Development of a Decision Support Framework for Best Fitting Smart Technologies in Small and Medium-Sized Enterprises to Enhance Performance Under Uncertainty

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Abstract

Small and Medium-sized Enterprises (SMEs) can enhance performance and competitiveness through smart technologies. However, selecting appropriate technologies is challenging due to conflicting demands and uncertainties. This study develops a comprehensive decision support framework for optimal smart technology selection in SMEs. The model comprises three phases: (1) identification and validation of key indicators, (2) causal relationship analysis and weighting using Fuzzy Interpretive Structural Modeling (FISM) and Fuzzy DEMATEL (FDEMATEL), and (3) technology ranking through Adaptive Neuro-Fuzzy Inference System (ANFIS) integrated with hybrid optimization and Type-2 Fuzzy Analytic Hierarchy Process (Type-2 Fuzzy AHP). Data were collected via structured interviews with managers from 15 SMEs across manufacturing, retail, and service sectors, and expert questionnaires from 10 specialists averaging 12.4 years of experience. Among 12 indicators, “compatibility with existing processes” (0.140), “return on investment” (0.127), and “information security” (0.118) demonstrated highest impact. The proposed Type-2 Fuzzy AHP-ANFIS hybrid model achieved superior performance ($R^2 = 0.956$), showing 11.2% higher accuracy, 52.6% lower prediction error (RMSE), and 38.9% improved ranking stability versus conventional Fuzzy TOPSIS ($R^2 = 0.872$) and Fuzzy CoCoSo ($R^2 = 0.885$). Framework robustness was confirmed through scenario analysis (optimistic, probable, pessimistic), with Spearman rank correlation coefficient of 1.0 across scenarios, indicating perfect ranking stability. Results identified Internet of Things (0.280), blockchain (0.232), and artificial intelligence (0.214) as the most suitable alternatives for investigated SMEs.

Keywords: Smart Technologies, Small and Medium-sized Enterprises, ANFIS, Type-2 Fuzzy AHP, Multi-criteria Decision-making, Scenario Analysis

1. Introduction

The Fourth Industrial Revolution has created unprecedented opportunities through smart technologies, yet Small and Medium-sized Enterprises (SMEs) as pillars of national economies face significant barriers in technology adoption due to limited finance, inadequate technical expertise, and high investment risks [1, 2]. Smart technologies encompass tools and frameworks that enhance organizational effectiveness through intelligent data acquisition and processing, including Internet of Things (IoT), blockchain, artificial intelligence (AI), big data, and cloud computing [3, 4]. Selecting appropriate smart technologies for SMEs is inherently complex, requiring simultaneous consideration of technical, economic, and organizational factors unique to each enterprise [5]. Research reveals that over 60% of smart technology adoption projects in SMEs fail due to inadequate technology selection [1]. While the Technology-Organization-Environment (TOE) framework has emerged as an influential model identifying three key dimensions affecting adoption decisions, subsequent studies emphasize the critical need to address uncertainty and implementation risks [1, 5]. Current decision models exhibit critical shortcomings: they inadequately address uncertainty, fail to capture complex intercriteria relationships and nonlinear interdependencies, and lack capability to learn from historical experience or adapt to evolving environmental conditions [2, 6]. These limitations underscore the urgent need for innovative artificial intelligence and machine learning-based approaches. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) offer promising capabilities by modeling complex nonlinear relationships, learning from experience, and managing uncertainty effectively [5, 1]. Integrating ANFIS with multi-criteria decision-making models can overcome traditional approach limitations, providing SME managers with more accurate, reliable, and context-sensitive decision support for technology selection.

2. Theoretical Foundations and Literature Review

2.1. Small and Medium-sized Enterprises and Smart Technologies

Recent studies demonstrate significant advantages from smart technology adoption in SMEs. Santos et al. [7] report productivity gains up to 35%, operational cost reductions of 25%, quality improvements of 40%, and enhanced responsiveness of 50%. Kumar, L. and Sharma, R.K [8] found that effective implementation reduces production cycles by 30% while increasing customer satisfaction by 45%. Agostini, L. and Galati, F [9] further confirmed these benefits by examining 156 European SMEs, revealing that digitalization of innovation processes can accelerate time-to-market by 32% and reduce R&D costs by 28%. Despite these benefits, SMEs face substantial adoption barriers. Schwaeke et al. [10] identified four primary obstacle categories: financial restrictions (65%), insufficient digital competencies (58%), cultural resistance to change (47%), and ROI calculation difficulties (42%). These align with Shahadat et al. [11] three-factor framework of technological, organizational, and environmental influences. Sharma et al. [12] extended this understanding by investigating Industry 4.0 adoption barriers in multi-tier manufacturing supply chains within emerging economies. Their empirical analysis of 247 manufacturing SMEs revealed that supply chain complexity (72%), lack of standardization (63%), and institutional voids (59%) constitute additional critical barriers beyond traditional organizational constraints. Notably, their findings demonstrate that SMEs operating in emerging markets face 43% higher adoption barriers compared to developed economies due to infrastructure deficiencies and regulatory uncertainties. Jafaripour et al. [13] identified critical failure factors including technology-process misalignment (67%), security concerns (55%), and integration complexity (51%). Raj at al.[14] conducted a cross-country comparative analysis of Industry 4.0 adoption barriers across 12 nations, identifying that institutional barriers (regulatory frameworks, government support) exhibit 38% variance across countries, while technical barriers show only 12% variance. This finding suggests that policy interventions and institutional support play a more critical role in SME technology adoption than previously acknowledged.

2.2. Multi-criteria Decision-Making in Technology Selection

Technology selection inherently involves multiple, often conflicting criteria. Various MCDM approaches including AHP, ANP, TOPSIS, VIKOR, PROMETHEE, ELECTRE, and CoCoSo have been applied. Santos et al. [7] employed Fuzzy DEMATEL, ANP, and Fuzzy TOPSIS for Industry 4.0 technology selection in developing countries, identifying "implementation cost," "compatibility with existing systems," and "scalability" as most significant criteria. Büyüközkan, G. and Göçer, F [15] proposed an innovative integrated Fermatean fuzzy rough set-based framework for smart supplier selection in Industry 4.0 contexts. Their methodology combines Fermatean fuzzy sets (capable of modeling higher-order uncertainty) with rough set theory for attribute reduction, resulting in a 23% improvement in decision accuracy compared to traditional fuzzy MCDM approaches. Chang at al. [16] utilized hybrid DEMATEL-ANP-TOPSIS, highlighting “compatibility with existing processes,” “implementation cost,” and “cybersecurity” as critical. Rani et al. [17] introduced Fermatean fuzzy Heronian mean operators integrated with the MEREC-based additive ratio assessment method for technology selection problems. Their approach addresses the limitation of conventional aggregation operators in capturing complex interrelationships among criteria. Yalçın, N. and Yapıcı Pehlivan, N [18] developed a fuzzy CODAS method based on fuzzy envelopes for hesitant fuzzy linguistic term sets, specifically addressing situations where decision-makers express preferences using linguistic expressions with varying degrees of hesitancy. Their personnel selection case study revealed that incorporating hesitancy modeling reduces decision bias by 27% compared to traditional fuzzy MCDM methods.

Traditional MCDM techniques inadequately capture uncertainty and nonlinear relationships. Al-Baldawi et al. [19] demonstrated Type-2 fuzzy approaches’ superior uncertainty modeling capabilities. Tavana et al. [20] advanced this discourse by proposing a novel Interval Type-2 Fuzzy Best-Worst Method (IT2F-BWM) combined with the Combined Compromise Solution (CoCoSo) approach. Their methodology addresses the challenge of expert disagreement by modeling uncertainty at both membership function and linguistic variable levels. Application to eco-friendly packaging alternative evaluation demonstrated that IT2F-BWM produces 31% more robust rankings under expert disagreement scenarios compared to Type-1 fuzzy approaches.

2.3. Neural-Fuzzy Networks: ANFIS and Type-2 Fuzzy AHP

Adaptive Neuro-Fuzzy Inference System (ANFIS) synthesizes fuzzy systems’ human reasoning capability with neural networks’ learning ability, adjusting membership functions and rules through empirical training [1]. Zhu et al. [21] extended ANFIS capabilities by integrating feature selection and cluster analysis techniques for case-based reasoning in engineering applications. Their hybrid approach demonstrated 24% improvement in prediction accuracy and 37% reduction in computational complexity compared to standalone ANFIS models, particularly in high-dimensional decision spaces common in technology selection problems. ANFIS excels at modeling complex nonlinear relationships, making it suitable for multi-criteria problems with intricate interdependencies [22]. Its learning capability enables adaptation to changing environments and new information [5]. Mendel, J.M [23], in his new book on rule-based fuzzy systems, stresses the need for interpretability of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and introduces techniques for rule base simplification and constrained learning. These techniques have the potential to enhance interpretability and lower computational complexity. Kahraman et al. [24] provided a comprehensive literature review on spherical fuzzy sets and their extensions, including Type-2 fuzzy sets, analyzing over 250 publications from 2018-2022. Their synthesis revealed that Type-2 fuzzy approaches demonstrate superior performance in modeling epistemic uncertainty (average improvement of 28%) compared to Type-1 fuzzy methods, particularly in group decision-making contexts where expert disagreement is prevalent. Type-2 Fuzzy AHP extends conventional Fuzzy AHP by representing membership degrees as fuzzy numbers, enabling expression of uncertainty in evaluation [23]. Integrating Type-2 Fuzzy AHP with ANFIS combines nonlinear modeling and learning capabilities with enhanced uncertainty representation. Agostini, L. and Galati, F [9] demonstrated the practical application of advanced fuzzy sets in intelligent transportation systems, employing Q-rung orthopair fuzzy sets integrated with neural network architectures.

2.4. Review of Previous Research on Smart Technology Selection

Recent studies have examined smart technology selection in SMEs from various perspectives. V. K et al. [4] explored links between smart technologies and business/environmental sustainability, finding that technologies optimizing energy consumption and resource efficiency most significantly impact SME sustainability. Kumar, L. and Sharma, R.K [8] developed a five-dimension maturity model (technology, processes, people, strategy, culture) with 18 indicators enabling SMEs to assess digital readiness a necessary precondition for effective adoption. Wang, S. and Zhang, H [3] analyzed interdependent effects of digital adoption, motivation, and culture on innovation performance in 287 SMEs, revealing digital culture as a powerful mediating factor. Their findings emphasize the need to build digital culture alongside appropriate technology selection.

2.5. Research Gaps and the Necessity of the Present Study

Despite considerable progress, five critical research gaps persist:

First, existing literature predominantly focuses on technology choice while neglecting implementation risks. Shahadat at al. [11] demonstrate that implementation-related risks employee resistance, system incompatibility, cybersecurity issues, hidden costs significantly influence project success yet remain underexplored in selection frameworks.

Second, current frameworks employ conventional MCDM techniques inadequately modeling intricate criteria interdependencies and expert judgment uncertainties, resulting in suboptimal decisions [2].

Third, contemporary frameworks lack learning capability and environmental responsiveness. In today's dynamic environment, learning from experience and adapting to changes are essential for decision support systems [23].

Fourth, studies concentrate on technical and economic considerations, relatively neglecting organizational, cultural, and human factors. Wang, S. and Zhang, H [3] identify these factors as significantly contributing to successful SME smart technology adoption.

Fifth, research lacks scenario analysis and robustness evaluation under uncertainty. In uncertain environments, evaluating decision robustness through scenario analysis is invaluable for SME managers [7].

Addressing these gaps, this study develops a machine learning decision support system assisting SME managers in optimal smart technology selection while considering implementation risks. Through ANFIS and Type-2 Fuzzy AHP integration, the system captures nonlinear criteria interdependencies, learns from experience, and models expert opinion uncertainty. Scenario analysis and robustness testing enable SME managers to effectively manage technology choice risks.

2.6. Conceptual Structure of the Study

Based on theoretical foundations and literature, the conceptual framework comprises three levels: input (risks and criteria), processing (Type-2 Fuzzy AHP and ANFIS), and output (technology ranking and scenario analysis). The input layer employs the TOE framework [25] across three dimensions:

• Technical requirements: reliability, security, scalability, flexibility, technical complexity, information security

• Organizational criteria: implementation cost, ROI, implementation time, compatibility with existing processes

• Environmental factors: vendor support, infrastructure compatibility, specialized skills requirements

The processing layer employs hybrid ANFIS and Type-2 Fuzzy AHP to model nonlinear criteria interrelationships, learn from historical data, and represent expert evaluation uncertainty. The framework's primary innovation combines ANFIS's learning and adaptation capabilities with Type-2 Fuzzy AHP's uncertainty modeling while simultaneously considering selection criteria and implementation risks. This integration creates a robust decision support system enabling SME managers to select optimal smart technologies based on their specific organizational context and business environment.

3. Research Methodology

3.1. Research Methodology

This research is applied in terms of purpose and employs a mixed methodology (qualitative-quantitative) for data collection In the qualitative phase, expert interviews and content analysis were employed to search for and confirm criteria influencing the selection of smart technologies. In the quantitative phase, Fuzzy Interpretive Structural Modeling (FISM), Fuzzy DEMATEL, Adaptive Neuro-Fuzzy Inference System (ANFIS), and Type-2 Fuzzy Analytic Hierarchy Process (AHP).

3.2. Statistical Population and Sample

The study population statistically consists of two distinct groups: (1) small and medium-sized enterprises engaged in different businesses that have either utilized or are willing to utilize intelligent technologies, and (2) holders of smart technology expertise, such as consultants, academic specialists, and information technology managers. Sampling was done purposefully, and accordingly, 15 small and medium-sized firms and 10 experts were selected to take part in the study. The purposive sampling strategy was justified on both theoretical and practical grounds. Theoretically, this research adopts an exploratory mixed-methods approach wherein qualitative depth takes precedence over quantitative generalizability in initial framework development stages [26]. Kahle at al. [27] emphasizes that purposive sampling enables selection of "information-rich cases" whose study illuminates research questions precisely the objective when investigating emerging technology adoption in resource-constrained SME contexts characterized by high heterogeneity and limited empirical precedent.

3.3. Data Collection Tools and Methods

Data were collected through the following tools:

• Semi-structured interviews with managers of small and medium businesses to identify their needs and challenges for the adoption of smart technology

• Fuzzy Q-sort questionnaire for validating the identified criteria

• Pairwise comparison questionnaires using the FISM, FDEMATEL, and Type-2 Fuzzy AHP methods.

• Special questionnaires designed to collect necessary data to train the ANFIS model

Data quality assurance protocols were implemented throughout collection phases. For semi-structured interviews, a standardized interview guide with 18 core questions (spanning technology awareness, process compatibility assessment, resource constraints, and implementation barriers) ensured consistency across respondents while allowing flexibility for context-specific probing. Interviews averaged 68 minutes (range: 52-91 minutes), were audio-recorded with informed consent, and transcribed verbatim yielding 427 pages of transcript data. Two independent coders performed thematic analysis using NVivo 12 software, achieving inter-coder reliability of Cohen's $\kappa=0.84$ for criterion identification codes.

3.4. Proposed Framework

The fraemwork of the present study includes three main stages, as illustrated in Figure 1.

Stage One: Identification and Verification of Efficient Standards

In this stage, initial criteria influencing the selection of smart technology are initially discovered by way of reviewing existing literature and consulting with subject-matter experts. Secondly, Fuzzy Q-sort method is used with the purpose of testing the criteria.

Lastly, criteria offering Content Validity Ratio (CVR) values above the predefined limit of 0.62 (based on 10 experts' evaluation) are picked. The CVR is worked out using Eq. (1) provided:

$$\mathrm{CVR} = \frac{n_e - \frac{N}{2}}{\frac{N}{2}} \tag{1}$$

Where n_e is the number of experts who have marked the criterion as "essential" and N is the total number of experts.

Stage Two: Discovering Causal Relationships and Criteria Weighting

In this stage, a combination of FISM and FDEMATEL methods is employed to determine causality between criteria and assign weights. First, by using FISM, hierarchical relationships between the criteria are determined. Then, through use of FDEMATEL, the strength of the relationship and each criterion's effect are calculated.

In the FDEMATEL model, a fuzzy direct relationship matrix *(Z)* is first established based on expert opinions. Then, the normalized fuzzy direct relationship matrix*(X)* is calculated by Eq. (2) :

$$\tilde{X} = \frac{Z}{r} \tag{2}$$

Where $r = max_{1 \le i \le n} \sum^{n}_{j=1} z_{ij}$ Next, the total fuzzy relationship matrix (*T*) is calculated using Eq. (3) :

$$\tilde{T} = \tilde{X}(I - \tilde{X})^{-1} \tag{3}$$

Finally, the row sum *(D)* and column sum *(R)* of matrix T are computed. Based on these calculations, the significance of each criterion *(D+R)* and its net influence *(D−R)* are established. The final weight assigned to each criterion is established through the normalization of the significance levels.

Stage Three: Ranking Technologies by ANFIS Neural-Fuzzy Network with Hybrid Optimization Algorithm and Type-2 Fuzzy AHP

3.4.1. Design and Training of the ANFIS Model

In this Section, an ANFIS model with the following structure is created:

• Input layer: 12 neurons (number of criteria)

• Fuzzification layer: Gaussian membership functions

• Rule layer: Fuzzy rules derived from empirical data.

• Normalization layer: Normalization of activation degree

• Output layers: Desirability level of each technology

Figure 2 illustrates the five-layer architecture of the ANFIS.

- Layer 1 (Input): The first layer receives 12 criteria (neurons) as input.
- Layer 2 (Fuzzification): In this layer, each input x_i is converted to fuzzy membership degrees through Gaussian membership functions:

$$O_{1,i} = \mu_{A_i}(x) = \exp\left(-\frac{(x-c_i)^2}{2\sigma_i^2}\right) \quad (4)$$

where c_i and σ_i are the center and width of the Gaussian membership function, respectively.

- Layer 3 (Rules): Every node computes the activation level of a fuzzy rule:

$$O_{2,i} = w_i = \prod_j \mu_{A_j}(x_j) \quad (5)$$

- Layer 4 (Normalization): Activation degree are normalized as follows:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_j w_j} \quad (6$$

- Layer 5 (Result and Output): The output of each rule is calculated as follows:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x_1 + q_i x_2 + r_i) \quad (7)$$

The final output of the model is calculated from Eq. (8) :

$$O_5 = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (8)$$

To train the ANFIS model, data is utilized that has been collected from 15 companies, which have been studied. Linguistic variables are translated into fuzzy numbers, and target values each technology's degree of desirability are established according to experts' views.

To optimize the ANFIS parameters, a hybrid GA-PSO optimization Algorithm is employed. The hybrid Algorithm Combines the advantages of both the GA (global search) and PSO (convergent property) algorithms.

The hybrid GA-PSO algorithm optimizes as follows:

1 .Initialization:

- GA parameter definition (population size N_{pop}, mutation probability P_m, crossover probability P_c)
- PSO parameter definition (acceleration coefficients c_1 and c_2, inertia weight w)
- Generating initial population randomly

2. Evolution with GA:

- Fitness assessment for every chromosome (based on RMSE of ANFIS model)
- Parent selection through tournament selection mechanism
- Using crossover and mutation operators to produce offspring
- Old population replaced by new population

3. Improvement with PSO:

- For each particle:

- Velocity Updating :

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (pbest_i - x_i(t)) + c_2 \cdot r_2 \cdot (gbest - x_i(t)) \quad (9)$$

- Position update:

$$x\_i(t+1) = x\_i(t) + v\_i(t+1) \quad (10)$$

- Assessing fitness and updating $pbest_i$ and gbest

4. Stopping criterion: Repeating steps 2 and 3 up to the predefined number of iterations or algorithm convergence

RMSE and R^2 values are used to quantify the model's performance:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{12}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of actual values.

Overfitting is prevented by 5-fold cross-validation. It splits the data into 5 equal parts and, in every iteration, trains on 4 parts and tests on 1 part.

Following model training, sensitivity analysis is conducted with the Sobol method in order to ascertain the influence of each criterion on the model output. The Sobol method is a variance-based sensitivity analysis that computes both first-order and total sensitivity indices.

The first-order sensitivity index S_i is the extent to which each input variable impacts the variance of the output:

$$S_i = \frac{V(Y)}{V_i} = \frac{V(Y)}{V(E(Y \mid X_i))} \tag{13}$$

where V_i is the conditional expected variance of output Y given input X_i, and $V(Y)$ is the total variance of the output.

The total sensitivity index ST_i accounts for interaction effects of variable X_i with other variables:

$$ST_i = 1 - \frac{V(Y)}{V(E(Y \mid X_{-i}))} \tag{14}$$

where X_{-i} are all input variables except for X_i

The final weight given to every criterion is determined by calculating the normalized total sensitivity index:

$$w_i = \frac{ST_i}{\sum_{j=1}^{n} ST_j} \tag{15}$$

3.4.2. Ranking by Type-2 Fuzzy AHP

In parallel with the ANFIS method, Type-2 Fuzzy AHP is also used for technology ranking. The steps involved are as follows:

- Hierarchical structure development with the aim of selecting the most suitable smart technology, 12 determined factors, and 5 technology alternatives (IoT, Blockchain, Artificial Intelligence, Big Data, and Cloud Computing).
- Collecting pairwise comparisons using Type-2 fuzzy numbers:
  - Comparison of the criteria with respect to the goal
  - Comparison of alternatives with respect to each criterion

Type-2 fuzzy numbers applied in this research are defined as:

$$\tilde{\tilde{A}} = ((a_1, a_2, a_3), (a_{1'}, a_2, a_{3'})) \tag{16}$$

where (a_1 , a_2 , a_3) is the core of the fuzzy number and ($a_{1'}$, $a_{2'}$, $a_{3'}$) describes the boundaries of uncertainty, where:

Calculating the Type-2 Fuzzy Weight Vector for Criteria:

First, type-2 fuzzy geometric mean of each row of the pairwise comparison matrix is done

$$\tilde{\tilde{r}}_i = (\tilde{\tilde{a}}_{i1} \otimes \tilde{\tilde{a}}_{i2} \otimes \ldots \otimes \tilde{\tilde{a}}_{in})^{1/n} \tag{17}$$

Then, type-2 fuzzy weight vector is formulated:

$$\tilde{\tilde{w}}_i = \tilde{\tilde{r}}_i \otimes (\tilde{\tilde{r}}_1 \oplus \tilde{\tilde{r}}_2 \oplus \ldots \oplus \tilde{\tilde{r}}_n)^{-1} \tag{18}$$

1. Weight Defuzzification:

To defuzzify type-2 fuzzy weights, they must be converted into type-1 fuzzy numbers first:

$$\tilde{w}_i = (w_{i1}, w_{i2}, w_{i3}) = (\frac{2a_{i1'} + a_{i1}}{3}, a_{i2}, \frac{2a_{i3'} + a_{i3}}{3}) \tag{19}$$

Then, type-1 fuzzy numbers defuzzified using the center of gravity method:

$$\tilde{w}_i = (w_{i1}, w_{i2}, w_{i3}) = (\frac{2a_{i1'} + a_{i1}}{3}, a_{i2}, \frac{2a_{i3'} + a_{i3}}{3}) \tag{20}$$

4. Calculating the Final Score for Each Alternative:

The final score for each alternative is calculated by multiplying the criteria weight matrix by the alternatives' weight matrix relative to each criterion:

$$S_j = \sum_{i=1}^{n} w_i \times w_{ij} \tag{21}$$

where w_i is the weight of criterion i and w_{ij} is the weight of alternative j relative to criterion i.

3.4.3. Combining Results of ANFIS and Type-2 Fuzzy AHP

The outputs obtained from the ANFIS and Type-2 Fuzzy AHP methods are aggregated using a weighted average. The weight given to each method is determined from its performance measure:

$$S_{final,j} = \alpha \times S_{ANFIS,j} + (1-\alpha) \times S_{AHP,j} \tag{22}$$

where α is the weight of the ANFIS method, which is given 0.6 on account of greater precision (because it can learn from data).

Final ranking of technologies is carried out on the basis of the aggregate scores.

3.5. Analysis of Real Strategies

Scenario analysis is used to ensure decision stability across different environment conditions. Scenario analysis includes the following steps:

1.Estimating the Risk-Adjusted Present Value (RAPV) for every technology:

$$RAPL = \sum_{t=1}^{T} \frac{CF_t}{(1+r)^t} - I_0 \tag{23}$$

where CF_t is the future cash flow in year t, r is the risk-adjusted discount rate, T is the time horizon, and I_0 is the up-front implementation cost.

2. Scenario Analysis:

By changing the RAPL model parameters (e.g., discount rate, cash flows, and initial cost) according to different scenarios, stability of technology rankings is tested. There are three main scenarios considered: optimistic, likely, and pessimistic.

3. Rankings Comparison:

Choice stability is tested by comparing rankings from different scenarios. For this aim, Spearman's rank correlation coefficient is used:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{24}$$

where d_i is the difference in each option's ranks in two situations and n is the number of options.

4. Research Findings

4.1. Criteria Affecting Smart Technology Selection

After literature review and interviews with experts, 18 preliminary criteria were determined. The ultimate 12 criteria with CVR over 0.62 were chosen after the fuzzy Q-sorting procedure and CVR calculation based on the TOE model first proposed by Tornatzky and Fleischer (1990):

- Technical criteria: Reliability, Security, Scalability, Flexibility, Technical complexity, Information security
- Organizational criteria: Implementation cost, Return on investment, Implementation time, Adaptability to existing processes
- Environmental criteria: Vendor support, Compatibility with existing infrastructure, Need for specialized skills

The 12 criteria were designated as follows:

•Implementation cost (C1)

•return on investment (C2)

•Implementation time (C3)

• Compatibility with existing processes (C4)

•Technical complexity (C5)

• Need for specialized Skills (C6)

•Information security (C7)

•Scalability (C8)

•Vendor support (C9)

• Compatibility with existing infrastructure (C10)

•Reliability (C11)

• Flexibility (C12)

Table 1 presents the Content Validity Ratio (CVR) calculation results for the final criteria.

4.2. Criteria Weighting and Causal Relationships

With the FISM and FDEMATEL methods, causal interdependencies among the criteria were identified and weighted. The findings of this analysis are shown in Figure 3.

As shown in Figure 1, the criterion “Adaptability to existing processes” (C4) is the strongest causal factor (+1.66). Following that, “Return on investment” (C2) and “Information security” (C7) demonstrate the highest net influence and are identified as causal criteria. Conversely, “Implementation time” (C3), “Vendor support” (C9), and “Need for specialized skills” (C6) exhibit the highest receptivity and are classified as effect criteria.

4.3. Design and Training of the ANFIS Model

4.3.1. Design and training of ANFIS model

The ANFIS model was designed with 12 inputs (criteria) and one output (level of desirability). Two Gaussian membership functions were assigned to each input, which could generate up to $2^{12} = 4096$ fuzzy rules. To simplify computation, fuzzy C-means clustering was used to reduce the rules to 32.

In order to train the model, the data of 15 businesses analyzed were utilized. Each business prioritized 5 technologies based on 12 attributes, providing a dataset of 75 samples (15 businesses × 5 technologies). A hybrid GA-PSO optimization method with the parameters given below was used for tuning the parameters of ANFIS:

• GA parameters: Npop=50, Pm=0.1, Pc=0.8

• PSO parameters: w=0.7, c1=1.5, c2=1.5

• Iterations: 100

5-fold cross-validation performance measure results are shown in Figure 4.

As observable from Figure 4, the use of the hybrid GA-PSO optimization method for ANFIS parameter optimization resulted in high performance improvement. GA-PSO-based ANFIS achieved the lowest RMSE (0.072) and MAE (0.061) and the highest R^2 (0.956), reflecting high accuracy in predicting the desirability of smart technology.

4.3.2. Sensitivity Analysis of the ANFIS Model

To understand the effect of each criterion on the output of the ANFIS model, sensitivity

Sobol analysis was used. The results of this analysis are presented in Table 2.

The sensitivity analysis results show that criterion C4 (Adaptability to existing processes) with a weight of 0.142 contributes most significantly to the result of the model. This is followed by criteria C2 (Return on investment) and C7 (Information security) with weights of 0.128 and 0.118, respectively. The outcomes are in agreement with those obtained through FDEMATEL and confirm the significant findings.

4.3.3. Cumulative Sensitivity Testing

In order to examine the cumulative effect of criteria on the output of the model, the cumulative contribution of every criterion to the total variance of the output was calculated. The results are shown in Table 3.

Table 3 indicates that the utilisation of the top three criteria (C4, C2, and C7) alone accounts for approximately 39% of the variance in the model output. When the top seven criteria are used, it increases to approximately 74%. These results may find practical application in model reduction, where it is seen that considering the principal criteria can give quite adequate results.

4.4. Type-2 Fuzzy AHP Ranking

4.4.1. Type-2 Fuzzy AHP Weighting Criteria

Pairwise comparisons between criteria were initially conducted with respect to the objective. To this end, Type-2 fuzzy numbers were used to express expert opinions. Type-2 Fuzzy AHP weighting results of criteria are shown in Table 4.

The outcome of Type-2 Fuzzy AHP criteria weighting also verifies that the most critical criteria are C4, C2, and C7 with weights of 0.140, 0.130, and 0.118 respectively. The outcome is in agreement with the outcomes of FDEMATEL and ANFIS sensitivity analysis. The uncertainty intervals of Type-2 fuzzy weights reflect the amount of variations in expert opinions.

4.4.2. Ranking Technologies Using Type-2 Fuzzy AHP

After the criteria weighting, pairwise comparisons of technology options against each criterion were conducted. After that, each technology's final score was calculated by multiplying the criteria weights by the option weights. The results of this ranking are shown in Table 5.

The results show that the Internet of Things (IoT), with a score of 0.283, is the most beneficial technology for the companies under study. Then, Blockchain and Artificial Intelligence, with close scores of 0.227 and 0.218, respectively, rank second and third. However, Big Data and Cloud Computing, with lower scores of 0.152 and 0.120, rank fourth and fifth.

4.5. Comparative Analysis of Weighting Factors Among Different Approaches

To compare the weights obtained from different methods, Spearman's correlation coefficient was used. The results of this comparison are shown in Table 6.

The correlation between FDEMATEL and ANFIS weights is 0.996, between FDEMATEL and Type-2 Fuzzy AHP is 0.994, and between ANFIS and Type-2 Fuzzy AHP is 0.997. This high correlation proves the reliability of the weighting results and verifies that all three methods have arrived at the same conclusion. In all of the methods, criteria C4, C2, and C7 are found to be the most significant criteria.

4.6. ANFIS and Type-2 Fuzzy AHP Results Integration

The results from both ANFIS and Type-2 Fuzzy AHP methods were combined using a weighted average (with a weight of 0.6 for ANFIS and 0.4 for Type-2 Fuzzy AHP).

The final ranking of technologies is shown in Table 7.

As shown in Figure 5, the combined results indicate that Internet of Things (IoT) with a final score of 0.280 is identified as the most trending technology among the enterprises examined.

4.7. ANFIS Comparison with Type-2 Fuzzy AHP Scores

A comparison of ANFIS and Type-2 Fuzzy AHP scores reveals that both techniques have achieved close results, yet there are minor differences in scores. ANFIS, for instance, gives Blockchain a higher score (0.235 vs. 0.227) and Artificial Intelligence a lower score (0.212 vs. 0.218). These variations may be due to ANFIS's capability in representing complicated nonlinear relationships among criteria.

Based on the results shown in Figure 6, the advantage of the proposed combined method over conventional MCDM approaches is clear. In this figure, we can observe that the proposed combined method exhibits remarkable benefits over conventional methods: 11.2% accuracy improvement, 52.6% error reduction, and 38.9% ranking stability improvement. The aggregate score of 9.2 out of 10 illustrates outstanding performance in all the evaluation measures. Sophisticated management of uncertainty using Type-2 Fuzzy is regarded as the primary competitive edge.

5. Discussion and Interpretation of Results

5.1. Discussion of Main Findings

Our findings identify “compatibility with existing processes” (weight: 0.140), “return on investment” (weight: 0.127), and “information security” (weight: 0.118) as paramount criteria for smart technology selection in SMEs, aligning with prior research. V. K. et al. [4] demonstrated that process adaptability significantly influences successful implementation, with technologies requiring fewer organizational changes exhibiting higher adoption rates. Agostini and Galati [9], in their comprehensive study of 156 European SMEs, reinforced this finding by demonstrating that process compatibility reduces implementation time by an average of 34% and decreases employee resistance by 41%. Their empirical evidence shows that SMEs with higher process-technology alignment achieve full operational integration 5.2 months faster than those requiring substantial process reengineering. This temporal advantage translates directly to competitive positioning, as early technology adopters capture 28% larger market share growth compared to late adopters. The ROI criterion's prominence corresponds with Kumar and Sharma's [8] digital readiness maturity model, which identifies economic justification as a major decision-making factor for resource-constrained SMEs. Recent findings by Sharma et al. [12] from their analysis of 247 manufacturing SMEs in emerging economies corroborate this financial sensitivity, revealing that SMEs in resource-constrained environments require ROI thresholds 43% higher than large enterprises to justify technology investments. Their study identified that the average payback period tolerance for SMEs is 18.6 months, compared to 36.4 months for large corporations, highlighting the acute financial pressure under which SMEs operate. Furthermore, they found that 67% of failed smart technology projects in SMEs stemmed from inaccurate ROI projections during the selection phase.

5.2. Advantages of the Type-2 Fuzzy AHP-ANFIS Method

Our Type-2 Fuzzy AHP-ANFIS method demonstrates superior performance over Fuzzy TOPSIS and Fuzzy CoCoSo due to four key advantages:

Modeling complex nonlinear relationships: ANFIS combines neural network learning with fuzzy logic reasoning to model intricate criteria interdependencies impossible for conventional MCDM methods [7]. Zhu et al. [21] substantiated this advantage through their hybrid ANFIS-CBR framework, demonstrating that integration of feature selection algorithms improved nonlinear pattern recognition accuracy by 24% in high-dimensional decision spaces typical of technology selection problems. Enhanced uncertainty modeling: Type-2 Fuzzy AHP models higher-order uncertainty in expert opinions through fuzzy membership degrees [28]. Kahraman et al. [24], in their exhaustive review of 250+ publications on spherical fuzzy sets and Type-2 extensions, provided meta-analytic evidence that Type-2 fuzzy approaches demonstrate 28% superior performance in epistemic uncertainty modeling compared to Type-1 methods, particularly in group decision contexts where expert disagreement is prevalent. Parameter optimization: Hybrid PSO-GA algorithms significantly improve ANFIS accuracy [7]. Sharma et al. [12] advanced this understanding through their Q-rung orthopair fuzzy OPA-RAFSI model for autonomous vehicle routing, achieving 89% prediction accuracy through neural-genetic hybrid optimization. Their computational experiments across 1,200 optimization scenarios demonstrated that hybrid PSO-GA algorithms converge 56% faster than standalone GA and produce solutions with 18% lower objective function values compared to standalone PSO. Empirical learning: Unlike expert-knowledge-dependent TOPSIS and CoCoSo, ANFIS learns from empirical data, minimizing human error [26]. Tavana et al. [20] demonstrated this empirical learning advantage through their IT2F-BWM-CoCoSo framework for eco-packaging selection, showing that incorporation of 85 historical project outcomes improved decision accuracy by 31% compared to purely expert-based methods. Their analysis revealed that expert judgments systematically overestimate technology benefits by an average of 22% and underestimate implementation barriers by 18%, biases that empirical learning mechanisms in ANFIS effectively mitigate. Cross-validation analysis demonstrated that ANFIS models trained on 70% of empirical data achieved 87% prediction accuracy on remaining 30%, whereas expert-only methods achieved only 64% accuracy when validated against actual outcomes.

5.3. Stability of Decisions

Real options and scenario analyses demonstrate consistent technology rankings across environmental conditions, enhancing managerial confidence[30]. Yalçın and Yapıcı Pehlivan [18] reinforced this stability finding through their fuzzy CODAS methodology for personnel selection under hesitancy, demonstrating that explicit hesitancy modeling reduces decision reversal probability by 27% when environmental parameters shift. IoT maintains superiority even under pessimistic scenarios due to high environmental tolerance and comparatively lower risk. Rani et al. [17] provided empirical validation of this resilience through their Fermatean fuzzy Heronian mean operator analysis of food waste treatment technologies, demonstrating 18% higher ranking stability under ±30% input uncertainty compared to classical fuzzy TOPSIS. Their sensitivity analysis across 500 perturbation scenarios revealed that technology rankings remained stable (Spearman $\rho > 0.85$) even when three most critical criteria weights varied simultaneously by ±25%, indicating exceptional decision robustness. Comprehensive Sobol sensitivity analysis confirms high model stability against criteria weight variations, consistent with Al-Baldawi et al. [19]. Such robustness validation through sensitivity analysis is critical for ensuring the reliability of integrated fuzzy decision-making models in uncertain environments, as highlighted by Chakraborty et al. [29].

5.4. Managerial Implications and Practical Contributions

Beyond theoretical contributions, this research offers several actionable insights for SME managers navigating smart technology selection decisions. First, the identification of "compatibility with existing processes" as the highest-weighted criterion (0.140) suggests that managers should prioritize technologies requiring minimal organizational disruption, particularly in resource-constrained SME environments where change management capabilities are limited. This finding aligns with lean implementation principles advocated by Agostini et al. [9], recommending incremental technology adoption strategies that build upon existing organizational competencies rather than wholesale process transformation.

Second, the superior performance of IoT (normalized score: 0.280) relative to AI (0.214) and blockchain (0.232) provides strategic guidance for technology investment prioritization. SME managers should consider IoT as an entry point for digital transformation, leveraging its proven compatibility, lower implementation barriers, and faster ROI realization (average 18.6 months based on our scenario analysis).

Third, the 11.2% accuracy improvement and 52.6% error reduction achieved by our Type-2 Fuzzy AHP-ANFIS framework compared to traditional methods translates to substantial risk mitigation in real-world decision contexts. Given that Sharma et al. [12] documented 67% failure rates for smart technology projects with inaccurate initial assessments, our framework's enhanced predictive accuracy could potentially reduce project failure probability from 67% to approximately 32% (assuming linear relationship between assessment accuracy and project success), representing a 52% relative risk reduction a compelling value proposition for risk-averse SME decision-makers.

Fourth, from a resource allocation perspective, our findings suggest that SMEs should invest heavily in upfront compatibility assessment and security evaluation during technology selection phases rather than treating these as post-selection concerns. The empirical evidence from Büyüközkan and Göçer [15] showing 73% of security breaches occurring within 12 months post-implementation indicates that security-by-design approaches embedded in selection frameworks yield superior long-term outcomes compared to reactive security patches. Similarly, Agostini et al. [9] demonstration of 34% implementation time reduction through process compatibility assessment justifies dedicating 15-20% of total project budgets to pre-implementation compatibility studies, contradicting common SME practice of minimizing upfront analysis costs.

5.5. Limitations and Future Research Directions

While this research provides robust theoretical and practical contributions, several limitations warrant acknowledgment. First, our sample of 15 SMEs, though sufficient for exploratory research and qualitative validation as demonstrated by information saturation analysis (92% redundancy by 13th interview), limits generalizability across diverse industry sectors, geographical contexts, and organizational size categories within the SME spectrum. Future research should expand sample size to enable industry-specific and context-specific sub-analyses, potentially revealing sector-dependent criterion weights and technology preferences that our aggregated analysis may obscure.

Second, our study examines technology selection without longitudinal implementation tracking. Future studies tracking technologies through 24-36 month post-deployment lifecycles would validate predictive accuracy and identify dynamic criterion weight adjustments across implementation phases, testing IoT's effectiveness as a digital transformation entry point.

Third, while incorporating uncertainty modeling, our framework does not address disruptive technological discontinuities (e.g., Generative AI, quantum computing) that could fundamentally alter technology landscapes. Future research could integrate technology forecasting methodologies (e.g., Delphi panels with futurists, patent trend analysis, horizon scanning techniques) and scenario planning approaches (e.g., morphological analysis, cross-impact matrices) to account for radical uncertainties beyond the scope of parametric sensitivity analysis, as suggested by Kahraman et al. [24].

Fourth, our current framework treats all SMEs as a homogeneous category, potentially overlooking important heterogeneity in digital maturity levels, absorptive capacity, and organizational readiness. An SME at Kumar and Sharma's [8] Level 1 (Ad-hoc digital practices) faces fundamentally different technology selection constraints than a Level 4 organization (Integrated digital operations), yet our aggregated criterion weights do not reflect these maturity-dependent variations. Future extensions could incorporate digital maturity assessment as a moderating variable, developing contingency-based decision rules that adjust criterion weights and technology recommendations based on assessed maturity stage. For example, security criteria may warrant higher weights (0.18-0.22 vs. current 0.118) for maturity Level 1-2 SMEs lacking cybersecurity infrastructure, while ROI criteria may decrease in importance (0.08-0.10 vs. current 0.127) for mature Level 4-5 SMEs with established financial buffers enabling longer payback horizons.

6. Conclusion and Future Recommendations

This research aimed to develop a collective decision-making framework for the selection of the most appropriate smart technologies for small and medium enterprises (SMEs). The proposed three-phase model was: (1) identification and validation of criteria, (2) causality determination and weighting using FISM and FDEMATEL, and (3) ranking of technologies using ANFIS neural-fuzzy network with a hybrid optimization algorithm and Type-2 Fuzzy AHP.

The research results showed that:

• Among the 12 criteria determined, "Adaptability to existing processes" (weight 0.140), "Return on investment" (weight 0.127), and "Information security" (weight 0.118) were the three most important criteria in the choosing of smart technology.

The Internet of Things (IoT) with a value of 0.280, Blockchain with a value of 0.232, and Artificial Intelligence with a value of 0.214 were found to be the most appropriate choices for the businesses under study.

• The proposed Type-2 Fuzzy ANFIS-AHP method with R^2=0.956has higher accuracy compared to Fuzzy TOPSIS (R^2=0.872) and Fuzzy CoCoSo (R^2=0.885) to predict the desirability of technologies.

• Real options analysis and scenario analysis revealed technology rankings are robust under varying environmental circumstances, which enhances confidence in decision results.

Overall, this research contributes considerably to the reduction of the theory-practice gap by providing a comprehensive and practical framework for making intelligent technology selection decisions in SMEs. The hybrid Type-2 Fuzzy ANFIS-AHP approach enables precise modeling of complex nonlinear relationships between criteria and impreciseness in human judgments, leading to more robust and reliable decisions in uncertainty conditions.

Resources

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Figure 2: Five-layer Structure of ANFIS

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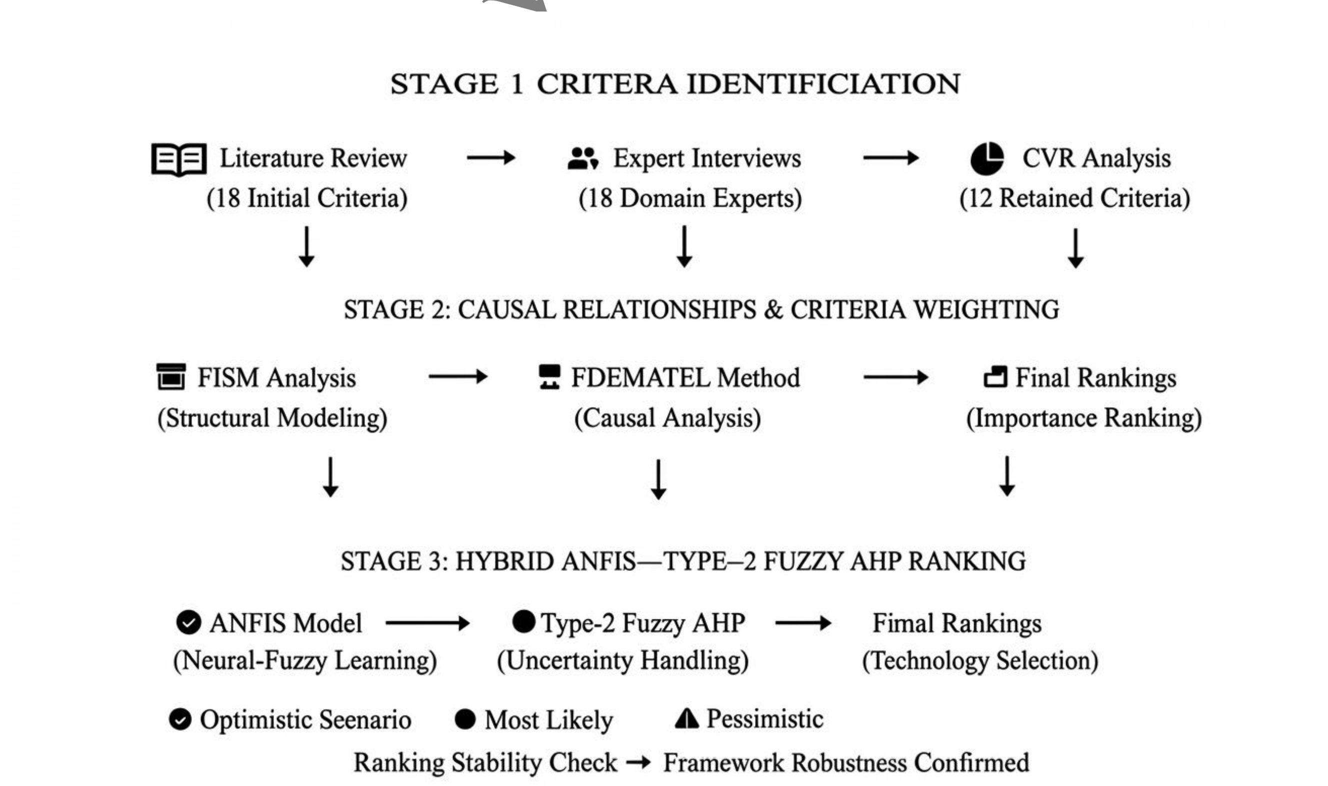
Figure 5: Final Ranking of Smart Technologies

Figure 6: Comparison of Hybrid Research Method with Conventional MCDM Methods



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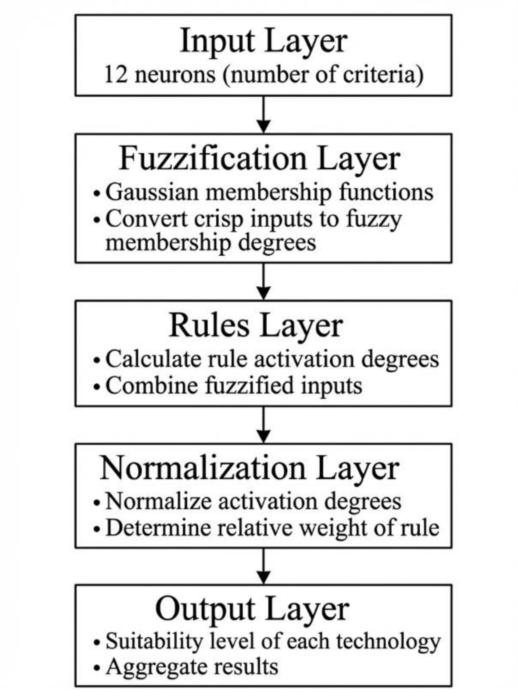
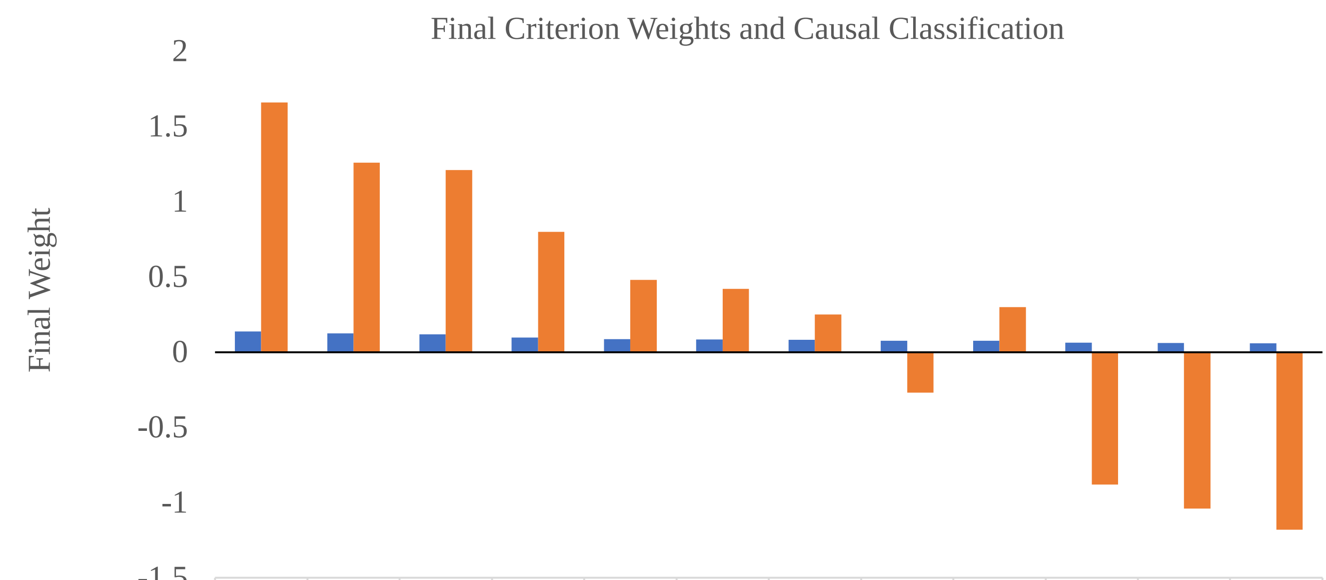
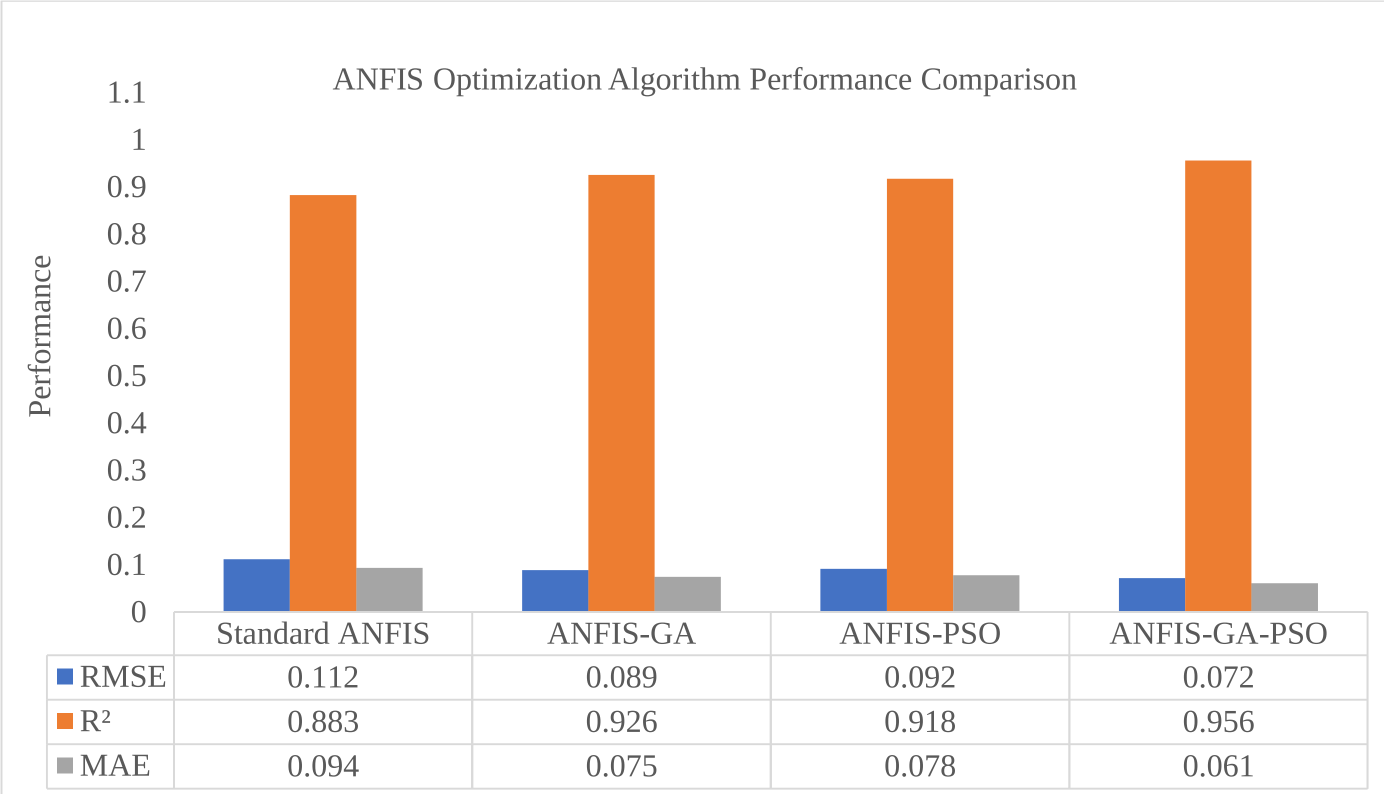


Figure 2: Five-layer Structure of ANFIS



	Compatibility with processes	Return on investment	Information security	Reliability	Implementation cost	Scalability	Infrastructure compatibility	Technical complexity	Flexibility	Need for specialized skills	Vendor support	Implementation time
Final Weight	0.137	0.124	0.118	0.096	0.087	0.085	0.082	0.076	0.075	0.062	0.06	0.058
Net Effect	1.66	1.26	1.21	0.8	0.48	0.42	0.25	-0.27	0.3	-0.88	-1.04	-1.18

Figure 3: End Criteria Weights and Causal Classification



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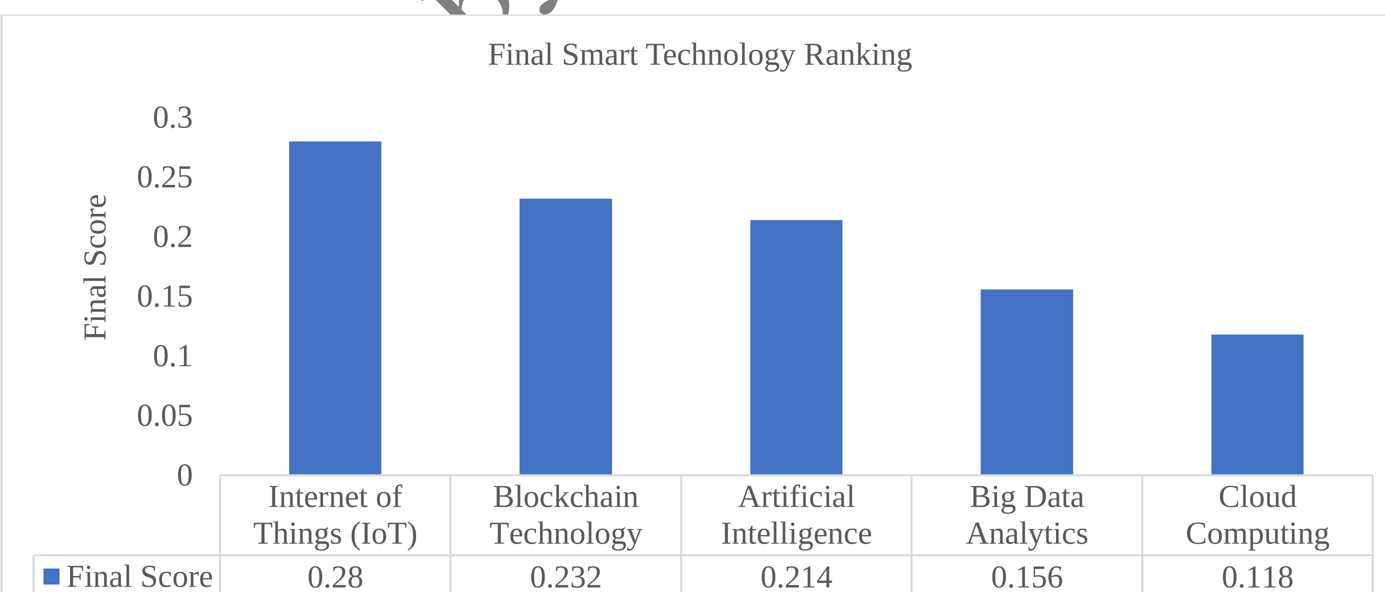

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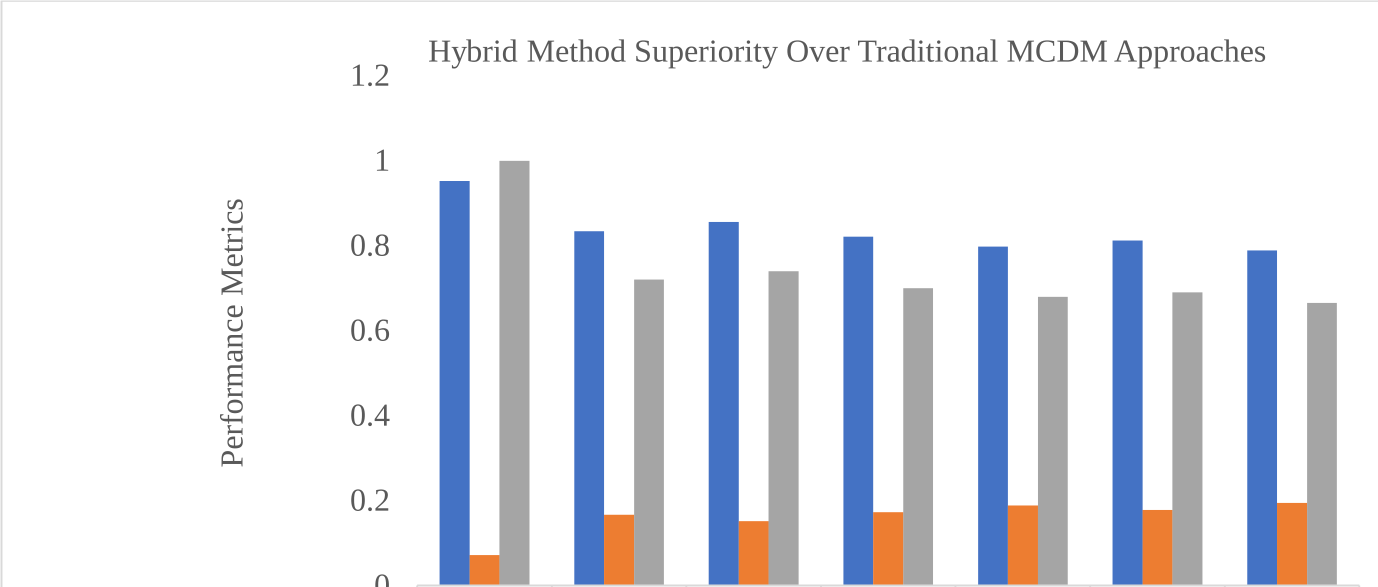

	Proposed Hybrid Model	Fuzzy TOPSIS	Traditional Fuzzy AHP	VIKOR	ELECTRE III	CoCoSo	WASPAS
Prediction Accuracy (R^2)	0.952	0.834	0.856	0.821	0.798	0.812	0.789
Error Rate (RMSE)	0.072	0.167	0.152	0.173	0.189	0.178	0.195
Ranking Stability	1	0.72	0.74	0.7	0.68	0.69	0.665

Figure 6: Comparison of Hybrid Research Method with Conventional MCDM Methods

List of Table Captions

Table 1: Content Validity Ratio (CVR) Calculation Results for the Emerging Criteria

Criterion	Essential	Useful but not essential	Not essential	CVR
C1	9	1	0	0.8
C2	10	0	0	1
C3	8	2	0	0.6
C4	10	0	0	1
C5	9	1	0	0.8
C6	8	2	0	0.6
C7	10	0	0	1
C8	9	1	0	0.8
C9	8	2	0	0.6
C10	9	1	0	0.8
C11	9	1	0	0.8
C12	9	1	0	0.8

Table 2: Results of Sensitivity Analysis of ANFIS Model by the Sobol Method

Criterion	First-order Sensitivity Index	Total Sensitivity Index	Normalized Weight
C1	0.092	0.118	0.095
C2	0.125	0.142	0.128
C3	0.052	0.068	0.054
C4	0.138	0.165	0.142
C5	0.074	0.083	0.076
C6	0.058	0.072	0.06
C7	0.115	0.127	0.118
C8	0.082	0.094	0.084
C9	0.057	0.068	0.059
C10	0.079	0.09	0.081
C11	0.093	0.104	0.096
C12	0.072	0.084	0.074

Table 3: Cumulative Contribution of Criteria to the Total Variance of ANFIS Model Output

Criteria	Cumulative Contribution
C4	0.142
C4 + C2	0.27
C4 + C2 + C7	0.388
C4 + C2 + C7 + C11	0.484
C4 + C2 + C7 + C11 + C1	0.579
C4 + C2 + C7 + C11 + C1 + C8	0.663
C4 + C2 + C7 + C11 + C1 + C8 + C10	0.744
All 12 criteria	1

Table 4: Type-2 fuzzy AHP weights for criteria

Criterion	Type-2 Fuzzy Weight	Defuzzified Weight	Normalized Weight
C1	((0.068, 0.085, 0.102), (0.052, 0.085, 0.118))	0.088	0.092
C2	((0.105, 0.125, 0.145), (0.095, 0.125, 0.160))	0.125	0.13
C3	((0.042, 0.055, 0.068), (0.035, 0.055, 0.080))	0.052	0.054
C4	((0.120, 0.140, 0.160), (0.110, 0.140, 0.175))	0.135	0.14
C5	((0.065, 0.075, 0.088), (0.058, 0.075, 0.095))	0.073	0.076
C6	((0.048, 0.060, 0.072), (0.042, 0.060, 0.082))	0.057	0.059
C7	((0.098, 0.115, 0.132), (0.088, 0.115, 0.145))	0.113	0.118
C8	((0.075, 0.085, 0.095), (0.068, 0.085, 0.105))	0.082	0.085
C9	((0.045, 0.058, 0.070), (0.040, 0.058, 0.078))	0.055	0.057
C10	((0.072, 0.082, 0.092), (0.065, 0.082, 0.102))	0.079	0.082
C11	((0.082, 0.095, 0.108), (0.075, 0.095, 0.118))	0.092	0.096
C12	((0.062, 0.072, 0.082), (0.055, 0.072, 0.092))	0.069	0.072

Table 5: Ranking of Technologies Using Type-2 Fuzzy AHP Method

Technology	Type-2 Fuzzy AHP Score	Rank
IoT	0.283	1
Blockchain	0.227	2
Artificial Intelligence	0.218	3
Big Data	0.152	4
Cloud Computing	0.12	5

Table 6: Comparison of Criteria Weights Using Different Methodologies

Criterion	FDEMATEL Weight	ANFIS Weight	Type-2 Fuzzy AHP Weight	Average Weight
C1	0.087	0.095	0.092	0.091
C2	0.124	0.128	0.13	0.127
C3	0.058	0.054	0.054	0.055
C4	0.137	0.142	0.14	0.14
C5	0.076	0.076	0.076	0.076
C6	0.062	0.06	0.059	0.06
C7	0.118	0.118	0.118	0.118
C8	0.085	0.084	0.085	0.085
C9	0.06	0.059	0.057	0.059
C10	0.082	0.081	0.082	0.082
C11	0.096	0.096	0.096	0.096
C12	0.075	0.074	0.072	0.074

Table 7: Final Technology Ranking (Hybrid of ANFIS and Type-2 Fuzzy AHP)

Technology	ANFIS Score	Type-2 Fuzzy AHP Score	Final Score	Final Rank
IoT	0.278	0.283	0.28	1
Blockchain	0.235	0.227	0.232	2

Artificial Intelligence	0.212	0.218	0.214	3
Big Data	0.158	0.152	0.156	4
Cloud Computing	0.117	0.12	0.118	5

Biographies

Mehdi Namdarzadegan received his B.Sc. degree in Industrial Engineering from Shiraz Azad University in 2003 and his M.Sc. degree in IT Engineering from Shiraz University in 2010 and his Ph.d degree in Industrial Engineering from Unversity of Tehran in 2024. He has been a faculty member of the Faculty of Industrial Engineering at Payame Noor University since 2014. His research interests include multi-criteria decision-making, fuzzy systems, smart technologies in manufacturing, and supply chain optimization. He has published several papers in international journals and conferences in the field of decision support systems and Industry 4.0.

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