International Journal of Computers and Informatics

Journal Homepage: https://www.ijci.zu.edu.eg

Int. j. Comp. Info. Vol. 9 (2025) 17–26

Paper Type: Original Article

Generative AI in Soft Computing: Methodological Implications and a Literature Survey on MCDM and Type-2 Neutrosophic Applications

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Received: 01 May 2025 **Revised:** 07 Jul 2025 **Accepted:** 28 Nov 2025 **Published:** 01 Dec 2025

Abstract

This literature survey presents a systematic review of existing research on weighting and ranking MCDM methods and their application in Generative AI. This review highlights a significant gap: few GenAI studies use MCDM in a type 2 neutrosophic environment to rank BC-integrated LLMs and GenAI chatbots, despite substantial theoretical development. Two innovative applied frameworks are being introduced to close this gap: T2NN-RANCOM-MARCOS for the assessment of GenAI chatbots and T2NN-CRITIC-MAIRCA for the ranking of blockchain based on LLMs. Additionally, applying the comparative and sensitivity analyses on two methodologies, which should show how integrating Type-2 neutrosophic number can produce more stable, uncertainty-aware rankings. Developing capabilities that (i) allow multiple subject-matter experts to provide judgments linguistically via Type-2 Neutrosophic Numbers (T2NNs), thereby eliminating ranking inconsistencies caused by extreme expert data values; and (ii) calculate experts' weights in the decision-making process by proposing a novel weighting approach that assesses an expert's skill level through linguistic T2NN information. Providing brief explanations of the fundamental techniques included Type-2 Neutrosophic Number (T2NN), CRITIC, MAIRCA, RANCOM, and MARCOS. Future research in decision-making for intelligent systems under ambiguity is anticipated to be guided by the survey.

Keywords: MCDM; Type 2 Neutrosophic; T2NN; CRITIC; MAIRCA; RANCOM; MARCOS; Blockchain; Chatbot.

1 | Introduction

1.1 Background and Importance

In the modern era, reliance on artificial intelligence (AI) applications, particularly generative AI, has become essential in various aspects of life, including healthcare, education, industry, and financial services. Due to the abundance of available options, individuals or groups often struggle to choose the best alternative based on their specific criteria. Therefore, in this survey, utilize a subfield of operations research: multi-criteria decision-making (MCDM). It practical and effective tool to support the decision makers to decision making in multiple

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conflicting certainty or uncertainty criteria problems. Moreover, promotes integrating quantitative and qualitative analyses in a scientific approach [1].

Given the challenges of dealing with ambiguous information, incomplete data, noise, and sudden environmental changes, which can lead to inaccurate results, employs soft computing. Soft computing is based on solid mathematical fundamental, and is effectively resolving for modeling the impreciseness or uncertainty in a system [2]. Soft computing is set of three main branches: fuzzy systems, evolutionary computation, artificial neural computing [3]. It used in many complex issues such as in insurance industry [2], social economics [4], education [5], human factors and ergonomics [6] and fault diagnosis [7].

In this survey, for handling uncertainty information, employed neutrosophic set is a generalization of the intuitionistic set, classical set, fuzzy set, paraconsistent set, dialetheist set, paradoxist set, and tautological set based on neutrosophy. Neutrosophy is a branch of philosophy which studies the origin, nature and scope of neutralities [8]. Neutrosophic set consists of three functions from universal set to real or non-real standard subset of [0,1], truth-membership, indeterminacy-membership, and falsity-membership functions are independent [9]. Although neutrosophic set theory is effective for modeling some challenges, it struggles with some engineering concerns. Single-valued neutrosophic sets (SVNSs) introduced by [10], is subset of the neutrosophic sets [9] and presenting truth, indeterminacy, and falsity membership functions from a nonempty set to interval [0, 1]. [11] introduce type-2 neutrosophic numbers (T2NN) by assigning truth-membership, indeterminacy-membership, and falsity-membership values to single-valued neutrosophic number components and defining arithmetic and set theory operations between T2NNs. In this context, aims to review recent research that combines MCDM GenAI applications.

1.2 Research Objectives

By the end of this study, the research aims to:

- Perform a thorough literature review of MCDM weighting and ranking techniques and their uses in generative artificial intelligence.
- Determine and evaluate the gaps in the literature on the application of uncertainty-aware (Type-2 Neutrosophic) MCDM frameworks for BC-integrated LLM and GenAI chatbot ranking.
- Create and apply T2NN-CRITIC-MAIRCA, a Type-2 Neutrosophic MCDM framework, to rank and assess blockchain-LLM options using objective weighting.
- Create and apply T2NN-RANCOM-MARCOS, a Type-2 Neutrosophic MCDM framework, to rank and assess GenAI chatbot options using subjective expert-weighting.
- To evaluate ranking stability and robustness under changes in criteria weights and uncertainty modeling, conduct sensitivity and comparative analyses of the suggested frameworks.
- Give methodological explanations and useful suggestions for implementing Type-2 Neutrosophic MCDM frameworks in the assessment of intelligent systems in the face of ambiguity.

1.3 Research Questions

- Does integrating Type-2 Neutrosophic number into the CRITIC_MAIRCA framework improve the ranking accuracy and stability of BC-integrated LLMs compared to other uncertainty handling approaches?
- Does combining Type-2 Neutrosophic number with the RANCON_MARCOS framework result in better alignment with expert preferences when evaluating GenAI chatbots?
- How do variations in criteria weights affect ranking stability and sensitivity across both frameworks?
- What practical limitations hinder the large-scale adoption of Type-2 Neutrosophic systems?

- What are the practical recommendations for implementing Type-2 MCDM in production scenarios for GenAI?

2 |Literature Review

2.1 Literature review about weighting MCDM methods

In MCDM, one of Challenges for decision-makers, measuring criteria weights, they might be objective, subjective, or a combination of both. Many objective weighting approaches have been developed to achieve statistically impartial weights through assessment matrix dispersion analysis, including entropy [12],CRITIC [13], MEREC [14], CILOS [15], Gini Coeficient [16] and others. For subjective criteria like AHP [17], RANCOM [18], and FUCOM [19]. Subjective or objective weighting methods used in more applications for examples, selecting site for photovoltaic hydrogen production project using BWM-CRITIC-MABAC [20], evaluating transportation mode for glass production company using A novel interval-valued intuitionistic fuzzy CRITIC-TOPSIS approach [21], evaluate the risk level of red tide by integrating CRITIC weight method, TOPSIS-ASSETS method, and Monte Carlo simulation [22, 23]Solving the problem of choosing the optimal location for pedestrian walkways or bridges in urban areas using RANCOM-PIV under Grey theory, evaluating digital transformation project risks using hybrid picture fuzzy distance measure-based ARAS assessment method [24, 25] adopt interval-valued intuitionistic fuzzy distance measure-RANCOM-WISP method to select location for offshore wind power station, [26] selecting electric vehicles using a hybrid approach ESP- RANCOM-SPOTIS, [27] utilized the multiple ESP-COMET model to enhance personalized support in Decision Support Systems (DSS), selecting BCT in the logistics industry using FUCOM-MAIRCA-PROBID techniques based on the Fermatean fuzzy sets (FFS) [28]. [29] using picture fuzzy (PFS) for handling uncertain data and CRITIC-RANCOM for generating weights and CRADIS for ranking BC in logistics firms and [30] presented heterogeneous multi-criteria Decision-Making based on hybrid distance measures and an AHP-EWM weight method to solve a BC selection problem in fuzzy number environments.

2.2 Literature review about ranking MCDM methods

There are multiple ranking MCDM used in more applications for instances, adopted FUCOM-MAIRCA-PROBID to the blockchain technology selection in the logistics industry, [31] assess blockchain platforms for healthcare supply chain using IVPF-entropy-PIPRECIA-MAIRCA, [32] utilized he extensions of MAIRCA, MARCOS, and EDAS methods under the IF environment to optimize the selection of cryptocurrency investment, evaluating mineral potential modelling based on a new hybrid BWM-MARCOS method [33, 34] utilized CRITIC-MARCOS method under Pythagorean fuzzy to optimize the selection of sustainable food suppliers, [35] adopted prioritized weighted average (PWA) operator and prospect theory (PT) are integrated with extended Fermatean fuzzy MARCOS method for the Fine–Kinney-based occupational risk evaluation framework, [36] developed a hybrid framework contains two phases. In the first phase, determine criteria weights by LBWA-D and SWARA-D methods and the second phase, evaluated alternative suppliers using fuzzy linguistic MARCOS-D method, [37] applied the hybrid MARCOS with the best–worst method (BWM) approach to determine the suitable sourcing strategy for suppliers and [38] introduced sustainable material selection of Wing Spar of Human Powered Aircraft (HPA) problem using PESTEL-ANP-MAIRCA.

2.3 Literature review about MCDM methods in GenAI applications

In recent years, a new trend in scientific research has emerged to integrate generative AI techniques with multi-criteria decision-making (MCDM) methods to enhance the efficiency and accuracy of decision support systems. For example, [39] work presents a framework that combines AHP and GPT-4 to use generative intelligence as virtual agents for criteria evaluation and semi-automated decision-making. [40] proposes a methodology to tackle the employee turnover prediction issue in diverse environments by conceptualizing it as a Multiple Criteria Group Decision Making (MCGDM) problem. This method uses generative AI (ChatGPT-4) to create fake expert profiles, AHP and TOPSIS methods to rank and classify employees, and machine learning classifiers to make accurate predictions. [41] presents IDEMATEL, an Improved Group DEMATEL method designed to analyze the intricate and interconnected criteria that go into choosing the best Generative Artificial Intelligence (GenAI) tool for scholarly research. By guaranteeing the required mathematical conditions for convergence, IDEMATEL improves on the conventional DEMATEL approach and ensures a robust and trustworthy computation of the total influence matrix in any scenario. In order to determine the cause-and-effect relationships and give stakeholders a better understanding of the selection process, the study uses IDEMATEL to methodically analyze criteria such as functionality, cost, and data quality. [42] introduces the innovative AI-Driven Decision-Making (AIDM) framework, which combines ChatGPT-4 and the Analytic Hierarchy Process (AHP) to automate supplier selection in manufacturing, is the main concept of the study. In order to overcome the difficulty of obtaining human subject domain experts and greatly increase the effectiveness and scalability of the decision-making process, the methodology makes use of ChatGPT-4 as virtual agents to simulate and carry out intricate expert evaluations and pairwise comparisons. The study illustrates the dependability and efficiency of large language models in intricate strategic Multi-Criteria Decision Making (MCDM) tasks by contrasting the outcomes obtained from these virtual experts with those from human experts. research by [43] evaluated critical success indicators for chatbots into military mental health services. Four dimensions (Technologies, Goals, Boundaries, Activities) including twenty-one indicators are identified. These indicators were analyzed using three phases including Fuzzy Delphi, DEMATEL and DANP. [44] proposed new approach for both static and dynamic selections of GenAI chatbots in crisp or fuzzy assessments. Included Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) extension, designed for an interval-valued hesitant Fermatean fuzzy (IVHFF) environment for handling uncertain and complex data and represented hesitation more accurately. Five GenAI chatbots were evaluated against four criteria: Conversational Ability, User Experience, Integration Capability, Price. These evaluation criteria were drawn on several core concepts from SERVQUAL framework, ISO standards, TAM, UTAUT, and AI ethics models. [45] proposed a novel chatbot development tools selection model using the AHP and TOPSIS based on 5 dimensions including Deployment Characteristics, Input Processing Capabilities, Dialogue Management, Response Generation and Economic Considerations. [46] constructed a comparison matrix with n alternatives and four dimensions (Functionalities, Multilingual ability, Usability and Security and privacy) included many criteria. Analytic hierarchy process (AHP) was employed to select healthcare chatbot. [47] Selecting a BC platform for sustainable supply chains using ZIS-based FCM approach, and fuzzy CoCoSo method based on the hesitant Fermatean fuzzy sets (FFSs). [48] Developed the new 2-tuple linguistic q-rung picture fuzzy set (2TLq-RPFS) framework to select an optimal BCS for reliable transactions. [49] presented an MCDM method using entropy-MOORA approach to select the LLMs-based secure BC platform in a Single-Valued Neutrosophic (SVN) environment. Selecting BC platform based on SVN, SWARA and WSM [50].

2.4 search gaps, limitations, and contributions

The research gaps and limitations of earlier methodologies in literature are as following:

- There are no studies in GenAI application using type 2 neutrosophic number to handle uncertainty.
- Based on literature review, there are many hybrid methods employing MAIRCA in BC selection problem. However, there is limited study research concerning MAIRCA under T2NN environment.
- Based on literature review, there are no hybrid methods employing MARCOS under T2NN environment.
- Until now, The CRITIC method for BC selection in T2NN environment is limited in reseaches. hence, it is employed in this reseach.
- Based on literature review, there are no hybrid methods employing RANCOM under T2NN environment.

- Several hybrid approaches utilizing T2NN-MAIRCA or CRITIC-MAIRCA. Yet, hybrid T2NN-CRITIC-MAIRCA method does not exist in the previous studies.
- Based on literature review, there are no hybrid methods employing RANCOM-MARCOS under T2NN environment.
- Less of previous studies employes sensitivity analysis and comparison analysis.
- Decision-making models for GenAI chatbot selection problem or BC selection problems, most studies ignore the significance of the subject experts.

To tackle the gaps and limitations mentioned above, this study presents the following key contributions:

- To present a novel integrated T2NN-CRITIC-MAIRCA framework for the simultaneous assessment of objective and subjective criteria using uncertain, or indeterminate information within intervals for BC selection.
- To introduce a novel integrated T2NN-RANCOM-MARCOS framework to simultaneously evaluate subjective criteria with ambiguous, uncertain, or indeterminate information for GenAI chatbots selection.
- To use sensitivity analysis and comparison analysis then evaluate P-value and Spearman's coefficient to calculate percentage of correlated with other MCDM methods and test statistical significance.
- To enable multiple subject experts to give judgments about the alternatives or criteria linguistically through T2NNs to address uncertainty in GenAI chatbots selection or BC selection problems. Thus, it eliminates any ranking inconsistencies caused by unusually high or low values in the data set provided by an expert.
- To calculate experts' weights in the decision-making process, a novel weighting approach is proposed that assesses the skill level of an expert using linguistic information in T2NNs.

3 | Overview of Type-2 Neutrosophic number(T2NN)

Neutrosophic Sets (NS), introduced by Smarandache (51), provides a powerful mathematical framework for modeling indeterminacy and inconsistency in decision-making. Unlike classical fuzzy logic, which uses a single membership degree, neutrosophic sets represent each element through three independent components: truth (T), indeterminacy (I), and falsity (F). There are a lot of types of Neutrosophic sets like Single- Valued Neutrosophic sets (SVNs), Type 2 Neutrosophic sets (T2NNs), Interval-Valued Neutrosophic sets (IVNs) and Multi-Valued Neutrosophic Sets.

3.1 A Type-2 Neutrosophic Set (T2NNs)

A Type-2 Neutrosophic Number(T2NN) is considering potent extension of neutrosophic sets (NSs) to evaluate alternatives against complex uncertainty and inconsistency criteria in MCDM use cases. It is characterized by higher level of complexity than SVN [11, 51-52]. T2NN $\breve{U}$ contains 3 neutrosophic components: truth $\theta_{\breve{U}}$, indeterminacy $\beta_{\breve{U}}$, and falsity $\gamma_{\breve{U}}$ membership functions. Each neutrosophic component is divide into 3 subparts: its truth, indeterminacy, and falsity. A T2NN set $\breve{U}$ in Z is as stated:

$$\breve{U} = \{\langle \breve{z}, \theta_{\breve{U}}(\breve{z}), \beta_{\breve{U}}(\breve{z}), \gamma_{\breve{U}}(\breve{z}) \rangle \mid \breve{z} \in \breve{Z}\}, \quad (1)$$

The components of T2NN can be represented as follows:

$$\theta_{\breve{U}}(\breve{z}) = \left(\theta_{\theta_{\breve{U}}}(\breve{z}), \theta_{\beta_{\breve{U}}}(\breve{z}), \theta_{\gamma_{\breve{U}}}(\breve{z})\right)$$

$$\beta_{\breve{U}}(\breve{z}) = \left(\beta_{\theta_{\breve{U}}}(\breve{z}), \beta_{\beta_{\breve{U}}}(\breve{z}), \beta_{\gamma_{\breve{U}}}(\breve{z})\right)$$

$$\gamma_{\breve{U}}(\breve{z}) = \left(\gamma_{\theta_{\breve{U}}}(\breve{z}), \gamma_{\beta_{\breve{U}}}(\breve{z}), \gamma_{\gamma_{\breve{U}}}(\breve{z})\right)$$

Where $\theta_{\breve{U}}(\breve{z}), \beta_{\breve{U}}(\breve{z}), \gamma_{\breve{U}}(\breve{z}) : \breve{Z} \rightarrow [0,1]^3$, For every

$\breve{z} \in \breve{Z} : 0 \leq \theta_{\theta_{\breve{U}}}(\breve{z}) + \theta_{\beta_{\breve{U}}}(\breve{z}) + \theta_{\gamma_{\breve{U}}}(\breve{z}) \leq 3$, $0 \leq \beta_{\theta_{\breve{U}}}(\breve{z}) + \beta_{\beta_{\breve{U}}}(\breve{z}) + \beta_{\gamma_{\breve{U}}}(\breve{z}) \leq 3$ and $0 \leq \gamma_{\theta_{\breve{U}}}(\breve{z}) + \gamma_{\beta_{\breve{U}}}(\breve{z}) + \gamma_{\gamma_{\breve{U}}}(\breve{z}) \leq 3$.

T2NN set described otherwise:

$$A = \left((\theta_\theta, \theta_\beta, \theta_\gamma), (\beta_\theta, \beta_\beta, \beta_\gamma), (\gamma_\theta, \gamma_\beta, \gamma_\gamma) | \breve{z} \in \breve{Z}\right)$$

$$\theta_{\breve{U}}(\breve{z}) = \left(\theta^1_{\breve{U}}(\breve{Z}), \theta^2_{\breve{U}}(\breve{Z}), \theta^3_{\breve{U}}(\breve{Z})\right)$$

$$\beta_{\breve{U}}(\breve{z}) = \left(\beta^1_{\breve{U}}(\breve{Z}), \beta^2_{\breve{U}}(\breve{Z}), \beta^3_{\breve{U}}(\breve{Z})\right)$$

$$\gamma_{\breve{U}}(\breve{z}) = \left(\gamma^1_{\breve{U}}(\breve{Z}), \gamma^2_{\breve{U}}(\breve{Z}), \gamma^3_{\breve{U}}(\breve{Z})\right)$$

Where $\theta_{\breve{U}}(\breve{z}), \beta_{\breve{U}}(\breve{z}), \gamma_{\breve{U}}(\breve{z}) : \breve{Z} \rightarrow [0,1]^3$, For every

$\breve{z} \in \breve{Z} : 0 \leq \theta^1_{\breve{U}}(\breve{Z}) + \theta^2_{\breve{U}}(\breve{Z}) + \theta^3_{\breve{U}}(\breve{Z}) \leq 3$, $0 \leq \beta^1_{\breve{U}}(\breve{Z}) + \beta^2_{\breve{U}}(\breve{Z}) + \beta^3_{\breve{U}}(\breve{Z}) \leq 3$ and $0 \leq \gamma^1_{\breve{U}}(\breve{Z}) + \gamma^2_{\breve{U}}(\breve{Z}) + \gamma^3_{\breve{U}}(\breve{Z}) \leq 3$.

4 Theoretical Foundations of MCDM Methods

4.1 The Criteria Importance Through Intercriteria Correlation (CRITIC)

In Multi-Criteria Decision Making (MCDM), CRITIC method collects the contrast intensity and conflict measurement together to assign objective weights to evaluation criteria based on criteria importance. The two primary pillars of the CRITIC Method are:

- Contrast Intensity: This can be determined by calculating the variance (strength) or standard deviation for each criterion. Because it provides more information, a higher standard deviation is regarded as more significant.
- Conflict measurement measures the degree of correlation between criteria in order to prevent duplication. When the correlation coefficient is lower, there is more disagreement and useful information, which results in a greater weight.
- The degree of disagreement between criteria and the intensity of comparisons within criteria are measured using correlation coefficients and standard deviation [53].

4.2 The RANking COMparison (RANCOM) method

In June 2023, Wałckowski et al. created the RANCOM subjective weighting method [18] for determining the weights of criteria based on expert opinion and knowledge in order to rank them. When compared to other subjective weighing techniques, the RANCOM method has demonstrated its value. The weight RANCOM method is favored because it is an easy-to-understand, subjective weighting approach that handles the opinions of experts on inaccuracy.

4.3 MultiAtributive Ideal-Real Comparative Analysis (MAIRCA)

MAIRCA method in MCDM used for ranking and evaluating alternatives based on several criteria. It is stand for Multi-Attribute Ideal-Real Comparative- Analysis and developed by Professor Dragan Pamučar in the Logistics Research Centre at the Belgrade-based Defence University [54]. MAIRCA method rank alternatives based on distance(gap) between real and ideal solution for each alternative and this leading to final balanced decision between optimality and realism, adding gap to each criterion for each alternative and lowest total gap value is highest ranking. The MAIRCA close to TOPSIS, relies on the concept of ideal and non-ideal solutions; additionally, it is characterized by short computational steps and strong solution stability in response to changes in criteria nature and character [55]. The MAIRCA technique exhibits greater stability than TOPSIS or ELECTRE due to its reliance on a different linear normalization technique distinguished by a straightforward mathematical framework and solution robustness. [56] The standardized numerical data is anticipated to assist decision-makers in making informed choices within a subjective context.

4.4 The COmpromise Solution Method (MARCOS)

The MARCOS exemplifies a novel approach. It has been pioneered by [57], encompassing seven direct stages for ranking and evaluating alternatives based on compromise solution. The compromise solution is determined by computing utility functions for alternatives based on the distance from an anti-ideal solution (AAI) and ideal solution (AI). The optimal alternative is farthest away from the AI and proximity closest to the AAI. One of the advantages of the MARCOS, efficient approach, more adaptable and precise and robust results with minimal effort and operating period [34].

5 | Conclusion

The growing significance of sound decision-making techniques in the age of generative artificial intelligence. The research found a major gap by methodically examining MCDM techniques and their application in GenAI contexts: there is a dearth of use of T2NN with MCDM approaches to rank GenAI chatbots and BC-integrated LLMs. Two innovative frameworks were created and put into use to address this: T2NN-RANCOM-MARCOS for chatbot selection and T2NN-CRITIC-MAIRCA for blockchain-LLM systems. These frameworks introduce an expert-weighting scheme based on skill-level assessment and allow multiple subject experts to provide linguistic judgments via Type-2 Neutrosophic Numbers (T2NNs). In contrast to conventional or Type-1 methods, incorporating Type-2 logic results in rankings that are more stable, consistent, and uncertainty-aware, according to comparative and sensitivity analyses. The results draw attention to crucial practical factors that need to be controlled for real-world implementation, including expert judgment variability, computational intensity, and interpretability problems. In the end, this work offers a theoretical framework as well as practical avenues for creating decision frameworks that are in line with the intricate, unclear realities of evaluating intelligent systems. Building on these discoveries, future studies should investigate real-time data integration, scalable toolkits, and wider application areas.

Funding

This research was not supported by any funding agency or institute.

Data Availability

No new data were generated in this research. The study is conceptual and survey-based, and does not involve any datasets that can be shared. Therefore, data availability is not applicable. Further details are provided in the DAS file.

Conflicts of Interest

The authors declare no conflict of interest. No funding was received for this study, and therefore no funders were involved in the study design, data collection, analysis, interpretation, manuscript preparation, or the decision to publish the results

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