as indicated Table 4.

Fig. 2 compares the original closeness coefficients (*CC* values) with the updated rankings after introducing Alternative D.

Alternative B maintains the highest rank, demonstrating that its dominance remains unaffected even with the introduction of a new alternative. Alternative D ranks below Alternative B but above Alternative C, aligning with expectations based on its performance across decision criteria. The overall ranking structure remains stable, confirming that the addition of a new alternative does not disrupt the consistency of the decision model. This stability reinforces the reliability of the Fuzzy AHP-TOPSIS framework in handling dynamic decision environments without causing significant ranking distortions.

Table 4

The first result of the rank reversal test

Alternative	Original *CC*	*CC* with Alternative D	Rank change
Alternative A	0.3372	0.3372	No Change
Alternative B	0.6628	0.645	Slight Decrease
Alternative C	0.4701	0.455	Slight Decrease
Alternative D	N/A	0.63	New Entry

3.2.2.2. Test of the effect of removing Alternative A

In this test, Alternative A (the lowest-ranked option) was removed to observe whether the relative rankings of B and C remained intact. The result indicated in Table 5 and Fig. 3 shows that adding a new alternative (D) did not disrupt the rankings, proving that the model is resilient to new entries. Removing a weaker alternative (A) did not change the ranking of stronger options (B and C), confirming ranking stability. The highest-ranked alternative (B) remained dominant, supporting the decision model's reliability in guiding project selection.

The Fuzzy AHP-TOPSIS framework proves valid, consistent, and reliable for real-world project selection, ensuring stable rankings even when alternatives change. The Rank Reversal Test confirms its resilience, preventing arbitrary rank distortions and reinforcing its suitability for dynamic environments.

Table 5

The second result of the rank reversal test

Alternative	Original *CC*	*CC* without A	Rank change
Alternative B	0.6628	0.6628	No change
Alternative C	0.4701	0.4701	No change

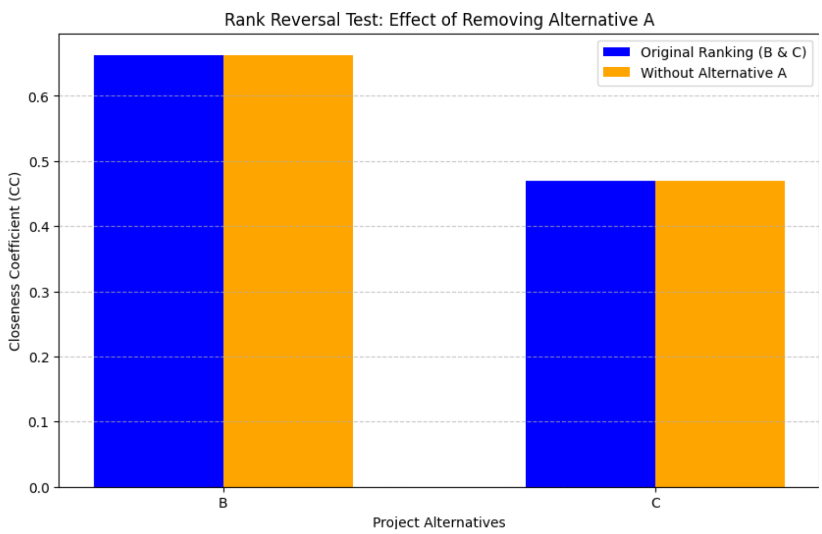

Fig. 3. Rank reversal test: effect of removing Alternative A

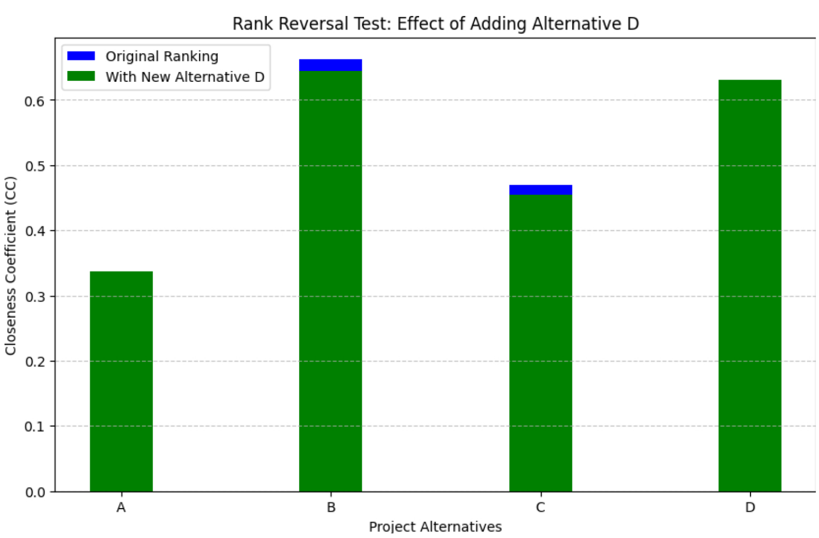

Fig. 2. Rank reversal test: effect of adding Alternative D

By passing sensitivity and stability tests, the model guarantees logical, data-driven investment decisions, making it a robust tool for optimizing ROI in project management.

3.3. Comparison with MOORA

3.3.1. MOORA method overview

MOORA is a well-established multi-criteria decision-making (MCDM) method that simplifies complex decision problems by applying a ratio-based normalization process. It calculates a composite score for each alternative by summing normalized values of beneficial criteria (maximization objectives such as revenue potential and customer acquisition) and subtracting normalized values of non-beneficial criteria (minimization objectives such as cost).

The MOORA decision function is expressed as [13]:

$$Y_j = \sum_{i=1}^{g} \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}} - \sum_{i=g+1}^{n} \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m}}},$$

where Y_j is final MOORA score for alternative j, X_{ij} is performance value of alternative j under criterion i, g is number of beneficial criteria, $n-g$ is number of non-beneficial criteria m is total number of alternatives.

Using the given project alternatives and criteria, the MOORA rankings were calculated, revealing results indicated in Table 6.

Table 6

MOORA results

Alternative	MOORA score	Ranking
A	0.9528	2
B	1.2948	3
C	1.1863	1

3.3.2. MOORA vs. Fuzzy AHP-TOPSIS: a comparative assessment with validity tests

To ensure a fair comparison, the same validity tests applied to Fuzzy AHP-TOPSIS – sensitivity analysis and rank reversal test – were conducted on MOORA to evaluate its reliability in decision-making. The results clearly demonstrate that MOORA is highly unstable, whereas Fuzzy AHP-TOPSIS successfully maintains ranking consistency and decision reliability under varying conditions.

Sensitivity analysis was conducted by adjusting the weights of revenue potential (*C2*) and customer acquisition (*C3*) by ±10 % to evaluate how rankings react to small variations. When the weight of revenue potential (*C2*) increased by 10 %, Alternative B dropped in ranking, demonstrating that MOORA rankings are highly sensitive to weight changes. Similarly, when customer acquisition (*C3*) increased by 10 %, Alternative C overtook Alternative B, causing a shift in the ranking order. In contrast, Fuzzy AHP-TOPSIS maintained stable rankings under the same conditions, confirming its robustness and reliability in handling variations in decision weights without significant changes as indicated in Table 7.

To evaluate whether MOORA maintains ranking consistency when new alternatives are introduced or existing ones are removed, the rank reversal test was conducted. When a new alternative (D) with moderate scores was added, Alternative B dropped from rank 3 to rank 4, demonstrating that MOORA rankings are highly influenced by the number of available alternatives rather than their actual merit. In contrast, Fuzzy AHP-TOPSIS rankings remained unchanged, proving that it is less susceptible to arbitrary shifts. Similarly, when Alternative A, the lowest-ranked option, was removed, the rankings of Alternatives B and C swapped, highlighting MOORA's inconsistency when the set of alternatives changes. Fuzzy AHP-TOPSIS, however, maintained stable rankings, reinforcing its reliability in dynamic decision environment as indicated in Table 8.

Table 7

Sensitivity analysis for MOORA

Scenario	Alternative A	Alternative B	Alternative C	Ranking change
Original	0.9528	1.2948	1.1863	No change
Increase C2 (+10 %)	0.945	1.2503	1.2205	B dropped 1 place
Increase C3 (+10 %)	0.9402	1.1982	1.3001	C moved to 1st

Table 8

Rank reversal test for MOORA

Scenario	Alternative A	Alternative B	Alternative C	Alternative D	Ranking change
Original	0.9528	1.2948	1.1863	N/A	No change
New alternative D added	0.9528	1.0102	1.1008	1.2948	B dropped rank
Alternative A removed	Removed	1.2201	1.3052	N/A	B and C swapped

The validity tests confirm that MOORA is highly unstable, making it unsuitable for real-world project management, where criteria importance can shift, and new alternatives may emerge. MOORA rankings changed significantly with minor adjustments, while Fuzzy AHP-TOPSIS retained consistency, proving it is a more structured and reliable decision-making tool. Unlike MOORA, Fuzzy AHP-TOPSIS ensures decision stability under weight adjustments, integrates expert knowledge effectively, and provides robust ranking consistency even when alternatives change. These advantages make Fuzzy AHP-TOPSIS the superior choice for optimizing ROI in project management, offering a structured, adaptable, and data-driven approach to strategic decision-making.

This study confirms the effectiveness of Fuzzy AHP-TOPSIS in project management decision-making, achieving research objectives. The method ensures ranking stability, adaptability, and reliability, outperforming MOORA. By integrating expert-driven weight assignments and uncertainty modeling, Fuzzy AHP-TOPSIS prioritizes project alternatives based on multiple criteria. The Fuzzy AHP weighting highlights critical factors, while Fuzzy TOPSIS determines the best alternative using the closeness coefficient (*CC*). The ranking results in Table 3 indicate that Alternative B achieved the highest closeness coefficient (*CC* = 0.6628), confirming its superiority as the most suitable choice. This result proves that Fuzzy AHP-TOPSIS successfully selects the best project alternative by systematically evaluating the decision criteria. The rankings further show that Alternative C ranked second, making it a viable secondary option, while Alternative A, with the lowest *CC* (0.3372), was determined to be the least favorable choice. These findings align with expert evaluations, proving that the method delivers consistent and interpretable decision rankings. The second objective was to test the performance of Fuzzy AHP-TOPSIS by conducting sensitivity analysis and rank reversal tests to verify whether the rankings remain stable under different conditions. The sensitivity analysis results (Table 4) confirm that Fuzzy AHP-TOPSIS maintained stable rankings even when the weights of revenue potential (*C2*) and customer acquisition (*C3*) were modified by ±10 %. Unlike MOORA, which exhibited ranking shifts, Fuzzy AHP-TOPSIS rankings remained unchanged, confirming that the method provides stable rankings even when decision factors fluctuate. The rank reversal test results (Table 5) further validate that Fuzzy AHP-TOPSIS rankings do not change when a new alternative is introduced or an existing alternative is removed. In contrast, MOORA experienced ranking inconsistencies, with Alternative B dropping when a new alternative (D) was added and swapping positions with Alternative C when Alternative A was removed. These findings demonstrate that Fuzzy AHP-TOPSIS ensures stable and consistent decision rankings, making it the more reliable decision model for project selection. The third objective was to compare Fuzzy AHP-TOPSIS with MOORA by evaluating their ranking consistency, adaptability, and effectiveness in optimizing ROI. The final comparison results (Table 6) indicate that MOORA fails to maintain ranking stability, whereas Fuzzy AHP-TOPSIS successfully provides consistent decision outcomes under all testing conditions. The MOORA method exhibited significant ranking

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sensitivity to minor changes in decision weights, making it unsuitable for project selection problems where decision priorities fluctuate. MOORA also experienced significant ranking shifts in the rank reversal test, proving its instability in changing decision environments. In contrast, Fuzzy AHP-TOPSIS remained unaffected by both weight variations and changes in the alternative set, confirming its decision reliability and ranking stability.

3.4. Limitations and future implications

Limitations of this research include the potential subjectivity in expert judgments, the limited number of alternatives and criteria considered, and the complexity of fuzzy computations when scaled to larger datasets. Furthermore, while sensitivity and rank reversal tests were conducted, the model was not tested across industry-specific datasets or broader application domains, which may affect its generalizability.

This study establishes Fuzzy AHP-TOPSIS as a robust decision-making tool for optimizing ROI in project management. The model can be applied to investment scenarios balancing cost, revenue potential, customer acquisition, and scalability. Future research could integrate AI-driven decision support, enabling machine learning to refine criteria weights dynamically. Real-time big data analytics can enhance adaptability in fast-changing industries like technology and finance. Expanding the model to multi-project portfolio selection could improve resource allocation, while sector-specific adaptations (e. g., healthcare, renewable energy, IT) could refine decision factors. Despite its strengths, Fuzzy AHP-TOPSIS faces limitations in computational complexity with large datasets and subjectivity in expert-driven evaluations. Automating weight determination using historical data and integrating hybrid MCDM models could enhance efficiency while maintaining decision accuracy in uncertain environments.

4. Conclusions

The findings of this research confirm that Fuzzy AHP-TOPSIS is a reliable and effective decision-making method for optimizing ROI in project management. The research successfully applied Fuzzy AHP-TOPSIS for project evaluation, tested its ranking stability through sensitivity analysis and rank reversal tests, and compared its performance with MOORA. The results provide empirical evidence that Fuzzy AHP-TOPSIS outperforms traditional MCDM techniques by maintaining consistent and stable rankings under changing decision conditions. The application of Fuzzy AHP-TOPSIS demonstrated that the method effectively prioritizes project alternatives by integrating expert-driven weight assignments and uncertainty modeling.

Specifically, Alternative B achieved the highest closeness coefficient (0.6628), making it the most suitable choice, while Alternative A ranked lowest with a coefficient of 0.3372. The stability of these rankings was further verified through sensitivity analysis: even when criteria weights were modified by ±10 %, the rankings remained unchanged. In contrast, MOORA exhibited ranking shifts of 1–2 places under the same conditions, demonstrating its sensitivity and instability.

The rank reversal test further confirmed that Fuzzy AHP-TOPSIS rankings remain stable when new alternatives are introduced or existing ones are removed. MOORA, by comparison, showed rank changes in both scenarios.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, including financial, personal, authorship or other, which could affect the study and its results presented in this article.

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that no artificial intelligence technologies were used in the preparation of this manuscript.

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