Baltic J. Modern Computing, Vol. 14 (2026), No. 1, pp. 156–173
https://doi.org/10.22364/bjmc.2026.14.1.08

Integrating Quantum Mechanics and Fuzzy Logic for Enhanced MCDM: A Case Study on Robot Evaluation

Cem ÖZKURT[1], Özkan CANAY[2], Ahmet KALA[3], Eyüp Altuğ TUNÇ [4], Nil Feyza ÖZDEMİR[5]

[1] AI And Data Science Research And Application Center, Sakarya University of Applied Sciences, Sakarya, Türkiye
[2] Department of Information Systems and Technologies, Faculty of Computer and Information Sciences, Sakarya University, Sakarya, Türkiye
[3] Department of Information Technologies, Sakarya University of Applied Sciences, Sakarya, Türkiye
[4] Department of Mechatronics Engineering, Faculty of Technology, Sakarya University of Applied Sciences, Sakarya, Türkiye
[5] Department of Electrical and Electronical Engineering, Faculty of Technology, Sakarya University of Applied Sciences, Sakarya, Türkiye

cemozkurt@subu.edu.tr; canay@sakarya.edu.tr; ahmetkala@subu.edu.tr; b210104012@subu.edu.tr; 23010103064@subu.edu.tr

ORCID 0000-0002-1251-7715, ORCID 0000-0001-7539-6001, ORCID 0000-0002-0598-1181, ORCID 0009-0007-5166-8077, ORCID 0009-0006-7171-3624

Abstract. Industrial robot selection represents a complex multi-criteria decision-making (MCDM) challenge, significantly impacting production processes in terms of precision, efficiency, and cost-effectiveness. This study aims to enhance the robot selection process by integrating traditional MCDM techniques with innovative weighting models based on fuzzy logic and quantum-inspired probabilistic modeling. The proposed approach combines classical and fuzzy MCDM methods including CODAS, TOPSIS, VIKOR, MOORA, fuzzy TOPSIS, fuzzy EDAS, and fuzzy VIKOR with five distinct weighting techniques: Best-Worst (BW), CRITIC, Entropy, Quantum-inspired, and Fuzzy Quantum-inspired. Quantum and Fuzzy Quantum weighting consistently ranked the IRB 1010-1.5/0.37 model as the most favorable across several methods, such as TOPSIS, CODAS, and Fuzzy TOPSIS, yielding scores up to 0.5563. Conversely, Entropy and CRITIC frequently identified the IRB 760 model as the optimal choice. Fuzzy EDAS selected IRB 760 with a top score of 5.589, while Fuzzy VIKOR highlighted IRB 140-6/0.8 as the most suitable alternative with a score of 0.000000. This research provides a decision support perspective for manufacturers navigating uncertain and complex environments by combining stochastic weight generation with fuzzy uncertainty representation. A quantum-inspired probabilistic weighting design and its fuzzy extension are integrated into the criterion-weighting stage of MCDM and evaluated comparatively against widely used classical weighting schemes.

Keywords: Quantum-inspired weighting, Fuzzy weighting, Multi-Criteria Decision-Making (MCDM), Robot Selection, Probabilistic modeling

1 Introduction

Industrial robot selection has been recognized as a multi-criteria decision-making (MCDM) problem in which several technical and economic criteria are required to be evaluated simultaneously. Because expert judgements and incomplete information are frequently involved in such evaluations, the decision environment is typically characterized by uncertainty; therefore, fuzzy MCDM approaches have been widely adopted to support robust ranking of alternatives (Chu and Lin, 2003; Kumar et al., 2017).

In this study, a quantum-inspired probabilistic criterion-weighting mechanism is integrated with classical and fuzzy MCDM methods to examine how alternative weighting schemes affect robot ranking outcomes. The proposed weighting mechanism is implemented entirely on classical computing infrastructure and is used as a stochastic generator of probability masses (via phase-angle sampling and $\sin^2(\cdot)$ mapping), which are subsequently fuzzified using triangular fuzzy numbers. Accordingly, quantum-mechanical concepts are employed as modeling inspiration rather than as operational quantum computation, and no claims regarding quantum computational speedups, qubit-level simulation, or hardware scalability are made for the proposed method.

Within the scope of the study, the industrial robot selection problem is addressed using classical MCDM methods (CODAS, TOPSIS, VIKOR, MOORA) and fuzzy MCDM methods (fuzzy TOPSIS, fuzzy EDAS, fuzzy VIKOR). For each method, criterion weights are obtained using BW (Best–Worst), CRITIC, Entropy, quantum-inspired, and fuzzy quantum-inspired weighting schemes, and the sensitivity of the resulting rankings to the adopted weighting approach is analyzed comparatively.

In light of these considerations, the following research questions are addressed.

- **RQ1**: To what extent does the quantum-inspired weighting model yield outcomes that are consistent with, or differ from, those obtained using classical weighting methods in multi-criteria decision-making (MCDM) problems?
- **RQ2**: To what extent does integrating fuzzy logic into the quantum-inspired weighting process influence the handling of uncertainty and the resulting rankings in high-uncertainty environments?
- **RQ3**: To what extent does the fuzzy quantum-inspired weighting approach affect ranking consistency patterns in problems such as industrial robot selection when compared with traditional weighting models?

Although weighting methods for criteria in decision-making processes have been extensively studied in the literature, quantum-inspired probabilistic weighting and its fuzzy hybridizations have been comparatively less explored in applied MCDM settings. Therefore, the development of hybrid weighting approaches that combine probabilistic modeling ideas with fuzzy logic for engineering problems characterized by uncertainty and complexity is expected to address a relevant gap in the applied decision-analysis literature. Table 1 summarizes representative recent studies on MCDM, quantum-inspired modeling, and fuzzy-logic-based approaches.

2 Literature review

As shown in Table 1, recent studies in the field of multi-criteria decision-making (MCDM) and quantum–fuzzy-based decision models have predominantly focused on integrating fuzzy logic and quantum computing to enhance uncertainty management and computational efficiency. Particularly after 2021, there has been a noticeable shift toward hybrid frameworks such as Fuzzy Quantum, Entropy–TOPSIS, and Quantum Fuzzy Neural Networks (QFNN), which combine classical decision-making principles with quantum-inspired algorithms. Furthermore, studies in 2023 and 2024 have emphasized sustainability-oriented and dynamic time-varying MCDM applications, indicating that research has evolved from static model development toward adaptive, intelligent, and data-driven decision frameworks.

2.1 Decision-Making and MCDM in Robot Selection

Decision-making is encountered in nearly every aspect of life. Robot selection is a complex decision-making problem shaped not only by technical performance criteria but also by the subjective evaluations

Table 1: Selected Literature on MCDM and Quantum Fuzzy Based Decision Models

Key Contribution	Year	Technique	Ref
By integrating FFQOA with the FTS modelling approach, a hybrid model called fuzzy-quantum time series forecasting model (FQTSFM) is designed.	2021	Fuzzy Quantum	(Singh, 2021)
Application of Entropy-based weighting and TOPSIS method for selecting arc welding robots in manufacturing.	2022	Entropy-TOPSIS	(Chodha et al., 2022)
A Quantum Fuzzy Neural Network (QFNN) is proposed for sarcasm and sentiment detection using simulated quantum circuits and fuzzy logic.	2024	Fuzzy Quantum	(Tiwari et al., 2024)
Analysis and prioritization of Industry 4.0 implementation challenges in the Indian automotive sector using the Best-Worst Method (BWM).	2021	BW	(Wankhede and Vinodh, 2021)
Selection of suitable thermoplastic material for automatic CPR device chassis using IF-CODAS, IF-TOPSIS and IF-VIKOR methods under sustainability criteria.	2022	Fuzzy MCDM	(Kağızman et al., 2022)
Application of an improved CRITIC method to evaluate thermal coal suppliers under short-term volatility, enhancing stability in weight assignments.	2023	CRITIC	(Zhong et al., 2023)
Proposal of the PUL-CODAS method combining probabilistic uncertain linguistic term sets with sinus entropy weighting for green supplier selection.	2021	CODAS	(Wei et al., 2021)
An analytical review of multi-objective optimization based on MOORA: Applications classified across domains using over 200 academic studies.	2023	MOORA	(Chakraborty et al., 2023)
A dynamic time-varying MCDM framework integrating an obstacle degree model is proposed to evaluate and monitor regional water resources carrying capacity changes over time.	2024	VIKOR	(Yang and Chen, 2024)

of multiple decision-makers (Goh, 1997). Individuals, businesses, and institutions in decision-making positions are often required to make choices by evaluating conflicting criteria in real-world settings. In such cases, scientific methods can be utilized to reach the most accurate decision. For this purpose, Multi-Criteria Decision-Making (MCDM) methods can be employed (Karaatlı and Dağ, 2018). In rational decision environments, the most preferred choice is typically constrained by limitations and management objectives. Thus, by evaluating decisions within these constraints and objectives, healthy and desirable solutions are obtained. Multi-criteria decision-making has developed rapidly in decision analysis, both theoretically and in applications. It has gained recognition for its logical structure and success in decision analysis, and today it has a wide range of applications (Arslankaya and Göraltay, 2019).

2.2 Quantum-Inspired Modeling in Decision-Making: Context

Quantum computing and quantum-enhanced learning have been actively investigated in the recent literature (Biamonte et al., 2017; Dunjko and Briegel, 2018). In the present study, these developments are used primarily as contextual motivation, whereas the proposed method itself is a classical, quantum-inspired weighting scheme that generates stochastic probability masses and integrates them with fuzzy uncertainty modeling. Therefore, the scope of the work is restricted to decision-modeling and algorithmic design on classical hardware, rather than to quantum-algorithm implementation or hardware-dependent performance claims.

3 Method

In this study, a classical, quantum-inspired probabilistic criterion-weighting mechanism is formulated and combined with fuzzy uncertainty modeling. Rather than simulating quantum states or implementing quantum circuits, phase-angle sampling and a $\sin^2(\cdot)$ mapping are employed to generate normalized probability masses that are subsequently represented as triangular fuzzy numbers. In this manner, a stochastic fuzzy weighting vector is obtained and transferred to conventional MCDM aggregators.

3.1 Data Description and Evaluation Criteria

The dataset used for the robot selection analysis was manually constructed by the authors based on official technical specifications published by ABB for its industrial robot models. The compiled dataset includes 58 ABB robot variants, each described by five quantitative evaluation criteria: payload capacity (kg), reach (mm), repeatability (mm), power consumption (kW), and cost (USD). Among these, payload capacity and reach were considered benefit-type criteria, whereas repeatability, power consumption, and cost were treated as cost-type criteria. These parameters were selected because they represent the most fundamental performance and economic indicators in industrial robot selection problems. Before the application of decision-making methods, all numerical values were normalized to ensure comparability across criteria. The proposed quantum and fuzzy quantum weighting models were then implemented using this dataset to evaluate the ranking performance and assess decision consistency under uncertainty.

3.2 System Overview

The system overview of the proposed method is shown in Figure 1. After preprocessing and harmonization, the pipeline splits into Quantum Criterion Weighting (QCW) and Fuzzy Quantum Criterion Weighting (FQ-CW). Both branches produce a weight vector that feeds a classical MCDM aggregator; constraints and management objectives act as side inputs, and optional entropy calibration regularizes FQ-CW. Sensitivity analysis and reporting precede the final recommendation; arrows indicate the processing flow.

The pipeline is modular and easy to follow. Each stage makes its inputs and outputs explicit, so results are repeatable and individual parts can be tested on their own. The QCW and FQ-CW branches can be enabled or skipped without changing how the downstream classical MCDM ranking operates. This makes it straightforward to check robustness and to compare outcomes across different datasets.

3.3 Quantum Theory (Conceptual Background)

Quantum theory introduces probabilistic representations of states and has inspired several modeling paradigms in decision sciences (Busemeyer et al., 2006; Merzbacher, 1998). In the present manuscript, these concepts are used at an abstract level to motivate a probability-mass generation mechanism for criterion weighting. No quantum operators, unitary evolution, Schrödinger dynamics, or qubit/state simulation is implemented; therefore, the methodological contribution is limited to a classical, quantum-inspired stochastic weighting design.

3.4 Quantum Criterion Weighting (Quantum-Inspired)

In the proposed framework, "quantum criterion weighting" refers to a quantum-inspired probability-mass generation mechanism rather than to quantum-state simulation. A phase angle θ_j is sampled for each criterion, and a probability mass is produced via $a_j = \sin^2(\theta_j)$ and normalized as $\alpha_j = a_j / \sum_k a_k$. In this manner, a stochastic but normalized weight vector $\boldsymbol{\alpha}$ is obtained on classical hardware.

The rationale of the design is summarized in Table 2.

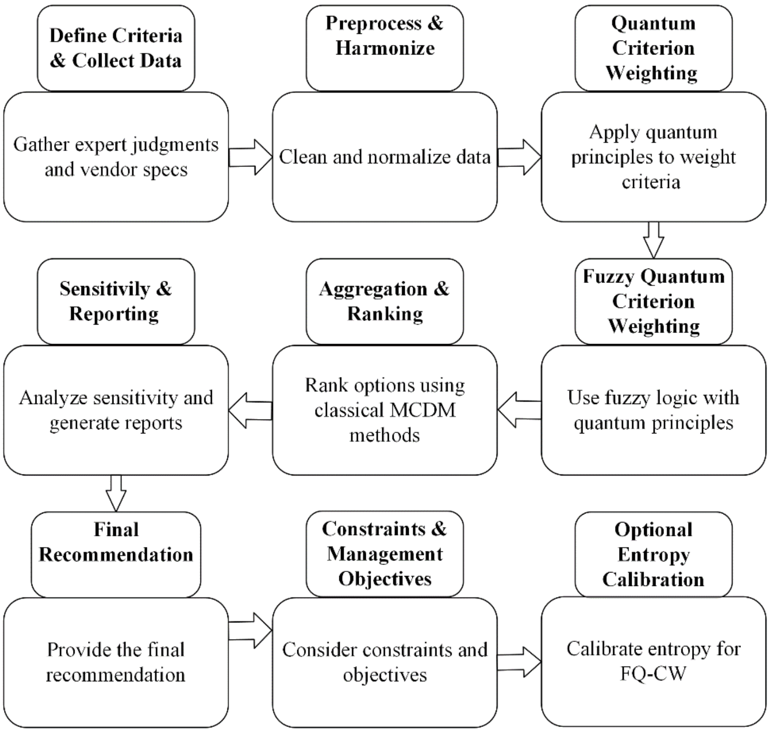

Fig. 1: Integration of QCW/FQ-CW with Classical MCDM

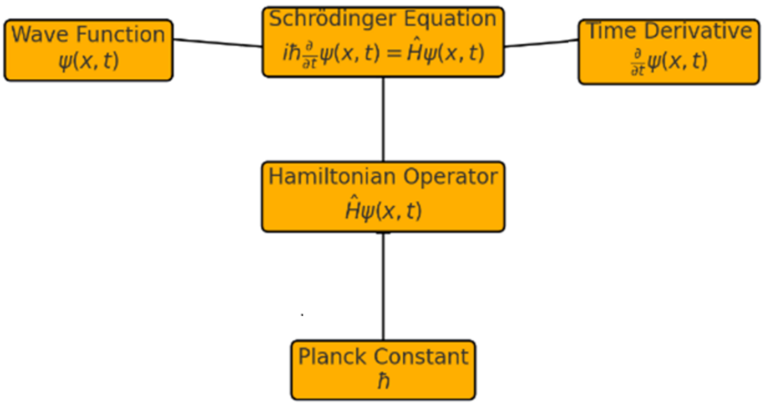

Fig. 2: Conceptual illustration of quantum state evolution (metaphor; not operationalized in the proposed algorithm)

3.5 Criterion Weighting with Fuzzy Quantum

Criterion weighting with fuzzy quantum is a novel method for multi-criteria decision-making (MCDM) problems that combines the probability-based superposition principles of quantum mechanics with the uncertainty management capabilities of fuzzy logic. While traditional methods assign deterministic weights to criteria, fuzzy quantum approaches incorporate both probabilistic and fuzzy uncertain ties simultane-

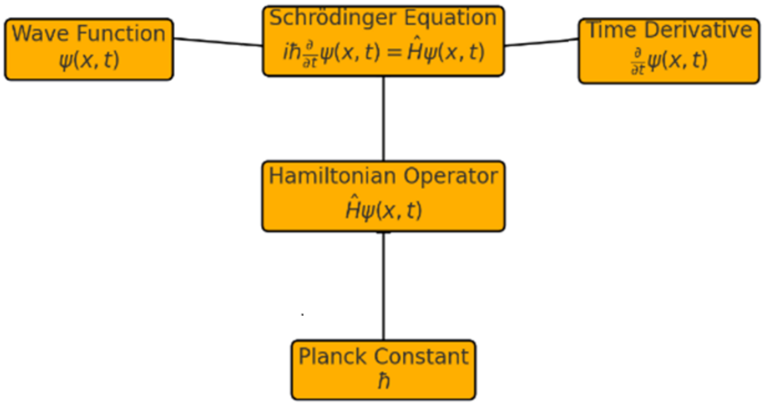

Fig. 3: Conceptual illustration of quantum state evolution (metaphor; not operationalized in the proposed algorithm)

Table 2: Rationale of Quantum-Inspired Criterion Weighting

Modeling Element	**Explanation**
Phase-angle sampling	A random phase θ_j is sampled to introduce stochasticity into the weight-generation process.
$\sin^2$ mapping	The nonnegative mapping $a_j = \sin^2(\theta_j)$ yields a probability-like mass in $[0, 1]$.
Normalization	The weight vector is normalized as $\alpha_j = a_j / \sum_k a_k$ so that $\sum_j \alpha_j = 1$.
Fuzzification (next subsection)	The probability masses are converted into triangular fuzzy weights to represent uncertainty.

ously to construct a more flexible and dynamic model. Pourabdollah et al. (2021) demonstrated that fuzzy inference systems can be considered in quantum-annealing contexts for certain optimization formulations (Pourabdollah et al., 2021). In the present study, the fuzzy quantum-inspired weighting stage is treated as a classical fuzzification of the probability masses produced by the quantum-inspired generator.

3.5.1 Quantum and Fuzzy Representation of Criteria To reflect real-world uncertainties, fuzzy triangular numbers $\tilde{c}_i = (\mu_i, \alpha_i, \beta_i)$ are used instead of classical amplitudes. In this way, the quantum decision vector is updated as follows:

$$\widetilde{\psi}(x) = \sum_i \widetilde{c}_i |K_i\rangle \tag{1}$$

The bra–ket notation is used purely as a symbolic representation of criterion indexing and does not imply a quantum-state representation in the proposed implementation.

This model is a hybrid representation that incorporates both quantum superposition and fuzzy uncertainty. The expression represents a hybrid model that includes both quantum and fuzzy variables.

3.5.2 Fuzzy Quantum-Inspired Weight Construction In the proposed framework, no unitary operators, Hamiltonians, or state-evolution equations are implemented. Instead, the quantum-inspired probability masses are transformed into triangular fuzzy numbers to represent uncertainty, and the resulting fuzzy weights are directly propagated to the MCDM stage.

3.5.3 Criterion Relationships (Scope Statement) In the present implementation, the criterion-weight generation step is performed independently for each criterion and does not include an explicit coupling mechanism. Therefore, criterion relationships are not modeled through joint amplitudes or entanglement-style constructions, and the fuzzy weights are obtained via fuzzification of the generated probability masses.

3.6 BW (Best-Worst) Weighting Method

The Best-Worst Method (BWM) is an effective multi-criteria decision-making approach that enables decision-makers to obtain more consistent and reliable weights by identifying the best and worst criteria (Ahmadi et al., 2017). The relative importance of the best criterion over the others, and how much each of the remaining criteria is better than the worst one, is expressed by the decision-maker using a scale ranging from 1 to 9. Based on these priority vectors, the following optimization model is constructed, and the criterion weights are obtained through its solution:

$$\min_{w,\xi} \xi \quad \text{s.t.} \quad \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, \quad \left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi \tag{2}$$

Here, w_j represents the weight of criterion j, $a_B j$ denotes the preference of the best criterion over criterion j, and a_{jW} denotes the preference of criterion jover the worst criterion, as formulated in Eq. (10). The BW method allows for the derivation of highly consistent weights with a minimal number of comparisons. This method is particularly preferred for large-scale problems due to its requirement for fewer pairwise comparisons.

3.7 CRITIC (Criteria Importance Through Intercriteria Correlation) Method

The CRITIC method, developed by Diakoulaki et al. (1995), offers an effective and data-driven approach for determining objective criterion weights without the need for subjective evaluation by simultaneously considering the conflict and information content among criteria (Alinezhad and Khalili, 2019). In this approach, the importance level of a criterion is calculated by combining its information content (standard deviation) and its independence from other criteria (correlation coefficient). The criterion weights are obtained by integrating the information and conflict levels for each criterion as follows:

$$C_j = \sigma_j \cdot \sum_{k=1}^{n} (1 - r_{jk}) \tag{3}$$

Here, C_j represents the information value of criterion j, σ_j is the standard deviation, and r_{jk} is the correlation coefficient between criteria j and k, as shown in Eq. (11). This method performs weight calculations entirely based on mathematical and statistical data, without requiring any subjective assessments.

3.8 Entropy Weighting Method

The entropy method is an objective technique used to determine criterion weights. This approach calculates the information content of each criterion to evaluate its importance in the decision-making process. The higher the variability and uncertainty level in the dataset, the more important the criterion becomes. On the other hand, entropy analysis methods based on the concept of information entropy introduced by Shannon allow for more accurate evaluations by measuring uncertainty and complexity, especially in cases where traditional processing methods fall short due to the noisy and incomplete structure of biomedical signals (Borowska, 2015). If a criterion exhibits high variation, it is considered to contain more information and is therefore assigned a higher weight. In this context, the entropy value e_j and the degree of diversification d_j for each criterion are calculated, and the weights are determined as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}, \qquad \text{where } d_j = 1 - e_j \tag{4}$$

Here, e_j denotes the entropy of criterion j, and d_j represents the degree of diversification of that criterion, as expressed in Eq. (12). The entropy method enables objective weighting without the need for decision-makers. It is particularly powerful in large datasets for determining the importance of criteria without relying on subjective expert opinions.

3.9 MCDM (Multi-Criteria Decision-Making Methods)

Multi-Criteria Decision-Making (MCDM) is a systematic set of methods used to determine the most appropriate alternative in decision problems that involve the simultaneous evaluation of multiple criteria. In real-life decision processes, factors such as cost, efficiency, and sustainability often differ and may even conflict with each other. MCDM methods provide objective and rational evaluations by balancing these criteria in complex situations. This allows decision-makers to compare alternatives by considering both quantitative and qualitative data and to select the most suitable option. These methods are widely applied in various fields, including engineering, management, healthcare systems, and energy planning. Additionally, they offer a flexible structure through different weighting and ranking techniques.

3.9.1 CODAS (Combinative Distance-Based Assessment) Method The Combinative Distance-based Assessment (CODAS) method, developed by Keshavarz Ghorabaee et al. is employed to address multi-criteria decision-making (MCDM) problems. CODAS evaluates the distance of alternatives from the ideal solution using both Euclidean and Taxicab distances to determine their desirability. This approach provides effective and consistent results, particularly in decision-making environments that require high sensitivity (Başer and Şatır). CODAS method is one of the multi criteria decision-making (MCDM) approaches that contributes to the decision-making process by calculating the distances of alternatives from the negative ideal solution. The CODAS method ranks alternatives based on their distances to the negative ideal solution, providing the decision-maker with a clear and comparative evaluation framework (Dragana and Radojko, 2022). In this method, the distance of each alternative to the negative ideal solution is calculated using both Euclidean and Taxicab (Manhattan) distances. These two distance components are then combined to obtain the overall scores of the alternatives:

$$S_i = d_i^E + \tau d_i^T \tag{5}$$

Here, S_i represents the score of alternative i; d_i^E and d_i^T denote the Euclidean and Taxicab distances, respectively, and τ is the threshold parameter, typically chosen as 0.02, as shown in Eq. (13).

3.9.2 TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) Method The TOPSIS method is a widely used, practical, and effective decision support tool in both academic research and applied studies, as it ranks alternatives based on their closeness to the ideal solution in multi-criteria decision-making processes ([Behzadian et al., 2012). It is one of the MCDM (Multi-Criteria Decision-Making) techniques that evaluates and ranks alternatives by calculating their distances from the positive ideal and negative ideal solutions. The distance of each alternative to the positive ideal solution is denoted by d_i^+ , and its distance to the negative ideal solution is denoted by d_i^- . The TOPSIS score is then calculated using the ratio of these two distances:

$$s_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{6}$$

Here, s_i represents the TOPSIS score of alternative i, as defined ine Eq.(14). This method aims for the preferred solution to be the one that is closest to the ideal solution and farthest from the negative solution.

3.9.3 VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) Method The VIKOR method is one of the multi-criteria decision-making (MCDM) techniques that evaluates and ranks alternatives based on their distances to the positive and negative ideal solutions. With its compromise-oriented approach, the VIKOR method offers a systematic way for decision-makers to select the alternative closest to the ideal solution by considering all types of criteria. It is particularly effective in fields that require precision, such as engineering and biomedical applications (Jahan et al., 2011). In this method, the total benefit difference (S_i) and the maximum criterion difference (R_i) are calculated for each alternative, and a compromise solution score Q_i is obtained based on these values. The VIKOR scores are computed using the following formula:

$$Q_i = v\frac{S_i - S_{\min}}{S_{\max} - S_{\min}} + (1 - v)\frac{R_i - R_{\min}}{R_{\max} - R_{\min}} \tag{7}$$

Here, v is the compromise coefficient, typically set to 0.5. The VIKOR method provides a balanced solution approach for multi-criteria problems, focusing on group benefit rather than individual optimum.

3.9.4 MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) Method The MOORA method is one of the multi-criteria decision-making (MCDM) techniques that ranks decision alternatives based on the weighted normalized values of criteria. By employing a multi objective decision-making structure based on ratio analysis, the MOORA method provides practical, flexible, and effective solutions to complex selection problems encountered in production environments, demonstrating high applicability in real-time decision-making processes (Chakraborty, 2011). In this method, benefit and cost criteria are evaluated separately, and their combined effect is calculated to obtain a net score. The MOORA score is calculated as follows:

$$MOORA_i = S_i^+ - S_i^- \tag{8}$$

Here, S_i^+ represents the total value of benefit criteria, while S_i^- represents the total value of cost criteria, as defined in Eq.(16).

3.9.5 Fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) Method The Fuzzy TOPSIS method is developed to better represent decision-makers' judgments in uncertain decision environments. It preserves the advantages of classical TOPSIS while offering more flexible and interpretable solutions to multi-criteria decision-making problems through fuzzy sets (Nădăban et al., 2016). In this method, criterion values are expressed as fuzzy numbers (typically triangular fuzzy numbers TFNs), and the distances of alternatives from the fuzzy positive and fuzzy negative ideal solutions are calculated. Alternatives are then ranked based on a similarity coefficient. The Fuzzy TOPSIS score is calculated as follows:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{9}$$

Here, CC_i denotes the fuzzy similarity coefficient of alternative i, while d_i^+ and d_i^- represent the distances to the fuzzy positive and fuzzy negative ideal solutions, respectively, as shown in Eq.(17).

3.9.6 Fuzzy EDAS (Evaluation based on Distance from Average Solution) Method The Fuzzy EDAS method is one of the multi-criteria decision-making (MCDM) techniques that evaluates and ranks alternatives based on their distances to the positive and negative ideal solutions. Fuzzy EDAS provides both flexibility and accuracy in multi-criteria group decision-making processes characterized by conflicting attributes and uncertainty, by evaluating alternatives based on their distance from the average solution (Jana and Pal, 2021). In this method, criterion values are represented using triangular fuzzy numbers (TFNs), and for each alternative, positive distance (PD) and negative distance (ND) scores are calculated. These values are then multiplied by their respective weights and normalized to obtain the final EDAS score:

$$S_i = \frac{1}{2}\left(\frac{PDS_i}{\max PDS_i} + \frac{NDS_i}{\max NDS_i}\right) \tag{10}$$

Here, PDS_i and NDS_i represent the positive and negative distance scores of alternative i, respectively, and S_i denotes the final fuzzy EDAS score, as defined in Eq.(18).

3.9.7 Fuzzy VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) Method The Fuzzy VIKOR method is one of the multi-criteria decision-making (MCDM) techniques that evaluates and ranks alternatives based on their distances to the positive and negative ideal solutions. The Fuzzy VIKOR method provides a rational and systematic decision-making approach that aims to comprehensively rank the performance of feasible alternatives by considering the weights of evaluation criteria in multi-criteria decision environments characterized by uncertainty (Chang, 2014). In this method, the criteria are expressed using triangular fuzzy numbers (TFNs), and for each alternative, the total benefit difference (S_i) and the maximum criterion difference (R_i) are calculated with respect to the positive and negative ideal solutions. Based on these two values, the Q_i score—representing the fuzzy compromise solution—is obtained using the formulation presented in Eq. (19). This equation integrates both benefit and regret measures through the compromise coefficient v, which is typically set to 0.5, to provide a balanced evaluation among competing alternatives:

$$Q_i = v\frac{S_i - S_{\min}}{S_{\max} - S_{\min}} + (1-v)\frac{R_i - R_{\min}}{R_{\max} - R_{\min}} \tag{11}$$

4 Conceptual Discussion: Quantum–Fuzzy Decision-Making (Non-operational)

This section provides conceptual interpretation only and does not describe implemented algorithmic mechanisms. The proposed method is a classical, quantum-inspired stochastic fuzzy weighting approach; therefore, the discussion below is included solely to contextualize common terminology used in the related literature.

Figure 4 is included as a conceptual narrative frequently used in quantum-inspired decision-model discussions (e.g., superposition/interference/collapse). It is not intended to represent an implemented sequence of algorithmic steps in the proposed method.

Figure 5 is presented as a high-level conceptual map and should not be interpreted as evidence of improved stability, discrimination, or performance of the proposed method in the absence of a formal robustness analysis or benchmarking.

4.1 Weighting Models and Decision Outcomes (Conceptual, Non-operational)

Quantum terminology (e.g., superposition or entanglement) is often used in the literature to motivate alternative probabilistic viewpoints; however, the present implementation does not simulate quantum states and does not include explicit coupling between criteria.

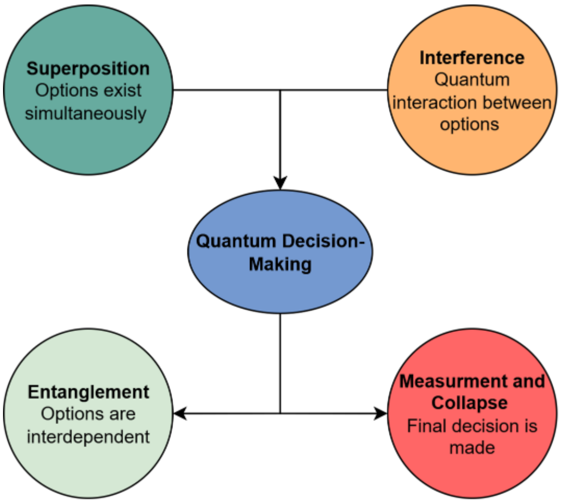

Fig. 4: Conceptual illustration of a quantum decision-making narrative (non-operational)

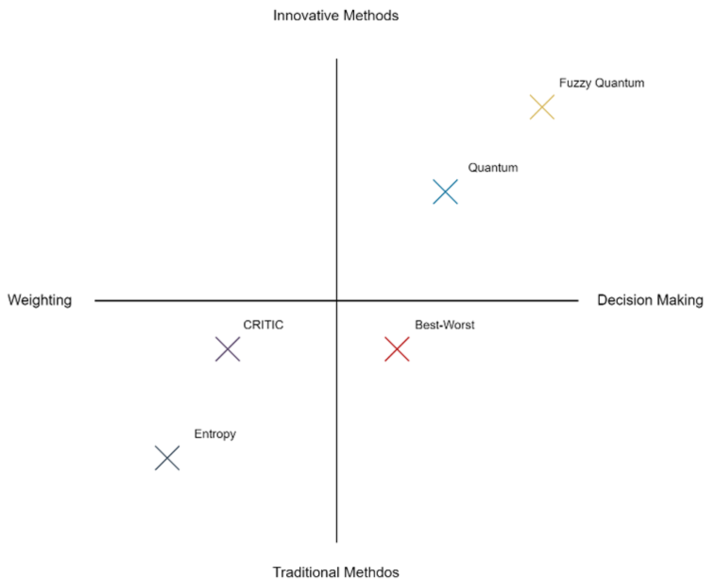

Fig. 5: Conceptual positioning of related ideas (non-operational; not an implemented framework)

In the implemented study, differences in alternative rankings are primarily driven by the selected weighting scheme (BW, CRITIC, Entropy, quantum-inspired, and fuzzy quantum-inspired) and by the downstream MCDM method; therefore, claims regarding stability, discrimination, or interdependency modeling are not asserted as formal properties without dedicated robustness metrics and benchmarking.

4.2 Algorithm: Quantum–Fuzzy Weighting Integration Step

The integration of quantum and fuzzy logic within the weighting process provides a robust framework for managing uncertainty and interdependence among criteria in multi-criteria decision-making (MCDM) systems. By combining the probabilistic representation of quantum mechanics with the linguistic flexibility of fuzzy logic, this algorithm enables a dynamic and adaptive weighting structure. The following steps formalize the process through which normalized decision data are enhanced with quantum-derived probability amplitudes and transformed into triangular fuzzy weights, ensuring that both the uncertainty and interaction effects are preserved before being transferred to the MCDM evaluation stage.

Step 1: Criterion direction and scale alignment (normalization)

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{\max_i x_{ij}}, C_j(\text{benefit}) \\ \dfrac{\min_i x_{ij}}{x_{ij}}, C_j(\text{cost}) \end{cases} \tag{12}$$

Equation (20) shows the normalization step that aligns all criteria to a common scale and direction. Benefit criteria are divided by the column maximum, while cost criteria use the column minimum. This ensures all criteria are comparable within the [0,1] range.

Step 2: Quantum-originated probability mass generation

$$\theta_j \sim U(0, \pi), \qquad a_j = \sin^2(\theta_j), \qquad \alpha_j = \frac{a_j}{\sum_{k=1}^{n} a_k}, \qquad \sum_j \alpha_j = 1 \tag{13}$$

Equation (21) generates a quantum-based probability distribution for each criterion. θ represents the random phase angle, while α denotes the normalized probability weight derived from the superposition effect.

Step 3: Fuzzification of quantum probability (TFN weighting)

$$\tilde{w}_j = \big(\max(\alpha_j - \delta, 0),\ \alpha_j,\ \min(\alpha_j + \delta, 1)\big) \tag{14}$$

Equation (22) represents the transformation of quantum probability weights into triangular fuzzy numbers (TFNs). α_j is the central value, and δ defines the uncertainty range, allowing the probability distribution to capture human judgment ambiguity.

Step 4: Normalized decision matrix with TFN

$$\tilde{r}_{ij} = r_{ij} \otimes \tilde{w}_{ij} = \big(r_{ij}\, l_j^{(w)},\ r_{ij}\, m_j^{(w)},\ r_{ij}\, u_j^{(w)}\big) \tag{15}$$

Equation (23) shows the multiplication of normalized criterion values with quantum–fuzzy weights to form the weighted decision matrix. As a result, each element is represented as a triangular fuzzy number (TFN).

Step 5: Reference Point Generation for MCDM Methods

$$\tilde{v}_j^{(k)} = \Phi_j^{(k)}\big(\{\tilde{r}_{ij}\}_{i=1}^{m}; \theta_j\big), \qquad k = 1, 2, \dots, K_j \tag{16}$$

In Equation (24), for each criterion, the method-specific reference point(s) are generated from the set of normalized–weighted values ($\tilde{r}_{ij}$). This process is expressed by a general generation function ϕ, defined according to method- or criterion-specific parameters θ_j. The resulting $\tilde{v}_j^{(k)}$ values form the fundamental reference points used by MCDM methods.

Step 6: Distance / difference measures between TFNs

$$d_E\big((l_1, m_1, u_1), (l_2, m_2, u_2)\big) = \sqrt{(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2} \tag{17}$$

$$d_T\big((l_1, m_1, u_1), (l_2, m_2, u_2)\big) = |l_1 - l_2| + |m_1 - m_2| + |u_1 - u_2| \tag{18}$$

Equation (25) and (26) represents the distance between two triangular fuzzy numbers (TFNs). d_E denotes the fuzzy Euclidean distance, while d_T refers to the fuzzy Taxicab (Manhattan) distance. These measures are used to determine how far each alternative is from the reference point.

Step 7: Fuzzy Quantum Weighted Decision Matrix and MCDM Integration

$$S_i = f(\tilde{R}, \tilde{W}) = f(r_{ij} \times \tilde{w}_j) \tag{19}$$

In Equation (27), this expression represents the integration of normalized criterion values (r_ij) with quantum–fuzzy weights $\tilde{w}_j$and their transfer into the multi-criteria decision-making (MCDM) model. The function f(.)varies depending on the selected method (e.g., CODAS, EDAS, TOPSIS, VIKOR, etc.) and is used to calculate the final scores (S_i) of the alternatives. At this stage, the resulting quantum–fuzzy weighted decision matrix forms a common decision space utilized for evaluation across all MCDM approaches.

Step 8: Ranking alternatives

$$A_{(1)} = \arg\max_i S_i, \qquad A_{(2)}, A_{(3)}, \ldots, A_{(m)} \tag{20}$$

In Equation (28) represents the ranking of alternatives in multi-criteria decision-making (MCDM) methods based on their final scores (S_i). All alternatives are ordered from the highest to the lowest score, and the one with the highest value $A_{(1)}$is selected as the most suitable alternative. This ranking approach is universally applicable to all MCDM methods.

5 Result

In this study, a comprehensive analysis was conducted using different weighting methods and Multi Criteria Decision-Making (MCDM) techniques to address the industrial robot selection problem. Both classical MCDM methods such as CODAS, TOPSIS, VIKOR, and MOORA, and fuzzy logic-based MCDM methods (fuzzy TOPSIS, fuzzy EDAS, fuzzy VIKOR) were applied to evaluate alternative robots and determine the most suitable selection. For each method, BW, CRITIC, Entropy, Quantum, and Fuzzy Quantum weighting techniques were employed, and the obtained results were analyzed comparatively.

Table 3: Best Robot Selection with Different Weighting Methods (Fuzzy MCDM Methods)

Weighting Method	**Fuzzy TOPSIS**		**Fuzzy EDAS**		**Fuzzy VIKOR**	
	Robot	Score	Robot	Score	Robot	Score
BW	IRB 5720-180/2.6	0.539944	IRB 760	5.385003	IRB 140-6/0.8	0.000000
CRITIC	IRB 1010-1.5/0.37	0.600000	IRB 760	2.135629	IRB 140-6/0.8	0.024323
Entropy	IRB 760	0.524325	IRB 760	5.589297	IRB 1600-6/1.2	0.010121
Quantum	IRB 1010-1.5/0.37	0.556295	IRB 1010-1.5/0.37	2.679314	IRB 140-6/0.8	0.066591
Fuzzy Quantum	IRB 1010-1.5/0.37	0.556331	IRB 1010-1.5/0.37	2.682965	IRB 140-6/0.8	0.049457

The results in Table 3 show that the optimal robot selection varies depending on the fuzzy MCDM method and weighting technique applied. While Fuzzy TOPSIS and Fuzzy Quantum methods highlighted the IRB 1010-1.5/0.37 model, Fuzzy EDAS selected IRB 760, and Fuzzy VIKOR identified IRB 140-6/0.8 as the best alternative. Moreover, the quantum-inspired and fuzzy quantum-inspired weighting schemes yielded rankings that differed from those produced by Entropy and CRITIC, indicating that the ranking outcome is sensitive to the adopted weighting design.

According to Table 4, while classical methods highlighted the IRB 760 model, the VIKOR method identified IRB 140-6/0.8 as the best alternative. However, when Quantum and Fuzzy Quantum weighting techniques were applied, the IRB 1010-1.5/0.37 model became more advantageous in several methods. These findings indicate that the selected alternative may change as a function of the adopted weighting scheme.

Table 4: Best Robot Selection with Different Weighting Methods (Classical MCDM Methods)

Weighting Method	CODAS		TOPSIS		VIKOR		MOORA	
	Robot	Score	Robot	Score	Robot	Score	Robot	Score
BW	IRB 760	0.492034	IRB 760	0.703721	IRB 140-6/0.8	0.000000	IRB 760	0.276357
CRITIC	IRB 760	0.345672	IRB 760	0.549528	IRB 140-6/0.8	0.058810	IRB 760	0.069460
Entropy	IRB 760	0.469126	IRB 760	0.554542	IRB 2000/1	0.029126	IRB 760	0.209345
Quantum	IRB 1010-1.5/0.37	0.379092	IRB 1010-1.5/0.37	0.556295	IRB 140-6/0.8	0.108056	IRB 5400-22	0.503426
Fuzzy Quantum	IRB 1010-1.5/0.37	0.381487	IRB 1010-1.5/0.37	0.556331	IRB 140-6/0.8	0.049457	IRB 5400-22	0.503426

5.1 Comparison of Classical, Quantum and Fuzzy Quantum Weighting

Weighting techniques play a critical role in the effectiveness of multi-criteria decision-making (MCDM) models. In recent years, advanced methods such as quantum and fuzzy quantum-based approaches have gained attention for their ability to model uncertainty and complex interactions. This section evaluates the impact of various weighting methods on decision quality through a comparative analysis.

Table 5: Comparison of Quantum, Fuzzy Quantum and Classical Weighting Methods

Feature	**Classical Weighting**	**Quantum Weighting**	**Fuzzy Quantum Weighting (Proposed)**
Uncertainty Handling	Fixed weights (deterministic)	Probability-based weights via superposition principle	Both quantum probabilities and fuzzy uncertainties are considered
Relationships Between Criteria	Independent criteria	Independent criteria (no coupling implemented)	Independent criteria with fuzzy uncertainty modeling
Weight Updating	Fixed or classically updated	Stochastically generated by phase-angle sampling	Stochastically generated and fuzzified as TFNs
Stability of Results	Singular and fixed result	Probabilistic weights within repeated runs	Probabilistic and fuzzy weights within repeated runs
Computational Complexity	Low	Low–medium (classical sampling)	Low–medium (sampling + fuzzification)
Dynamic Decision-Making	None (static system)	Provides stochastic variability via repeated sampling	Provides stochastic and fuzzy variability (sampling + TFN fuzzification)
Real-World Applications	Suitable for fixed decision process	Provides an alternative modeling perspective for uncertainty	Provides an alternative modeling perspective with fuzzy uncertainty representation

As shown in Table 5, the weighting design plays a crucial role in MCDM outcomes, making the comparative analysis of weighting methods particularly important. The table presents a comparison of classical, quantum-inspired, and fuzzy quantum-inspired weighting approaches across several dimensions. Classical weighting techniques rely on fixed and deterministic values and assume independence between criteria, making them suitable for static decision environments. In contrast, the quantum-inspired approach generates probabilistic weights through classical sampling and normalization, whereas the fuzzy quantum-inspired approach additionally represents uncertainty by fuzzifying these weights as TFNs.

6 Discussion

In this study, the industrial robot selection problem has been examined under multiple classical and fuzzy MCDM procedures while systematically varying the criterion-weighting scheme. The quantum-inspired and fuzzy quantum-inspired schemes have functioned as stochastic generators of probability masses and their fuzzy counterparts, and the resulting weights have been propagated through standard ranking mechanisms.

The comparative results indicate that the identified best alternative is sensitive to the adopted weighting method, which is consistent with the well-known role of weighting in MCDM. In particular, the quantum-inspired schemes have produced rankings that differ from those obtained by Entropy and CRITIC, suggesting that stochastic probability-mass generation can act as an alternative regularization mechanism in the weighting stage. Moreover, the fuzzy extension has been observed to support uncertainty representation by assigning TFN-valued weights rather than point estimates.

It is emphasized that the proposed approach has been implemented entirely on classical hardware and has not operationalized quantum-mechanical coupling mechanisms between criteria (e.g., entanglement-based joint amplitudes, unitary evolution, or Schrödinger dynamics). Therefore, the contribution has been restricted to a classical, quantum-inspired probabilistic fuzzy weighting design and its empirical integration with established MCDM methods.

With respect to the research questions, the effect of the quantum-inspired weighting on decision outcomes (RQ1) has been assessed via cross-method ranking comparisons; the role of fuzzification under uncertainty (RQ2) has been examined by TFN-based weighting and fuzzy MCDM outputs; and ranking consistency patterns associated with the fuzzy quantum-inspired scheme (RQ3) have been discussed by comparing best-alternative consistency across methods.

It is noted that these consistency patterns are discussed qualitatively and are not presented as formal statistical robustness properties in the absence of variance estimates, confidence intervals, or dedicated stability metrics.

A key limitation is that no computational complexity analysis or runtime benchmarking has been provided, and thus no performance claims beyond methodological modeling have been made. Future work may include (i) formal sensitivity/stability analyses under repeated sampling, (ii) explicit modeling of inter-criterion dependence through correlated sampling or coupling terms, and (iii) runtime evaluations on larger datasets to characterize practical scalability.

7 Conclusion and Future Works

In this study, a classical, quantum-inspired probabilistic weighting mechanism has been integrated with fuzzy uncertainty modeling and combined with conventional MCDM ranking methods for industrial robot selection. The weighting stage has been constructed by phase-angle sampling followed by $\sin^2(\cdot)$ mapping and normalization, and the resulting probability masses have been fuzzified as triangular fuzzy numbers when the fuzzy quantum-inspired variant has been applied.

It has been observed that the selected best alternative and the stability of rankings may vary across weighting schemes and MCDM procedures. In this respect, the proposed quantum-inspired and fuzzy quantum-inspired schemes have been shown to provide an additional perspective for sensitivity analysis in criterion weighting under uncertainty, without requiring subjective expert elicitation.

It is emphasized that inter-criterion dependence has not been explicitly modeled and that the presented framework does not implement quantum operators, unitary evolution, entanglement-based coupling, qubit simulation, or hardware-based quantum computation. Accordingly, the scope of the contribution has been restricted to classical decision modeling.

For future work, (i) correlated or copula-based sampling strategies may be introduced to represent inter-criterion dependence, (ii) convergence and stability under repeated sampling may be evaluated formally, and (iii) computational cost and scalability may be assessed through runtime benchmarking on larger and more diverse datasets.

Acknowledgment

The author would like to thank the reviewers for their insightful comments and suggestions, which significantly improved the quality of this paper.

References

Abdelgaber, N., Nikolopoulos, C. (2020, December). Overview on quantum computing and its applications in artificial intelligence. In *2020 IEEE Third International Conference on Artificial Intelligence and Knowledge Engineering (AIKE)* (pp. 198–199). IEEE.

Ahmadi, H. B., Kusi-Sarpong, S., Rezaei, J. (2017). Assessing the social sustainability of supply chains using Best Worst Method. *Resources, Conservation and Recycling*, 126, 99–106.

Alinezhad, A., Khalili, J. (2019). New methods and applications in multiple attribute decision making (MADM) (Vol. 277, pp. 199–203). Cham: Springer.

Arslankaya, D., Göraltay, K. (2019). Çok kriterli karar verme yöntemlerinde güncel yaklaşımlar.

Başer, E., Şatır, Ö. Ü. E. Kuantum Hesaplama.

Behzadian, M., Otaghsara, S. K., Yazdani, M., Ignatius, J. (2012). A state-of the-art survey of TOPSIS applications. *Expert Systems with Applications*, 39(17), 13051–13069.

Biamonte, J., Wittek, P., Pancotti, N., Rebentrost, P., Wiebe, N., Lloyd, S. (2017). Quantum machine learning. *Nature*, 549(7671), 195–202.

Borowska, M. (2015). Entropy-based algorithms in the analysis of biomedical signals. *Studies in Logic, Grammar and Rhetoric*, 43(1), 21–32.

Busemeyer, J. R., Wang, Z., Townsend, J. T. (2006). Quantum dynamics of human decision-making. *Journal of Mathematical Psychology*, 50(3), 220–241.

Chakraborty, S., Datta, H. N., Kalita, K., Chakraborty, S. (2023). A narrative review of MOORA in decision making. *Opsearch*, 60(4), 1844–1887.

Chakraborty, S. (2011). Applications of the MOORA method for decision making in manufacturing environment. *IJAMT*, 54(9), 1155–1166.

Chang, T. H. (2014). Fuzzy VIKOR method: A case study of the hospital service evaluation in Taiwan. *Information Sciences*, 271, 196–212.

Chella, A., Gaglio, S., Pilato, G., Vella, F., Zammuto, S. (2022). A quantum planner for robot motion. *Mathematics*, 10(14), 2475.

Chodha, V., Dubey, R., Kumar, R., Singh, S., Kaur, S. (2022). Selection of industrial arc welding robot with TOPSIS and Entropy MCDM techniques. *Materials Today: Proceedings*, 50, 709–715.

Chu, T. C., Lin, Y. C. (2003). A fuzzy TOPSIS method for robot selection. *IJAMT*, 21(4), 284–290.

Coccia, M. (2024). Converging AI and quantum technologies. *Technologies*, 12(5), 66.

Çolak, M., Kaya, İ. (2017). Prioritization of renewable energy alternatives by an integrated fuzzy MCDM model. *Renewable and Sustainable Energy Reviews*, 80, 840–853.

Dasgupta, S. (2024). Stability of quantum computers. *arXiv:2404.19082*.

Değirmenci, M., Utku, Ş. (2000). Yönetim ve örgüt yapısına kuantum mekaniği açısından bir bakış. *Doğuş Üniversitesi Dergisi*, 1(2), 76–83.

Dragana, V. K., Radojko, L. U. K. I. Ć. (2022). Efficiency analysis of agriculture in Serbia based on the CODAS method. *International Review*, (1–2), 33.

Du, J., Li, H., Xu, X., Shi, M., Wu, J., Zhou, X., Han, R. (2003). Experimental implementation of the quantum random-walk algorithm. *Physical Review A*, 67(4), 042316.

Dunjko, V., Briegel, H. J. (2018). Machine learning & AI in the quantum domain. *Reports on Progress in Physics*, 81(7), 074001.

Friedman, J. R., Patel, V., Chen, W., Tolpygo, S. K., Lukens, J. E. (2000). Quantum superposition of distinct macroscopic states. *Nature*, 406(6791), 43–46.

Ghosh, S., Opala, A., Matuszewski, M., Paterek, T., Liew, T. C. (2019). Quantum reservoir processing. *npj Quantum Information*, 5(1), 35.

Goh, C. H. (1997). Analytic hierarchy process for robot selection. *Journal of Manufacturing Systems*, 16(5), 381–386.

Hayal Gerçeklerinin Gücü. Kuantum Bilgisayarlar.

Hadap, S., Patil, M. (2024). Quantum Computing in Artificial Intelligence: A Paradigm Shift. *IJARSCT*, 530–534.

Harrow, A. W., Hassidim, A., Lloyd, S. (2009). Quantum algorithm for linear systems of equations. *Physical Review Letters*, 103(15), 150502.

Horodecki, R., Horodecki, P., Horodecki, M., Horodecki, K. (2009). Quantum entanglement. *Reviews of Modern Physics*, 81(2), 865–942.

Jahan, A., Mustapha, F., Ismail, M. Y., Sapuan, S. M., Bahraminasab, M. (2011). A comprehensive VIKOR method for material selection. *Materials & Design*, 32(3), 1215–1221.

Jain, Y. K., Likhitkar, B., Verma, P., Mishra, P. K., Rathore, D. S., Bhokare, M. S. (2025, March). Leveraging Quantum Computing for MCDM in Strategic Business Planning. In *AUTOCOM 2025* (pp. 1492–1496). IEEE.

Jana, C., Pal, M. (2021). Extended bipolar fuzzy EDAS for group decision-making. *Computational and Applied Mathematics*, 40(1), 9.

Kağızman, A., Deveci, K., Sezer, V. (2022). Selection of Suitable Automatic CPR Device Chassis Material Using Intuitionistic Fuzzy TOPSIS, VIKOR, and CODAS Methods.

Karaatlı, M., & Dağ, O. (2018). Türk Milli Erkek Futbol Takımına ÇKKV ile futbolcu seçimi. *SDU IIBF Dergisi*, 23(4), 1433–1454.

Koçhan, M. (2024). Kuantum fiziğinin bulanık mantık perspektifinden tasviri. *Hitit İlahiyat Dergisi*, 23(1), 300–335.

Kumar, A., Sah, B., Singh, A. R., Deng, Y., He, X., Kumar, P., Bansal, R. C. (2017). A review of MCDM towards sustainable renewable energy. *Renewable and Sustainable Energy Reviews*, 69, 596–609.

Lamata, L. (2017). Basic protocols in quantum reinforcement learning with superconducting circuits. *Scientific Reports*, 7(1), 1609.

Lohia, A. (2024). Quantum AI: Enhancing ML with Quantum Computing. *Journal of Quantum Science and Technology*, 1(2), 6–11.

Merzbacher, E. (1998). *Quantum Mechanics*. John Wiley & Sons.

Nădăban, S., Dzitac, S., Dzitac, I. (2016). Fuzzy TOPSIS: a general view. *Procedia Computer Science*, 91, 823–831.

Nagaraj, G., Upadhayaya, N., Matroud, A., Sabitha, N., VK, R., Nagaraju, R. (2023, March). Impact of quantum computing on improving AI. In *ICIDCA 2023* (pp. 447–452). IEEE.

Pourabdollah, A., Acampora, G., Schiattarella, R. (2021). Fuzzy logic on quantum annealers. *IEEE Transactions on Fuzzy Systems*, 30(8), 3389–3394.

Pyrkov, A., Aliper, A., Bezrukov, D., Lin, Y. C., Polykovskiy, D., Kamya, P., Zhavoronkov, A. (2023). Quantum computing for near-term applications in generative chemistry and drug discovery. *Drug Discovery Today*, 28(8), 103675.

Schuld, M., Sinayskiy, I., Petruccione, F. (2015). An introduction to quantum machine learning. *Contemporary Physics*, 56(2), 172–185.

Singh, P. (2021). FQTSFM: A fuzzy-quantum time series forecasting model. *Information Sciences*, 566, 57–79.

Tiwari, P., Zhang, L., Qu, Z., Muhammad, G. (2024). Quantum fuzzy neural network for multimodal sentiment and sarcasm detection. *Information Fusion*, 103, 102085.

Vadisetty, R., Polamarasetti, A. (2024, November). Quantum Computing For Cryptographic Security With AI. In *ICCMA 2024* (pp. 252–260). IEEE.

Wankhede, V. A., Vinodh, S. (2021). Analysis of Industry 4.0 challenges using best worst method: A case study. *Computers & Industrial Engineering*, 159, 107487.

Wei, C., Wu, J., Guo, Y., Wei, G. (2021). Green supplier selection based on CODAS in probabilistic uncertain linguistic environment. *Technological and Economic Development of Economy*, 27(3), 530–549.

Wichert, A. (2020). *Principles of Quantum Artificial Intelligence: Quantum Problem Solving and Machine Learning*.

Wiebe, N., Kapoor, A., Svore, K. M. (2014). Quantum deep learning. *arXiv:1412.3489*.

Xiong, Q., Fei, Y., Du, Q., Zhao, B., Di, S., Shan, Z. (2024). A modified lightweight quantum CNN for malicious code detection. *Quantum Science and Technology*, 10(1), 015007.

Yang, X., Chen, Z. (2024). Exploiting temporal features in water resource carrying capacity assessment based on extended VIKOR. *Sustainable Cities and Society*, 114, 105801.

Zheng, P., Zubatyuk, R., Wu, W., Isayev, O., Dral, P. O. (2021). AI-enhanced quantum chemical method with broad applicability. *Nature Communications*, 12(1), 7022.
Zhong, S., Chen, Y., Miao, Y. (2023). Using improved CRITIC method to evaluate thermal coal suppliers. *Scientific Reports*, 13(1), 195.

Received July 28, 2025 , revised February 1, 2026, accepted February 10, 2026