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Neuromorphic AI Chip Selection Using a Bipolar Intuitionistic Fuzzy BWM-MAIRCA Framework

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ABSTRACT

To address the increasing diversity of neuromorphic artificial intelligence (AI) chip architectures, whose technological capabilities and performance characteristics vary considerably across competing alternatives, this study develops an integrated bipolar intuitionistic fuzzy (BIF) Best-Worst Method (BWM) and Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) framework, termed BIF-BWM-MAIRCA, for neuromorphic AI chip selection in a multi-criteria group decision-making (MCGDM) environment under uncertainty. The framework uses bipolar intuitionistic fuzzy numbers to capture both positive and negative expert evaluations and a BIF weighted averaging operator to aggregate individual assessments into a collective decision matrix. BWM then derives the criterion weights, and MAIRCA ranks the competing alternatives based on the gaps between their theoretical and real performance. The framework's applicability is demonstrated through a case study in which three experts evaluate eight neuromorphic AI chips against five criteria. The results show the framework's ability to integrate uncertain expert evaluations, quantify the relative importance of the criteria, and prioritize alternatives within a single decision-making structure, while sensitivity and comparative analyses confirm the stability of the top-ranked alternative and the methodological advantages of the proposed approach. The framework thus provides a formal mathematical basis for neuromorphic AI chip selection under bipolar uncertainty and conflicting expert preferences.

Keywords: *Neuromorphic AI chip selection; Multi-criteria group decision-making; Bipolar intuitionistic fuzzy sets; Best-Worst Method; MAIRCA; Criteria weighting; Decision support system.*

1. Introduction

Artificial intelligence (AI) has become an essential technology that underpins intelligent decision-making across a wide range of domains, such as healthcare, autonomous systems, robotics, smart manufacturing, and edge computing. The Dartmouth Summer Research Project laid the groundwork for AI as an academic discipline by launching systematic research into intelligent machines and computational intelligence [1]. Since then, AI systems have improved steadily through advances in machine learning and deep neural networks, along with growing power and hardware requirements. Today's AI workloads increasingly push the limits of conventional von Neumann computing architectures because of their computational demands and power consumption. Neuromorphic processors emulate biological neurons and synapses in specialized hardware architectures that support low-latency and energy-efficient processing compared with traditional AI accelerators [2]. Recent advances in neuromorphic hardware technologies have expanded the deployment of intelligent systems in resource-constrained environments. The growing demand for real-time inference has stimulated the development of AI chips with enhanced computational capability, adaptive learning mechanisms, and improved hardware efficiency [3]. In addition, progress in neuromorphic architectures has broadened their application in autonomous robotics, intelligent sensing, edge devices, brain-inspired computing, and cyber-physical systems [4]. The integration of emerging device technologies and novel hardware designs has further strengthened the performance and scalability of neuromorphic processors, making them an important component of future AI computing platforms [5]. Moreover, considerable research is still underway to refine neuromorphic chip design through new materials, circuit architectures, and electromagnetic optimization methods that improve computational efficiency and reliability [6].

As the number of available neuromorphic AI chips continues to increase, selecting the most appropriate alternative has become a complex MCGDM problem. Candidate processors vary substantially in computational efficiency, energy efficiency, scalability, learning ability, hardware compatibility, and implementation cost. These criteria are often conflicting, and expert evaluations are frequently uncertain and imprecise. Furthermore, experts may hold both positive and negative views of the same alternative, and the decision-making process must retain both views. Therefore, an effective decision-making framework that represents bipolar uncertainty while evaluating multiple criteria is essential for identifying the most suitable neuromorphic AI chip. To this end, this research proposes a BIF-BWM-MAIRCA decision-making model for selecting neuromorphic AI chips in an MCGDM environment. The proposed approach integrates the expressive power of bipolar intuitionistic fuzzy sets (BIFSs), the consistency-based weighting mechanism of BWM, and the utility-based ranking procedure of MAIRCA. Specifically, BIFSs capture positive and negative expert judgments while preserving the uncertainty inherent in qualitative assessments. BWM then derives the criterion weights from a small number of structured pairwise comparisons, whereas MAIRCA prioritizes the alternatives by comparing their theoretical and real preference values. Thus, this study aims to combine bipolar uncertainty modelling, systematic criterion weighting, and utility-based

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evaluation of alternatives into a single integrated approach. The proposed method provides a structured decision-support mechanism for selecting neuromorphic AI chips under complex, uncertain evaluation conditions.

1.1 Motivation and Research Problem

The rapid evolution of neuromorphic computing has led to the emergence of numerous AI chips with diverse architectural characteristics and computational capabilities. These processors are designed to implement brain-inspired intelligence and are optimized for computational efficiency and low energy consumption. However, their performance varies significantly across critical evaluation aspects, including computational power, energy efficiency, scalability, learning adaptability, hardware compatibility, communication efficiency, and implementation cost. Consequently, selecting an appropriate neuromorphic AI chip has become a strategic decision that significantly influences the performance, reliability, and sustainability of intelligent computing systems. Unlike conventional engineering selection problems, assessing neuromorphic AI chips involves several criteria, none of which is sufficient on its own, and many of which cannot be measured precisely. In real-world scenarios, the selection process usually relies on the recommendations of a committee of technical experts from different fields, who have varying evaluation preferences. These experts frequently make judgments based on linguistic assessments that are qualitative, uncertain, vague, hesitant, and subjective. Most importantly, experts may hold both positive and negative views of the same alternative at the same time. For example, a chip may offer high processing speed but poor energy efficiency. Such conflicting assessments should not be collapsed into a single numerical score. This requirement exposes the limitation of conventional fuzzy representations, which do not explicitly distinguish between positive and negative evaluation perspectives. Moreover, aggregating heterogeneous expert opinions and ensuring consistent group assessments is difficult. Criterion weights are also crucial, because inappropriate weights can significantly affect the validity of the resulting rankings. Therefore, an effective decision-support system should handle bipolar uncertainty, obtain consistent criterion weights, and provide a systematic ranking of the alternatives.

To address these real-world needs, we design a novel BIF-BWM-MAIRCA framework for the neuromorphic AI chip selection problem in an MCGDM setting. The framework uses BIFSs to capture both positive and negative expert evaluations, considering membership, non-membership, and the associated hesitation in both evaluation dimensions. This representation models experts' conflicting preferences more completely than conventional one-sided fuzzy approaches. BWM then calculates criterion weights from pairwise comparisons involving only the best and worst criteria, reducing the required number of judgments. Finally, MAIRCA compares the theoretical and real performance assessments to determine the priorities of the competing alternatives. By combining bipolar uncertainty modelling, consistent criterion weighting, and utility-based ranking, the proposed framework provides a holistic decision-making tool for neuromorphic AI chip selection in complex and uncertain scenarios. The underlying motivation and research problem are conceptually summarized in Figure 1.

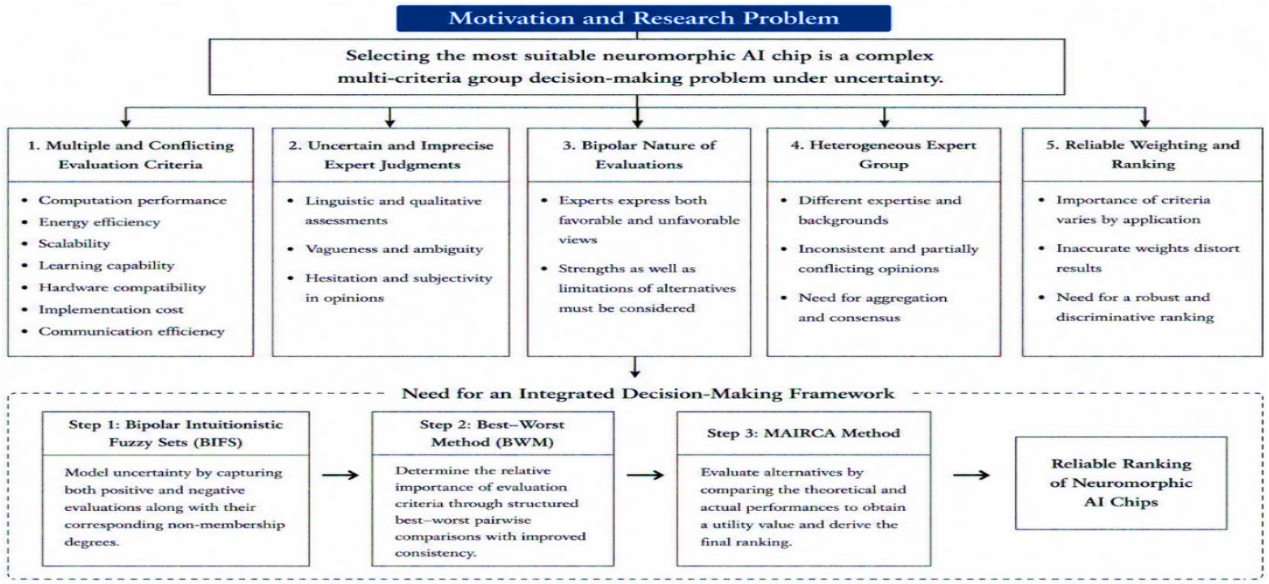


Fig. 1: Motivation and research problem for neuromorphic AI chip selection and the proposed BIF-BWM-MAIRCA decision-making framework.

1.2 Contributions

This study proposes a BIF-BWM-MAIRCA decision-making framework to systematically evaluate and select neuromorphic AI chips in an MCGDM environment. The main contributions and methodological novelties of this study are summarized as follows:

The framework uses BIFSs to simultaneously represent positive and negative expert assessments, accounting for membership, non-membership, and hesitation. This

preserves the opposing evaluation perspectives that may arise when assessing competing neuromorphic AI chips.

BWM is integrated into the BIF decision-making framework to derive the criterion weights systematically. This integration prioritizes the evaluation criteria through structured best-to-others and others-to-worst comparisons and minimizes the required pairwise comparisons.

The MAIRCA method is extended to the BIF context to measure the gaps between the theoretical and real performance assessments of the alternatives. This extends gap-based alternative evaluation to decision environments characterized by bipolar and intuitionistic uncertainty.

The proposed methodology combines bipolar uncertainty representation, criterion weighting, and utility-based prioritization of alternatives within a single computational procedure. It provides a structured way to aggregate diverse expert evaluations and discriminate among competing alternatives under uncertain evaluation conditions.

The applicability of the proposed framework is demonstrated through a realistic case study on neuromorphic AI chip selection, supported by sensitivity and comparative analyses, which show its capacity to provide consistent, reliable, and practical decision support for complex engineering selection problems under uncertainty.

1.3 Paper Layout

The remainder of this paper is organized as follows. Section 2 presents the literature review: Section 2.1 provides an overview of BWM and its recent developments, and Section 2.2 reviews the evolution and applications of the MAIRCA method. Section 3 introduces the fundamental concepts needed to develop the methodology. Section 4 presents the BIF model and the aggregation operators used to integrate the experts' assessments. Section 5 develops the proposed BIF-BWM-MAIRCA-based MCGDM framework and details the computational procedure for criterion weighting and alternative evaluation. Section 6 demonstrates the framework's applicability through a neuromorphic AI chip selection case study. Section 7 examines the framework's robustness through a sensitivity analysis. Section 8 compares the proposed methodology with existing approaches. Finally, Section 9 summarizes the main findings, limitations, and future research directions.

2. Literature Review

Neuromorphic computing is a transformative computing paradigm that seeks to overcome the computational and energy constraints of traditional AI hardware by adopting brain-inspired architectures. Neuromorphic AI chips emulate biological neural processing and offer features such as parallel and event-driven processing, enabling low-power computation, real-time learning, and efficient execution of spiking neural networks. Schuman et al. [7] surveyed the fundamental concepts, hardware implementations, and research prospects of neuromorphic computing. Building on these advances, Davies et al. [8] proposed Loihi, a programmable neuromorphic many-core processor with on-chip learning capabilities, which demonstrated the feasibility of energy-efficient neuromorphic hardware. Sandamirskaya et al. [9] explored neuromorphic architectures in robotics, focusing on their suitability for real-time perception and adaptive learning. More recently, Chen et al. [10] reviewed advances in neuromorphic chip architectures and their applications. These advances have driven the adoption of neuromorphic processors in robotics, edge intelligence, healthcare, and other resource-constrained applications.

The growing diversity of neuromorphic AI chips has made their selection increasingly challenging. Competing architectures differ in performance, energy efficiency, scalability, learning ability, communication efficiency, and implementation cost. Because these features can conflict, a systematic multi-criteria evaluation is necessary. Kwon and Cho [11] applied the Analytic Hierarchy Process (AHP) to semiconductor chip selection, while Montes Sánchez [12] explored the design and evaluation of neuromorphic and edge AI systems. Muhsen et al. [13] developed a fuzzy MCDM framework integrating the Opinion Weight Criteria Method (OWCM) and the Combined Compromise Solution (CoCoSo) for evaluating network-on-chip architectures for real-time applications. Their study shows that uncertainty-aware decision methods can be applied to hardware evaluation. More recent fuzzy MCDM studies have considerably enhanced the analysis of uncertain and conflicting preferences. Anjum et al. [14] integrated intuitionistic fuzzy modelling with entropy-based weighting and CRADIS ranking for sustainable energy management in smart factories. Jana et al. [15] presented bipolar fuzzy Dombi prioritized aggregation operators for multiple-attribute decision-making, and Jana et al. [16] extended this idea to a hybrid MCDM approach combining bipolar and interval-valued bipolar fuzzy structures. These studies show that fuzzy extensions are applicable to complex decision problems involving uncertain and multidirectional preferences.

A critical examination shows that these methods differ in how they represent uncertainty, weight criteria, and rank alternatives. For example, entropy-based weighting [14] uses evaluation data to determine each criterion's importance, whereas BWM uses structured comparisons with respect to the best and worst criteria. Similarly, bipolar fuzzy approaches [15, 16] can handle positive and negative preference information, but they neither model intuitionistic hesitation nor integrate bipolar intuitionistic fuzzy modelling with BWM and MAIRCA for neuromorphic AI chip selection. Thus, the reviewed literature has not sufficiently examined an integrated approach to bipolar uncertainty, systematic criterion prioritization, and utility-based alternative evaluation. To address this gap, the present study proposes a BIF-BWM-MAIRCA framework to represent experts' uncertain assessments, calculate criterion weights, and prioritize neuromorphic AI chips in an MCGDM setting.

2.1 Literature Review of BWM

BWM has become a widely adopted criterion-weighting technique in multi-criteria decision-making (MCDM) because it produces reliable weights with fewer pairwise comparisons and improved consistency. Rezaei [17] introduced BWM as an optimization-based technique that determines criterion weights by comparing criteria with the best and worst criteria, reducing the evaluation burden without compromising decision reliability. To handle imprecise preference information, Guo and Zhao [18] extended BWM to a fuzzy environment, allowing linguistic assessments to be used in the weighting process. In the same year, Salimi [19] demonstrated BWM's applicability to the quality assessment of scientific outputs, confirming its effectiveness in complex evaluation problems. BWM has since been extended to a broad range of engineering and management applications by combining it with advanced decision-making models. Tian et al. [20] applied BWM in an intuitionistic fuzzy environment with an improved TOPSIS method for green supplier selection, demonstrating its ability to handle uncertainty in sustainability-related decision problems. Ecer and Pamucar [21] combined fuzzy BWM with the CoCoSo method to create a robust framework for sustainable supplier selection in fuzzy environments. In recent years, BWM has been increasingly applied to emerging technological and sustainability problems. Khan et al. [22] used BWM to investigate the barriers to implementing blockchain technology in food supply chains, showcasing its real-world applicability in analysing complex industrial systems. Ecer [23] provided a comprehensive review of BWM, discussing its methodological evolution, current applications, and future research directions, and confirmed its status as a mature and flexible weighting technique. Moreover, ur Rehman [24] integrated BWM with a bipolar fuzzy EDAS model for clean energy technology assessment, and Ali et al. [25] combined BWM with a complex q-rung orthopair fuzzy MARCOS model for big data security evaluation. These advances demonstrate that BWM is flexible and applicable in complex fuzzy environments and various hybrid MCDM frameworks, making it a suitable candidate for tackling MCGDM problems in multi-attribute and uncertain contexts.

2.2 Literature Review of MAIRCA

The MAIRCA method has emerged as an effective ranking technique in MCDM because it evaluates alternatives by comparing their theoretical and real performances. Pamučar et al. [26] introduced the MAIRCA method and demonstrated its applicability to selecting railway level crossings for investment in security equipment, establishing its effectiveness in engineering decision-making problems. Researchers have progressively embedded MAIRCA in advanced fuzzy environments to improve its capability to handle uncertainty. García Mestanza and Bakhat [27] combined fuzzy AHP with MAIRCA for overtourism assessment, and Ecer [28] extended MAIRCA using intuitionistic fuzzy sets for COVID-19 vaccine selection. Hadian et al. [29] applied MAIRCA to flood susceptibility assessment, demonstrating the method's versatility in environmental and geospatial decision analysis. More recently, researchers have integrated MAIRCA with higher-level fuzzy decision-making models. Mishra et al. [30] introduced an interval-valued intuitionistic fuzzy distance measure-based MAIRCA algorithm to assess sustainable wastewater treatment technologies, improving robustness in uncertain decision-making scenarios. Likewise, Karami and Mousavi [31] proposed an interval-valued fuzzy group decision-making framework incorporating an improved MAIRCA method for sustainable project selection, further confirming MAIRCA's adaptability to complex group decision-making problems. These developments show that MAIRCA has matured into a reliable, versatile ranking method that can be embedded in sophisticated fuzzy frameworks to tackle complex engineering and management decision problems.

3. Basic Concepts

The proposed BIF-BWM-MAIRCA framework relies on several fundamental concepts from fuzzy set theory. Hence, this section presents the basic definitions of fuzzy sets, intuitionistic fuzzy sets, and bipolar fuzzy sets, which provide the mathematical foundations for representing uncertainty, hesitation, and bipolar preference information in MCGDM problems.

Definition 1 [32]: A fuzzy set (FS) $\acute{K}$ on $Ự$ is mathematically expressed as

$$\acute{K} = \{(\tilde{u}, Ÿ(\tilde{u}))|\tilde{u} \in Ự\}$$

where the mapping $Ÿ: Ự \to [0,1]$ specifies the membership degree of each element. For each element $\tilde{u}$ in $Ự$, the value $Ÿ(\tilde{u})$ measures its degree of membership in the fuzzy set. Specifically, $Ÿ(\tilde{u}) = 0$ indicates that $\tilde{u}$ is completely excluded from the set, $Ÿ(\tilde{u}) = 1$ indicates full membership, and values between 0 and 1 represent partial membership.

Definition 2 [33]: An intuitionistic fuzzy set (IFS) $\acute{K}$ on $Ự$ is defined as

$$\acute{K} = \{(\tilde{u}, Ÿ^{m}(\tilde{u}), Ÿ^{n}(\tilde{u}))|\tilde{u} \in Ự\}$$

where $Ÿ^{m}: Ự \to [0,1]$ and $Ÿ^{n}: Ự \to [0,1]$ denote the membership and non-membership functions, respectively. These functions satisfy the condition

$$0 \leq Ÿ^{m}(\tilde{u}) + Ÿ^{n}(\tilde{u}) \leq 1 \; \forall \; \tilde{u} \in Ự.$$

The difference between unity and the sum of these two degrees represents the hesitation degree, defined as

$$\check{h}(\tilde{u}) = 1 - (Ÿ^{m}(\tilde{u}) + Ÿ^{n}(\tilde{u}))$$

which reflects the amount of indeterminacy in evaluating the status of an element and becomes zero when the available information is completely specified.

Definition 3 [34]: A bipolar fuzzy set (BFS) $\acute{K}$ on $Ự$ is defined as

$$\acute{K} = \left\{\left(\tilde{u}, \left(\ddot{Y}^{p}(\tilde{u}), \ddot{Y}^{n}(\tilde{u})\right)\right) | \tilde{u} \in U'\right\}$$

where $\ddot{Y}^{p}: U' \to [0,1]$ denotes the positive membership function, expressing the degree to which an element satisfies the desired property, and $\ddot{Y}^{n}: U' \to [-1,0]$ denotes the negative membership function, indicating the extent to which the same element is associated with the counter-property.

4. Bipolar Intuitionistic Fuzzy Model

This section presents the mathematical framework of the BIF model adopted in this study. It introduces the definition of BIFSs, their fundamental operational laws, the score and accuracy functions used to compare BIF information, and the bipolar intuitionistic fuzzy weighted averaging (BIFWA) and bipolar intuitionistic fuzzy weighted geometric (BIFWG) operators, which collectively provide the theoretical basis for the proposed BIF-BWM-MAIRCA decision-making framework.

Definition 4 [35]: A BIFS $\acute{K}$ on U' is defined as

$$\acute{K} = \left\{\left(\tilde{u}, \left(\ddot{Y}^{pm}(\tilde{u}), \ddot{Y}^{pn}(\tilde{u})\right), \left(\ddot{Y}^{nm}(\tilde{u}), \ddot{Y}^{nn}(\tilde{u})\right)\right) | \tilde{u} \in U'\right\}$$

where $\ddot{Y}^{pm}: U' \to [0,1], \ddot{Y}^{pn}: U' \to [0,1]$ represent the positive membership and non-membership functions, respectively, while $\ddot{Y}^{nm}: U' \to [-1,0], \ddot{Y}^{nn}: U' \to [-1,0]$ represent the negative membership and non-membership functions. These functions satisfy $0 \le \ddot{Y}^{pm}(\tilde{u}) + \ddot{Y}^{pn}(\tilde{u}) \le 1$ and $-1 \le \ddot{Y}^{nm}(\tilde{u}) + \ddot{Y}^{nn}(\tilde{u}) \le 0$ for every $\tilde{u} \in U'$. The incompleteness associated with the positive evaluation is represented by the positive hesitation degree $\check{h}^{p}(\tilde{u}) = 1 - \left(\ddot{Y}^{pm}(\tilde{u}) + \ddot{Y}^{pn}(\tilde{u})\right)$, whereas the uncertainty corresponding to the negative evaluation is expressed by the negative hesitation degree $\check{h}^{n}(\tilde{u}) = -1 - \left(\ddot{Y}^{nm}(\tilde{u}) + \ddot{Y}^{nn}(\tilde{u})\right)$. For simplicity, a bipolar intuitionistic fuzzy number (BIFN) is represented as $\acute{K} = \left((\ddot{Y}^{pm}, \ddot{Y}^{pn}), (\ddot{Y}^{nm}, \ddot{Y}^{nn})\right)$.

Definition 5 [36]: Let $\acute{K}_1 = \{(\tilde{u}, (\ddot{Y}_1^{pm}(\tilde{u}), \ddot{Y}_1^{pn}(\tilde{u})), (\ddot{Y}_1^{nm}(\tilde{u}), \ddot{Y}_1^{nn}(\tilde{u}))) | \tilde{u} \in U'\}$ and $\acute{K}_2 = \{(\tilde{u}, (\ddot{Y}_2^{pm}(\tilde{u}), \ddot{Y}_2^{pn}(\tilde{u})), (\ddot{Y}_2^{nm}(\tilde{u}), \ddot{Y}_2^{nn}(\tilde{u}))) | \tilde{u} \in U'\}$ denote two BIFSs. Then

$$\acute{K}_1 \subseteq \acute{K}_2 \text{ if } \ddot{Y}_1^{pm}(\tilde{u}) \le \ddot{Y}_2^{pm}(\tilde{u}), \ddot{Y}_1^{pn}(\tilde{u}) \ge \ddot{Y}_2^{pn}(\tilde{u}), \ddot{Y}_1^{nm}(\tilde{u}) \le \ddot{Y}_2^{nm}(\tilde{u}), \ddot{Y}_1^{nn}(\tilde{u}) \ge \ddot{Y}_2^{nn}(\tilde{u}) \; \forall \; \tilde{u} \in U'$$

$$\acute{K}_1 = \acute{K}_2 \Leftrightarrow \acute{K}_1 \subseteq \acute{K}_2 \text{and} \acute{K}_2 \subseteq \acute{K}_1$$

$$\acute{K}_1 \cup \acute{K}_2 = \left\{\left(\begin{matrix}\tilde{t}, \left(\max\left(\ddot{Y}_1^{pm}(\tilde{u}), \ddot{Y}_2^{pm}(\tilde{u})\right), \min\left(\ddot{Y}_1^{pn}(\tilde{u}), \ddot{Y}_2^{pn}(\tilde{u})\right)\right), \\ \left(\max\left(\ddot{Y}_1^{nm}(\tilde{u}), \ddot{Y}_2^{nm}(\tilde{u})\right), \min\left(\ddot{Y}_1^{nn}(\tilde{u}), \ddot{Y}_2^{nn}(\tilde{u})\right)\right)\end{matrix}\right) | \tilde{u} \in U'\right\}$$

$$\acute{K}_1 \cap \acute{K}_2 = \left\{\left(\begin{matrix}\tilde{t}, \left(\min\left(\ddot{Y}_1^{pm}(\tilde{u}), \ddot{Y}_2^{pm}(\tilde{u})\right), \max\left(\ddot{Y}_1^{pn}(\tilde{u}), \ddot{Y}_2^{pn}(\tilde{u})\right)\right), \\ \left(\min\left(\ddot{Y}_1^{nm}(\tilde{u}), \ddot{Y}_2^{nm}(\tilde{u})\right), \max\left(\ddot{Y}_1^{nn}(\tilde{u}), \ddot{Y}_2^{nn}(\tilde{u})\right)\right)\end{matrix}\right) | \tilde{u} \in U'\right\}$$

$$\acute{K}_1^{c} = \left\{\left(\tilde{t}, \left(\ddot{Y}_1^{pn}(\tilde{u}), \ddot{Y}_1^{pm}(\tilde{u})\right), \left(\ddot{Y}_1^{nn}(\tilde{u}), \ddot{Y}_1^{nm}(\tilde{u})\right)\right) | \tilde{u} \in U'\right\}$$

Definition 6: Let $\acute{K}_1 = \left((\ddot{Y}_1^{pm}, \ddot{Y}_1^{pn}), (\ddot{Y}_1^{nm}, \ddot{Y}_1^{nn})\right)$ and $\acute{K}_2 = \left((\ddot{Y}_2^{pm}, \ddot{Y}_2^{pn}), (\ddot{Y}_2^{nm}, \ddot{Y}_2^{nn})\right)$ denote two BIFNs and $\Phi > 0$. Their operational rules are given below.

$$\acute{K}_1 \oplus \acute{K}_2 = \begin{pmatrix}\left(\ddot{Y}_1^{pm} + \ddot{Y}_2^{pm} - \ddot{Y}_1^{pm}\ddot{Y}_2^{pm}, \quad \ddot{Y}_1^{pn}\ddot{Y}_2^{pn}\right), \\ \left(-(\ddot{Y}_1^{nm}\ddot{Y}_2^{nm}), \quad \ddot{Y}_1^{nn} + \ddot{Y}_2^{nn} + \ddot{Y}_1^{nn}\ddot{Y}_2^{nn}\right)\end{pmatrix}$$

$$\acute{K}_1 \otimes \acute{K}_2 = \begin{pmatrix}\left(\ddot{Y}_1^{pm}\ddot{Y}_2^{pm}, \quad \ddot{Y}_1^{pn} + \ddot{Y}_2^{pn} - \ddot{Y}_1^{pn}\ddot{Y}_2^{pn}\right), \\ \left(\ddot{Y}_1^{nm} + \ddot{Y}_2^{nm} + \ddot{Y}_1^{nm}\ddot{Y}_2^{nm}, \quad -(\ddot{Y}_1^{nn}\ddot{Y}_2^{nn})\right)\end{pmatrix}$$

$$\Phi \odot \acute{K}_1 = \begin{pmatrix}\left(1 - \left(1 - \ddot{Y}_1^{pm}\right)^{\Phi}, \quad \left(\ddot{Y}_1^{pn}\right)^{\Phi}\right), \\ \left(-|\ddot{Y}_1^{nm}|^{\Phi}, \quad -1 + \left(1 + \ddot{Y}_1^{nn}\right)^{\Phi}\right)\end{pmatrix}$$

$$\acute{K}_1^{\Phi} = \begin{pmatrix}\left(\left(\ddot{Y}_1^{pm}\right)^{\Phi}, \quad 1 - \left(1 - \ddot{Y}_1^{pn}\right)^{\Phi}\right), \\ \left(-1 + \left(1 + \ddot{Y}_1^{nm}\right)^{\Phi}, \quad -|\ddot{Y}_1^{nn}|^{\Phi}\right)\end{pmatrix}$$

Definition 7: For ranking and discrimination purposes, each BIFN $\acute{K}_1 = \left((\ddot{Y}_1^{pm}, \ddot{Y}_1^{pn}), (\ddot{Y}_1^{nm}, \ddot{Y}_1^{nn})\right)$ is evaluated using its score and accuracy functions, which are defined as follows.

$$\delta\left(\acute{K}_1\right) = \frac{1}{4}\left(2 + \ddot{Y}_1^{pm} - \ddot{Y}_1^{pn} + \ddot{Y}_1^{nm} - \ddot{Y}_1^{nn}\right) \qquad (1)$$

$$\alpha\left(\acute{K}_1\right) = \frac{1}{4}\left(\ddot{Y}_1^{pm} + \ddot{Y}_1^{pn} - \ddot{Y}_1^{nm} - \ddot{Y}_1^{nn}\right) \qquad (2)$$

Definition 8: Consider a collection of $'n'$ BIFNs $\acute{K}_v = \left((\ddot{Y}_v^{pm}, \ddot{Y}_v^{pn}), (\ddot{Y}_v^{nm}, \ddot{Y}_v^{nn})\right)$, where $v = 1, 2, \cdots, n$, and let $w = (w_1, w_2, \cdots, w_n)^T$ be the weight vector such that $0 \le w_v \le 1$ and $\sum_{v=1}^{n} w_v = 1$. Then, the BIFWA operator is defined as

$$\begin{aligned}\text{BIFWA}\left(\acute{K}_1, \acute{K}_2, \cdots, \acute{K}_n\right) &= \oplus_{v=1}^{n} w_v \acute{K}_v \\ &= w_1\acute{K}_1 \oplus w_2\acute{K}_2 \oplus \cdots \oplus w_n\acute{K}_n\end{aligned}$$

$$\text{BIFWA}\left(\acute{K}_1, \acute{K}_2, \cdots, \acute{K}_n\right) = \begin{pmatrix}\left(1 - \prod_{v=1}^{n}(1 - \ddot{Y}_v^{pm})^{w_v}, \quad \prod_{v=1}^{n}(\ddot{Y}_v^{pn})^{w_v}\right), \\ \left(-\prod_{v=1}^{n}|\ddot{Y}_v^{nm}|^{w_v}, -1 + \prod_{v=1}^{n}(1 + \ddot{Y}_v^{nn})^{w_v}\right)\end{pmatrix} \qquad (3)$$

Definition 9: Consider a collection of $'n'$ BIFNs $\acute{K}_v = \left((\ddot{Y}_v^{pm}, \ddot{Y}_v^{pn}), (\ddot{Y}_v^{nm}, \ddot{Y}_v^{nn})\right)$, where $v = 1, 2, \cdots, n$, and let $w = (w_1, w_2, \cdots, w_n)^T$ be the weight vector such that $0 \le w_v \le 1$ and $\sum_{v=1}^{n} w_v = 1$. Then, the BIFWG operator is defined as

$$\begin{aligned}\mathrm{BIFWG}(\acute{\mathrm{K}}_1,\acute{\mathrm{K}}_2,\cdots,\acute{\mathrm{K}}_\eta) &= \otimes_{\nu=1}^{\eta}\acute{\mathrm{K}}_\nu{}^{\omega_\nu}\\ &= \acute{\mathrm{K}}_1{}^{\omega_1}\otimes\acute{\mathrm{K}}_2{}^{\omega_2}\otimes\cdots\otimes\acute{\mathrm{K}}_\eta{}^{\omega_\eta}\end{aligned}$$

$$\mathrm{BIFWG}(\acute{\mathrm{K}}_1,\acute{\mathrm{K}}_2,\cdots,\acute{\mathrm{K}}_\eta) = \begin{pmatrix}\left(\prod_{\nu=1}^{\eta}(\ddot{\mathrm{Y}}_\nu^{\flat\eta})^{\omega_\nu}, 1-\prod_{\nu=1}^{\eta}(1-\ddot{\mathrm{Y}}_\nu^{\flat\eta})^{\omega_\nu}\right),\\ \left(-1+\prod_{\nu=1}^{\eta}(1+\ddot{\mathrm{Y}}_\nu^{\eta\eta})^{\omega_\nu}, -\prod_{\nu=1}^{\eta}|\ddot{\mathrm{Y}}_\nu^{\eta\eta}|^{\omega_\nu}\right)\end{pmatrix} \quad (4)$$

5. BIF-BWM-MAIRCA Framework for Multi-Criteria Group Decision-Making

This section presents the proposed BIF-BWM-MAIRCA framework for solving MCGDM problems under a bipolar intuitionistic fuzzy environment. The proposed methodology enables the simultaneous consideration of positive and negative evaluations while effectively addressing the uncertainty inherent in experts' judgments. Consider an MCGDM problem involving a set of alternatives $\ddot{\alpha} = \{\ddot{\alpha}_1, \ddot{\alpha}_2, \cdots, \ddot{\alpha}_k\}$ and a set of criteria $\epsilon = \{\epsilon_1, \epsilon_2, \cdots, \epsilon_l\}$. The relative importance of the evaluation criteria is represented by the normalized weight vector $\omega = (\omega_1, \omega_2, \cdots, \omega_l)^T$, where $\omega_j \geq 0\ (j = 1,2,\cdots,l)$ and $\sum_{j=1}^{l}\omega_j = 1$. The evaluation is performed by a panel of $\dot{\varphi} = \{\dot{\varphi}^{(1)}, \dot{\varphi}^{(2)}, \cdots, \dot{\varphi}^{(\chi)}\}$ decision experts, each of whom independently assesses the performance of every alternative with respect to each evaluation criterion. The assessment provided by expert $\dot{\varphi}^{(\acute{z})}$ for alternative $\ddot{\alpha}_i$ under criterion ϵ_j is expressed directly as a BIFN, denoted by $\acute{\mathrm{K}}_{ij}^{(\acute{z})} = \left(\left(\ddot{\mathrm{Y}}_{ij}^{\flat\eta(\acute{z})}, \ddot{\mathrm{Y}}_{ij}^{\flat\eta(\acute{z})}\right), \left(\ddot{\mathrm{Y}}_{ij}^{\eta\eta(\acute{z})}, \ddot{\mathrm{Y}}_{ij}^{\eta\eta(\acute{z})}\right)\right)$. The following steps present the detailed computational procedure of the proposed BIF-BWM-MAIRCA methodology.

Step 1: Construct individual BIF decision matrices $\dot{\mathrm{M}}^{(\acute{z})} = \left(\acute{\mathrm{K}}_{ij}^{(\acute{z})}\right)_{k\times l}$ corresponding to each expert as:

$$\dot{\mathrm{M}}^{(\acute{z})} = \begin{array}{c} \\ \ddot{\alpha}_1 \\ \vdots \\ \ddot{\alpha}_k \end{array}\begin{array}{c} \begin{array}{ccc}\epsilon_1 & \cdots & \epsilon_l\end{array} \\ \begin{pmatrix}\acute{\mathrm{K}}_{11}^{(\acute{z})} & \cdots & \acute{\mathrm{K}}_{1l}^{(\acute{z})}\\ \vdots & \ddots & \vdots\\ \acute{\mathrm{K}}_{k1}^{(\acute{z})} & \cdots & \acute{\mathrm{K}}_{kl}^{(\acute{z})}\end{pmatrix}\end{array}$$

Step 2: Normalize the individual BIF decision matrices according to the criterion type (benefit or cost) as follows:

$$\acute{\mathrm{K}}_{ij}^{(\acute{z})} = \begin{cases}\left(\left(\ddot{\mathrm{Y}}_{ij}^{\flat\eta(\acute{z})}, \ddot{\mathrm{Y}}_{ij}^{\flat\eta(\acute{z})}\right), \left(\ddot{\mathrm{Y}}_{ij}^{\eta\eta(\acute{z})}, \ddot{\mathrm{Y}}_{ij}^{\eta\eta(\acute{z})}\right)\right) & ; \quad \text{if } \epsilon_j \text{ is of the benefit type}\\ \left(\left(\ddot{\mathrm{Y}}_{ij}^{\flat\eta(\acute{z})}, \ddot{\mathrm{Y}}_{ij}^{\flat\eta(\acute{z})}\right), \left(\ddot{\mathrm{Y}}_{ij}^{\eta\eta(\acute{z})}, \ddot{\mathrm{Y}}_{ij}^{\eta\eta(\acute{z})}\right)\right) & ; \quad \text{if } \epsilon_j \text{ is of the cost type}\end{cases}$$

Step 3: The normalized individual decision matrices $\dot{\mathrm{M}}^{(\acute{z})} = \left(\acute{\mathrm{K}}_{ij}^{(\acute{z})}\right)_{k\times l}$ are combined into a normalized collective BIF decision matrix $\dot{\mathrm{M}} = \left(\acute{\mathrm{K}}_{ij}\right)_{k\times l}$ using the BIFWA operator (Definition 8):

$$\acute{\mathrm{K}}_{ij} = \mathrm{BIFWA}\left(\acute{\mathrm{K}}_{ij}^{(1)}, \acute{\mathrm{K}}_{ij}^{(2)}, \cdots, \acute{\mathrm{K}}_{ij}^{(\chi)}\right) = \begin{pmatrix}\left(1-\prod_{\acute{z}=1}^{\chi}\left(1-\ddot{\mathrm{Y}}_{ij}^{\flat\eta(\acute{z})}\right)^{\bar{\omega}_{\acute{z}}}, \prod_{\acute{z}=1}^{\chi}\left(\ddot{\mathrm{Y}}_{ij}^{\flat\eta(\acute{z})}\right)^{\bar{\omega}_{\acute{z}}}\right),\\ \left(-\prod_{\acute{z}=1}^{\chi}\left|\ddot{\mathrm{Y}}_{ij}^{\eta\eta(\acute{z})}\right|^{\bar{\omega}_{\acute{z}}}, -1+\prod_{\acute{z}=1}^{\chi}\left(1+\ddot{\mathrm{Y}}_{ij}^{\eta\eta(\acute{z})}\right)^{\bar{\omega}_{\acute{z}}}\right)\end{pmatrix}$$

The associated expert weight vector $\bar{\omega} = \left(\bar{\omega}_1, \bar{\omega}_2, \cdots, \bar{\omega}_\chi\right)^T$ is determined using the normal distribution-based weighting scheme [37] given in equation (5). The resulting collective decision matrix serves as the basis for the subsequent stages of the proposed decision-making framework.

$$\bar{\omega}_{\acute{z}} = \frac{\exp\left[-\frac{\left(\acute{z}-\frac{\chi+1}{2}\right)^2}{2\ddot{\theta}_1^2}\right]}{\sum_{\acute{z}=1}^{\chi}\exp\left[-\frac{\left(z-\frac{\chi+1}{2}\right)^2}{2\ddot{\theta}_1^2}\right]} \quad \text{where, } \ddot{\theta}_1 = \sqrt{\frac{1}{\chi}\sum_{\acute{z}=1}^{\chi}\left(\acute{z}-\frac{\chi+1}{2}\right)^2} \quad (5)$$

Step 4: Determine the criteria weights using the BWM. The computational procedure is summarized as follows.

Step 4.1: Assume that the decision problem consists of v evaluation criteria represented by $\epsilon = (\epsilon_1, \epsilon_2, \cdots, \epsilon_l)$. These criteria constitute the basis for evaluating the available alternatives.

Step 4.2: Decision-makers identify the most important (best) and least important (worst) criteria based on their knowledge and experience. Let ϵ_b and ϵ_w denote the best and worst criteria, respectively.

Step 4.3: The best criterion is compared with each of the other criteria using a 1–9 preference scale, where 1 denotes equal importance, and 9 denotes extreme preference. These comparisons produce the Best-to-Others preference vector:

$$\hbar_b = (\mathfrak{t}_{b1}, \mathfrak{t}_{b2}, \cdots, \mathfrak{t}_{bl})$$

where $\mathfrak{t}_{bj}$ expresses the degree to which the best criterion ϵ_b is preferred over criterion ϵ_j. Clearly, $\mathfrak{t}_{bb} = 1$.

Step 4.4: Each criterion is then compared with the worst criterion using the same preference scale. The resulting Others-to-Worst preference vector is expressed as

$$\hbar_w = (\mathfrak{t}_{1w}, \mathfrak{t}_{2w}, \cdots, \mathfrak{t}_{lw})^T$$

where $\mathfrak{t}_{jw}$ represents the preference intensity of criterion ϵ_j over the worst criterion ϵ_w. Clearly, $\mathfrak{t}_{ww} = 1$.

Step 4.5: Let $\omega = (\omega_1, \omega_2, \cdots, \omega_l)^T$ denote the unknown weight vector of the criteria, where $\omega_j \geq 0$ and $\sum_{j=1}^{l}\omega_j = 1$. Ideally, the weight ratios should satisfy

$$\frac{\omega_b}{\omega_j} = \mathfrak{t}_{bj} \quad \text{and} \quad \frac{\omega_j}{\omega_w} = \mathfrak{t}_{jw}$$

Since perfect consistency is seldom achieved in practice, the optimal weights are obtained by minimizing the maximum absolute deviation between the elicited preference values and the corresponding weight ratios. The optimization model is formulated as

Minimize: $\mathfrak{q}$

Subject to:

$$\left|\frac{\omega_b}{\omega_j} - \mathfrak{t}_{bj}\right| \leq \mathfrak{q}\ \forall\, j,$$

$$\left|\frac{\mathrm{w}_j}{\mathrm{w}_w} - \mathrm{t}_{jw}\right| \leq \mathrm{q}\ \forall\, j,$$

$$\mathrm{w}_j \geq 0\ \forall\, j,$$

$$\sum_{j=1}^{l} \mathrm{w}_j = 1.$$

Step 4.6: To simplify the computation, the nonlinear model can be approximated by the following linear optimization model, which yields a unique solution:

Min: q

Subject to:

$$\left|\mathrm{w}_b - \mathrm{t}_{bj}\mathrm{w}_j\right| \leq \mathrm{q}\ \forall\, j,$$

$$\left|\mathrm{w}_j - \mathrm{t}_{jw}\mathrm{w}_w\right| \leq \mathrm{q}\ \forall\, j,$$

$$\mathrm{w}_j \geq 0\ \forall\, j,$$

$$\sum_{j=1}^{l} \mathrm{w}_j = 1.$$

The solution of this optimization model provides the optimal normalized weights for all evaluation criteria together with the minimum inconsistency value q, where a smaller value indicates more consistent comparisons.

Step 5: Construct the theoretical preference matrix, which represents the expected performance of each alternative under the assumption that all alternatives have an equal a priori probability of selection. Accordingly, the theoretical preference assigned to alternative $\ddot{\alpha}_i$ is calculated as

$$\dot{\mathrm{P}}_{\ddot{\alpha}_i} = \frac{1}{k}\ , i = 1, 2, \ldots k$$

such that

$$\sum_{i=1}^{k} \dot{\mathrm{P}}_{\ddot{\alpha}_i} = 1.$$

Subsequently, the theoretical preference matrix $\dot{\mathrm{T}}_{\mathrm{p}} = \left(\mathrm{t}_{ij}\right)_{k\times l}$ is established by multiplying these a priori preferences by the BWM-derived criterion weights:

$$\mathrm{t}_{ij} = \dot{\mathrm{P}}_{\ddot{\alpha}_i} \times \mathrm{w}_j$$

where w_j is the BWM-derived weight of criterion ϵ_j. The resulting matrix serves as the theoretical benchmark for evaluating the real performance of the alternatives in the subsequent stages of the proposed BIF-BWM-MAIRCA approach.

Step 6: Construct the real BIF evaluation matrix by combining the normalized collective BIF decision matrix with the theoretical preference matrix. Specifically, multiply each normalized collective BIFN by its corresponding theoretical preference value using the BIF scalar multiplication operation (Definition 6). The real evaluation matrix is therefore expressed as

$$\bar{\mathrm{R}} = \left(\bar{\mathrm{r}}_{ij}\right)_{k\times l}$$

where

$$\bar{\mathrm{r}}_{ij} = \mathrm{t}_{ij} \odot \acute{\mathrm{K}}_{ij}$$

for $(i = 1, 2, \cdots, k)$ and $(j = 1, 2, \cdots, l)$, where t_{ij} denotes the theoretical preference value, $\acute{\mathrm{K}}_{ij}$ represents the normalized collective BIF evaluation, and $\odot$ is the BIF scalar multiplication operator defined in Definition 6. The resulting matrix reflects each alternative's real performance across every evaluation criterion in the BIF environment.

Step 7: Next, compute the score of each element in the real BIF evaluation matrix using equation (1). The gap matrix is then established by computing the absolute difference between the theoretical preference value and the score of the real BIF evaluation. Accordingly, the gap value associated with alternative $\ddot{\alpha}_i$ under criterion ϵ_j is calculated as

$$\mathrm{g}_{ij} = \left|\mathrm{t}_{ij} - \delta\left(\bar{\mathrm{r}}_{ij}\right)\right|$$

where t_{ij} denotes the theoretical preference value and $\delta\left(\bar{\mathrm{r}}_{ij}\right)$ represents the score of the corresponding real BIF evaluation. The resulting gap matrix is expressed as

$$\mathrm{G} = \left(\mathrm{g}_{ij}\right)_{k\times l}$$

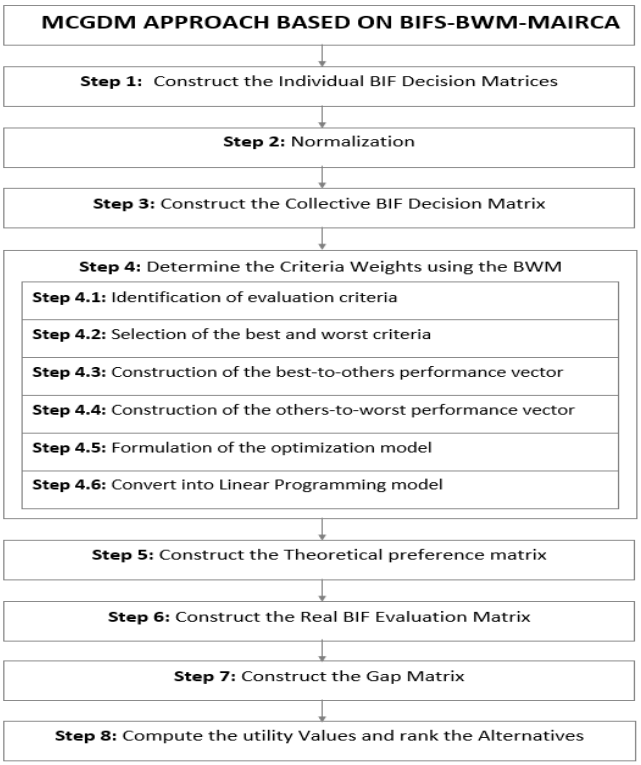


Fig. 1: Flowchart of the proposed BIF-BWM-MAIRCA MCGDM methodology.

Step 8: Obtain the overall utility value of each alternative by summing its gap values across all evaluation criteria. The utility value of alternative $\ddot{\alpha}_i$ is calculated as

$$q_i = \sum_{j=1}^{l} g_{ij}$$

Finally, the alternatives are ranked in ascending order of their utility values. The alternative with the smallest utility value is considered the most desirable, as it exhibits the minimum distance from the theoretical ideal solution. Figure 2 illustrates the computational workflow of the proposed BIF-BWM-MAIRCA methodology.

6. Case Study: Neuromorphic AI Chip Selection for Edge Intelligence Applications

The rapid growth of edge AI has created increasing demand for computing platforms capable of executing intelligent tasks with high computational efficiency and minimal energy consumption. Conventional CPU- and GPU-based accelerators often struggle to satisfy the stringent power, latency, and real-time processing requirements of autonomous edge devices. Inspired by the biological nervous system, neuromorphic AI chips have emerged as an appealing solution because they are event-driven, massively parallel, and highly energy-efficient. These characteristics make them particularly suitable for autonomous robots, intelligent sensors, wearable healthcare devices, unmanned aerial vehicles, industrial automation, and Internet of Things (IoT) applications. Despite these benefits, the available neuromorphic processors differ significantly in hardware architecture, learning capability, scalability, software ecosystem, and deployment efficiency. Consequently, selecting the most appropriate neuromorphic AI chip is a complex MCGDM problem involving multiple conflicting evaluation criteria and uncertain expert judgments. To address this issue, the proposed BIF-BWM-MAIRCA framework is employed to identify the most suitable neuromorphic AI platform.

A committee of three domain experts independently evaluates eight neuromorphic AI chips with respect to five benefit-type criteria using BIFNs. The criterion weights are first determined using BWM, after which the MAIRCA method is used to obtain the final ranking of the candidate chips. The candidate neuromorphic AI chips considered in the evaluation are described in Table 1.

Table 1: Description of the neuromorphic AI chip alternatives considered in the case study.

Alternatives	Description
$\breve{\alpha}_1$	A high-performance neuromorphic processor emphasizing large-scale parallel processing and efficient implementation of complex spiking neural networks for real-time artificial intelligence applications.
$\breve{\alpha}_2$	A memory-centric neuromorphic computing platform that integrates processing and memory resources to reduce inference latency and improve energy efficiency in AI workloads.
$\breve{\alpha}_3$	A low-power neuromorphic processor developed for embedded intelligence, enabling adaptive event-driven computation in resource-constrained applications.
$\breve{\alpha}_4$	A scalable neuromorphic computing architecture capable of running large neural network models through distributed parallel processing for advanced cognitive applications.
$\breve{\alpha}_5$	An ultra-low-power neuromorphic processor specifically designed for continuous sensing, intelligent perception, and always-on edge AI applications.
$\breve{\alpha}_6$	A compact intelligent processor designed for battery-powered applications that demand rapid response, efficient learning, and real-time intelligent decision-making.
$\breve{\alpha}_7$	A vision-oriented neuromorphic platform that uses event-driven computation for real-time object recognition and scene understanding.
$\breve{\alpha}_8$	A next-generation neuromorphic computing architecture that delivers energy-efficient, scalable, reliable, and balanced computational performance across a range of intelligent edge systems.

The alternatives are evaluated using the following five benefit-type criteria, for which a higher assessment value indicates better performance. The evaluation criteria considered in the neuromorphic AI chip selection process are presented in Table 2.

Table 2: Evaluation criteria and their descriptions for neuromorphic AI chip selection.

Symbol	Criterion	Description
ϵ_1	Reliability and Robustness	Reliability refers to the processor's ability to perform consistently under different operating conditions, environmental disturbances, and long-term deployment. Robust neuromorphic processors exhibit stable and predictable computational behaviour and tolerance to hardware and communication faults, enabling reliable operation in mission-critical applications.
ϵ_2	Computational Performance	This criterion assesses the ability of the neuromorphic processor to execute complex spiking neural network models and AI inference. It indicates the processor's capability to deliver high throughput, low latency, and efficient parallel computing in real deployment scenarios. Chips with superior computational performance can handle more sophisticated AI workloads while maintaining real-time responsiveness.
ϵ_3	Learning and	This criterion assesses the processor's capability to support adaptive intelligence through online

	Adaptability	learning, synaptic plasticity, and efficient implementation of spiking neural network algorithms. Neuromorphic chips that can learn and adapt dynamically are better suited to intelligent systems operating in uncertain and continuously changing environments.
ϵ_4	Scalability and System Integration	Scalability and integration indicate how easily the neuromorphic processor can be integrated into existing edge computing architectures and scaled up to support increasingly complex applications. This criterion covers hardware compatibility, software ecosystem maturity, communication interfaces, and deployment flexibility across heterogeneous intelligent systems.
ϵ_5	Energy Efficiency	Energy efficiency is the ability of the neuromorphic processor to perform intelligent computations with minimal energy consumption. Because many edge AI systems have limited battery capacity or tight energy budgets, processors with lower power consumption extend battery life, reduce heat dissipation, and support environmentally sustainable deployment.

To provide a comprehensive evaluation, the decision-making committee comprises three experts with complementary expertise in artificial intelligence, neuromorphic computing, and embedded intelligent systems. The expertise and assessment perspectives of the participating experts are presented in Table 3.

Table 2. Profiles of the decision-making experts involved in the evaluation process.

Expert	Specialization	Professional Profile	Assessment Perspective
$\varphi^{(1)}$	Neuromorphic Computing	An experienced researcher with expertise in brain-inspired computing architectures, spiking neural networks, and neuromorphic processor technologies.	Assesses computational capability, learning mechanisms, and processing speed.
$\varphi^{(2)}$	Embedded AI and Edge Computing	An expert in embedded intelligent systems with hands-on experience in low-power AI hardware and edge computing applications.	Evaluates energy efficiency, hardware deployment and system integration.
$\varphi^{(3)}$	Computer Architecture and Intelligent Hardware	An expert in advanced processor architecture design, parallel computing, and AI hardware optimization.	Analyzes scalability, operational reliability, architectural robustness, and overall system performance.

Step 1: Each expert independently evaluates the candidate neuromorphic AI chips with respect to the selected criteria using BIFNs. The resulting individual decision matrices represent the initial assessment information provided by the experts. The individual assessment provided by Expert 1 is presented in Table 4.

Table 3: BIF decision matrix of Expert 1.

	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
$\breve{\alpha}_1$	$\begin{pmatrix}(0.34,0.54),\\(-0.65,-0.21)\end{pmatrix}$	$\begin{pmatrix}(0.87,0.12),\\(-0.46,-0.51)\end{pmatrix}$	$\begin{pmatrix}(0.23,0.65),\\(-0.65,-0.16)\end{pmatrix}$	$\begin{pmatrix}(0.37,0.51),\\(-0.54,-0.31)\end{pmatrix}$	$\begin{pmatrix}(0.24,0.56),\\(-0.26,-0.58)\end{pmatrix}$
$\breve{\alpha}_2$	$\begin{pmatrix}(0.65,0.29),\\(-0.24,-0.56)\end{pmatrix}$	$\begin{pmatrix}(0.45,0.49),\\(-0.65,-0.23)\end{pmatrix}$	$\begin{pmatrix}(0.38,0.54),\\(-0.34,-0.63)\end{pmatrix}$	$\begin{pmatrix}(0.81,0.17),\\(-0.28,-0.61)\end{pmatrix}$	$\begin{pmatrix}(0.54,0.43),\\(-0.62,-0.31)\end{pmatrix}$
$\breve{\alpha}_3$	$\begin{pmatrix}(0.39,0.55),\\(-0.72,-0.24)\end{pmatrix}$	$\begin{pmatrix}(0.07,0.87),\\(-0.39,-0.45)\end{pmatrix}$	$\begin{pmatrix}(0.91,0.04),\\(-0.63,-0.34)\end{pmatrix}$	$\begin{pmatrix}(0.39,0.56),\\(-0.76,-0.21)\end{pmatrix}$	$\begin{pmatrix}(0.26,0.67),\\(-0.45,-0.51)\end{pmatrix}$
$\breve{\alpha}_4$	$\begin{pmatrix}(0.57,0.32),\\(-0.28,-0.65)\end{pmatrix}$	$\begin{pmatrix}(0.45,0.53),\\(-0.27,-0.56)\end{pmatrix}$	$\begin{pmatrix}(0.32,0.51),\\(-0.71,-0.24)\end{pmatrix}$	$\begin{pmatrix}(0.26,0.67),\\(-0.42,-0.51)\end{pmatrix}$	$\begin{pmatrix}(0.74,0.21),\\(-0.29,-0.39)\end{pmatrix}$
$\breve{\alpha}_5$	$\begin{pmatrix}(0.72,0.15),\\(-0.09,-0.67)\end{pmatrix}$	$\begin{pmatrix}(0.65,0.34),\\(-0.63,-0.23)\end{pmatrix}$	$\begin{pmatrix}(0.71,0.18),\\(-0.41,-0.51)\end{pmatrix}$	$\begin{pmatrix}(0.79,0.11),\\(-0.61,-0.32)\end{pmatrix}$	$\begin{pmatrix}(0.07,0.76),\\(-0.74,-0.08)\end{pmatrix}$
$\breve{\alpha}_6$	$\begin{pmatrix}(0.43,0.21),\\(-0.46,-0.49)\end{pmatrix}$	$\begin{pmatrix}(0.52,0.32),\\(-0.71,-0.21)\end{pmatrix}$	$\begin{pmatrix}(0.28,0.65),\\(-0.38,-0.47)\end{pmatrix}$	$\begin{pmatrix}(0.61,0.21),\\(-0.65,-0.23)\end{pmatrix}$	$\begin{pmatrix}(0.56,0.41),\\(-0.48,-0.42)\end{pmatrix}$
$\breve{\alpha}_7$	$\begin{pmatrix}(0.09,0.56),\\(-0.37,-0.58)\end{pmatrix}$	$\begin{pmatrix}(0.71,0.21),\\(-0.56,-0.32)\end{pmatrix}$	$\begin{pmatrix}(0.78,0.21),\\(-0.51,-0.27)\end{pmatrix}$	$\begin{pmatrix}(0.07,0.67),\\(-0.45,-0.48)\end{pmatrix}$	$\begin{pmatrix}(0.49,0.42),\\(-0.71,-0.28)\end{pmatrix}$
$\breve{\alpha}_8$	$\begin{pmatrix}(0.76,0.13),\\(-0.23,-0.56)\end{pmatrix}$	$\begin{pmatrix}(0.35,0.56),\\(-0.29,-0.59)\end{pmatrix}$	$\begin{pmatrix}(0.29,0.54),\\(-0.29,-0.45)\end{pmatrix}$	$\begin{pmatrix}(0.51,0.34),\\(-0.35,-0.51)\end{pmatrix}$	$\begin{pmatrix}(0.52,0.35),\\(-0.38,-0.51)\end{pmatrix}$

The individual assessment provided by Expert 2 is summarized in Table 5.

Table 4: BIF decision matrix of Expert 2.

	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
$\breve{\alpha}_1$	$\begin{pmatrix}(0.36,0.43),\\(-0.34,-0.56)\end{pmatrix}$	$\begin{pmatrix}(0.56,0.32),\\(-0.42,-0.44)\end{pmatrix}$	$\begin{pmatrix}(0.45,0.32),\\(-0.48,-0.12)\end{pmatrix}$	$\begin{pmatrix}(0.32,0.62),\\(-0.72,-0.22)\end{pmatrix}$	$\begin{pmatrix}(0.38,0.52),\\(-0.42,-0.43)\end{pmatrix}$
$\breve{\alpha}_2$	$\begin{pmatrix}(0.67,0.23),\\(-0.45,-0.51)\end{pmatrix}$	$\begin{pmatrix}(0.31,0.62),\\(-0.61,-0.36)\end{pmatrix}$	$\begin{pmatrix}(0.71,0.21),\\(-0.91,-0.03)\end{pmatrix}$	$\begin{pmatrix}(0.59,0.41),\\(-0.48,-0.52)\end{pmatrix}$	$\begin{pmatrix}(0.51,0.41),\\(-0.39,-0.42)\end{pmatrix}$
$\breve{\alpha}_3$	$\begin{pmatrix}(0.08,0.67),\\(-0.42,-0.19)\end{pmatrix}$	$\begin{pmatrix}(0.07,0.67),\\(-0.37,-0.55)\end{pmatrix}$	$\begin{pmatrix}(0.38,0.32),\\(-0.72,-0.22)\end{pmatrix}$	$\begin{pmatrix}(0.39,0.53),\\(-0.62,-0.31)\end{pmatrix}$	$\begin{pmatrix}(0.31,0.52),\\(-0.07,-0.78)\end{pmatrix}$

$\breve{\alpha}_4$	$\begin{pmatrix}(0.19,0.56),\\(-0.52,-0.32)\end{pmatrix}$	$\begin{pmatrix}(0.35,0.46),\\(-0.81,-0.13)\end{pmatrix}$	$\begin{pmatrix}(0.09,0.69),\\(-0.56,-0.32)\end{pmatrix}$	$\begin{pmatrix}(0.05,0.86),\\(-0.71,-0.21)\end{pmatrix}$	$\begin{pmatrix}(0.52,0.37),\\(-0.51,-0.32)\end{pmatrix}$
$\breve{\alpha}_5$	$\begin{pmatrix}(0.65,0.32),\\(-0.69,-0.22)\end{pmatrix}$	$\begin{pmatrix}(0.92,0.03),\\(-0.92,-0.03)\end{pmatrix}$	$\begin{pmatrix}(0.53,0.32),\\(-0.28,-0.62)\end{pmatrix}$	$\begin{pmatrix}(0.72,0.22),\\(-0.88,-0.11)\end{pmatrix}$	$\begin{pmatrix}(0.75,0.21),\\(-0.82,-0.13)\end{pmatrix}$
$\breve{\alpha}_6$	$\begin{pmatrix}(0.41,0.48),\\(-0.81,-0.17)\end{pmatrix}$	$\begin{pmatrix}(0.27,0.45),\\(-0.42,-0.46)\end{pmatrix}$	$\begin{pmatrix}(0.37,0.61),\\(-0.41,-0.56)\end{pmatrix}$	$\begin{pmatrix}(0.61,0.27),\\(-0.06,-0.92)\end{pmatrix}$	$\begin{pmatrix}(0.28,0.54),\\(-0.17,-0.72)\end{pmatrix}$
$\breve{\alpha}_7$	$\begin{pmatrix}(0.93,0.05),\\(-0.31,-0.52)\end{pmatrix}$	$\begin{pmatrix}(0.61,0.32),\\(-0.12,-0.76)\end{pmatrix}$	$\begin{pmatrix}(0.71,0.28),\\(-0.23,-0.37)\end{pmatrix}$	$\begin{pmatrix}(0.21,0.65),\\(-0.62,-0.31)\end{pmatrix}$	$\begin{pmatrix}(0.19,0.43),\\(-0.37,-0.51)\end{pmatrix}$
$\breve{\alpha}_8$	$\begin{pmatrix}(0.04,0.57),\\(-0.82,-0.13)\end{pmatrix}$	$\begin{pmatrix}(0.34,0.51),\\(-0.64,-0.33)\end{pmatrix}$	$\begin{pmatrix}(0.52,0.42),\\(-0.51,-0.24)\end{pmatrix}$	$\begin{pmatrix}(0.81,0.11),\\(-0.72,-0.24)\end{pmatrix}$	$\begin{pmatrix}(0.92,0.04),\\(-0.71,-0.21)\end{pmatrix}$

The BIF assessments provided by Expert 3 are summarized in Table 6.

Table 5: BIF decision matrix of Expert 3.

	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
$\breve{\alpha}_1$	$\begin{pmatrix}(0.38,0.42),\\(-0.27,-0.32)\end{pmatrix}$	$\begin{pmatrix}(0.72,0.22),\\(-0.46,-0.33)\end{pmatrix}$	$\begin{pmatrix}(0.52,0.42),\\(-0.53,-0.25)\end{pmatrix}$	$\begin{pmatrix}(0.28,0.42),\\(-0.33,-0.51)\end{pmatrix}$	$\begin{pmatrix}(0.39,0.35),\\(-0.67,-0.28)\end{pmatrix}$
$\breve{\alpha}_2$	$\begin{pmatrix}(0.65,0.13),\\(-0.42,-0.24)\end{pmatrix}$	$\begin{pmatrix}(0.43,0.39),\\(-0.64,-0.35)\end{pmatrix}$	$\begin{pmatrix}(0.63,0.24),\\(-0.23,-0.52)\end{pmatrix}$	$\begin{pmatrix}(0.31,0.42),\\(-0.43,-0.39)\end{pmatrix}$	$\begin{pmatrix}(0.46,0.28),\\(-0.41,-0.25)\end{pmatrix}$
$\breve{\alpha}_3$	$\begin{pmatrix}(0.34,0.56),\\(-0.15,-0.62)\end{pmatrix}$	$\begin{pmatrix}(0.25,0.46),\\(-0.38,-0.44)\end{pmatrix}$	$\begin{pmatrix}(0.42,0.34),\\(-0.52,-0.11)\end{pmatrix}$	$\begin{pmatrix}(0.62,0.31),\\(-0.42,-0.44)\end{pmatrix}$	$\begin{pmatrix}(0.72,0.12),\\(-0.37,-0.42)\end{pmatrix}$
$\breve{\alpha}_4$	$\begin{pmatrix}(0.67,0.26),\\(-0.41,-0.35)\end{pmatrix}$	$\begin{pmatrix}(0.53,0.32),\\(-0.29,-0.43)\end{pmatrix}$	$\begin{pmatrix}(0.51,0.33),\\(-0.29,-0.48)\end{pmatrix}$	$\begin{pmatrix}(0.45,0.23),\\(-0.17,-0.64)\end{pmatrix}$	$\begin{pmatrix}(0.43,0.38),\\(-0.82,-0.04)\end{pmatrix}$
$\breve{\alpha}_5$	$\begin{pmatrix}(0.19,0.42),\\(-0.31,-0.62)\end{pmatrix}$	$\begin{pmatrix}(0.79,0.21),\\(-0.81,-0.12)\end{pmatrix}$	$\begin{pmatrix}(0.37,0.42),\\(-0.39,-0.27)\end{pmatrix}$	$\begin{pmatrix}(0.42,0.16),\\(-0.28,-0.53)\end{pmatrix}$	$\begin{pmatrix}(0.63,0.26),\\(-0.28,-0.37)\end{pmatrix}$
$\breve{\alpha}_6$	$\begin{pmatrix}(0.32,0.52),\\(-0.52,-0.24)\end{pmatrix}$	$\begin{pmatrix}(0.49,0.34),\\(-0.33,-0.52)\end{pmatrix}$	$\begin{pmatrix}(0.22,0.56),\\(-0.42,-0.48)\end{pmatrix}$	$\begin{pmatrix}(0.53,0.32),\\(-0.42,-0.36)\end{pmatrix}$	$\begin{pmatrix}(0.37,0.36),\\(-0.27,-0.62)\end{pmatrix}$
$\breve{\alpha}_7$	$\begin{pmatrix}(0.26,0.35),\\(-0.46,-0.53)\end{pmatrix}$	$\begin{pmatrix}(0.5,0.36),\\(-0.53,-0.21)\end{pmatrix}$	$\begin{pmatrix}(0.36,0.42),\\(-0.28,-0.36)\end{pmatrix}$	$\begin{pmatrix}(0.66,0.34),\\(-0.67,-0.24)\end{pmatrix}$	$\begin{pmatrix}(0.62,0.25),\\(-0.63,-0.22)\end{pmatrix}$
$\breve{\alpha}_8$	$\begin{pmatrix}(0.53,0.27),\\(-0.31,-0.32)\end{pmatrix}$	$\begin{pmatrix}(0.34,0.24),\\(-0.54,-0.32)\end{pmatrix}$	$\begin{pmatrix}(0.51,0.23),\\(-0.17,-0.42)\end{pmatrix}$	$\begin{pmatrix}(0.43,0.21),\\(-0.12,-0.54)\end{pmatrix}$	$\begin{pmatrix}(0.27,0.53),\\(-0.47,-0.48)\end{pmatrix}$

Step 2: As all evaluation criteria are of the benefit type, the original BIF decision information is retained, and no additional normalization is required.

Step 3: The weight of each expert is determined using the normal distribution-based weighting scheme in equation (5), which yields the normalized expert weight vector $\bar{\mathfrak{w}} = (0.2429, 0.5142, 0.2429)^T$. The individual BIF decision matrices are then aggregated using the BIFWA operator (Definition 8) with these expert weights. This process yields a normalized collective BIF decision matrix that reflects the overall consensus of the expert panel and provides the decision information required for the subsequent BWM-MAIRCA stages. The resulting collective decision matrix is presented in Table 7.

Table 6. Normalized aggregated BIF decision matrix for neuromorphic AI chip evaluation.

	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
$\breve{\alpha}_1$	$\begin{pmatrix}(0.360,\\0.452)\end{pmatrix},\begin{pmatrix}(-0.376,\\-0.436)\end{pmatrix}$	$\begin{pmatrix}(0.707,\\0.230)\end{pmatrix},\begin{pmatrix}(-0.439,\\-0.434)\end{pmatrix}$	$\begin{pmatrix}(0.423,\\0.406)\end{pmatrix},\begin{pmatrix}(-0.529,\\-0.163)\end{pmatrix}$	$\begin{pmatrix}(0.323,\\0.538)\end{pmatrix},\begin{pmatrix}(-0.556,\\-0.324)\end{pmatrix}$	$\begin{pmatrix}(0.351,\\0.481)\end{pmatrix},\begin{pmatrix}(-0.419,\\-0.440)\end{pmatrix}$
$\breve{\alpha}_2$	$\begin{pmatrix}(0.660,\\0.212)\end{pmatrix},\begin{pmatrix}(-0.380,\\-0.469)\end{pmatrix}$	$\begin{pmatrix}(0.377,\\0.523)\end{pmatrix},\begin{pmatrix}(-0.627,\\-0.328)\end{pmatrix}$	$\begin{pmatrix}(0.630,\\0.273)\end{pmatrix},\begin{pmatrix}(-0.513,\\-0.353)\end{pmatrix}$	$\begin{pmatrix}(0.614,\\0.333)\end{pmatrix},\begin{pmatrix}(-0.410,\\-0.516)\end{pmatrix}$	$\begin{pmatrix}(0.506,\\0.378)\end{pmatrix},\begin{pmatrix}(-0.442,\\-0.356)\end{pmatrix}$
$\breve{\alpha}_3$	$\begin{pmatrix}(0.232,\\0.611)\end{pmatrix},\begin{pmatrix}(-0.373,\\-0.336)\end{pmatrix}$	$\begin{pmatrix}(0.117,\\0.652)\end{pmatrix},\begin{pmatrix}(-0.377,\\-0.502)\end{pmatrix}$	$\begin{pmatrix}(0.618,\\0.196)\end{pmatrix},\begin{pmatrix}(-0.644,\\-0.227)\end{pmatrix}$	$\begin{pmatrix}(0.456,\\0.472)\end{pmatrix},\begin{pmatrix}(-0.593,\\-0.322)\end{pmatrix}$	$\begin{pmatrix}(0.436,\\0.387)\end{pmatrix},\begin{pmatrix}(-0.165,\\-0.662)\end{pmatrix}$

$\breve{\alpha}_4$	$\begin{pmatrix}(0.442,\\0.406),\\(-0.422,\\-0.428)\end{pmatrix}$	$\begin{pmatrix}(0.423,\\0.436),\\(-0.483,\\-0.335)\end{pmatrix}$	$\begin{pmatrix}(0.271,\\0.536),\\(-0.506,\\-0.345)\end{pmatrix}$	$\begin{pmatrix}(0.217,\\0.588),\\(-0.442,\\-0.419)\end{pmatrix}$	$\begin{pmatrix}(0.569,\\0.325),\\(-0.499,\\-0.280)\end{pmatrix}$
$\breve{\alpha}_5$	$\begin{pmatrix}(0.594,\\0.284),\\(-0.346,\\-0.469)\end{pmatrix}$	$\begin{pmatrix}(0.855,\\0.087),\\(-0.814,\\-0.104)\end{pmatrix}$	$\begin{pmatrix}(0.551,\\0.297),\\(-0.333,\\-0.526)\end{pmatrix}$	$\begin{pmatrix}(0.688,\\0.172),\\(-0.610,\\-0.286)\end{pmatrix}$	$\begin{pmatrix}(0.622,\\0.302),\\(-0.616,\\-0.185)\end{pmatrix}$
$\breve{\alpha}_6$	$\begin{pmatrix}(0.394,\\0.400),\\(-0.634,\\-0.278)\end{pmatrix}$	$\begin{pmatrix}(0.396,\\0.387),\\(-0.450,\\-0.424)\end{pmatrix}$	$\begin{pmatrix}(0.315,\\0.607),\\(-0.405,\\-0.521)\end{pmatrix}$	$\begin{pmatrix}(0.592,\\0.265),\\(-0.172,\\-0.770)\end{pmatrix}$	$\begin{pmatrix}(0.382,\\0.458),\\(-0.245,\\-0.640)\end{pmatrix}$
$\breve{\alpha}_7$	$\begin{pmatrix}(0.769,\\0.144),\\(-0.356,\\-0.538)\end{pmatrix}$	$\begin{pmatrix}(0.615,\\0.297),\\(-0.250,\\-0.587)\end{pmatrix}$	$\begin{pmatrix}(0.671,\\0.288),\\(-0.293,\\-0.345)\end{pmatrix}$	$\begin{pmatrix}(0.330,\\0.559),\\(-0.584,\\-0.341)\end{pmatrix}$	$\begin{pmatrix}(0.398,\\0.375),\\(-0.493,\\-0.398)\end{pmatrix}$
$\breve{\alpha}_8$	$\begin{pmatrix}(0.424,\\0.332),\\(-0.475,\\-0.306)\end{pmatrix}$	$\begin{pmatrix}(0.342,\\0.434),\\(-0.507,\\-0.403)\end{pmatrix}$	$\begin{pmatrix}(0.469,\\0.386),\\(-0.341,\\-0.342)\end{pmatrix}$	$\begin{pmatrix}(0.688,\\0.169),\\(-0.391,\\-0.395)\end{pmatrix}$	$\begin{pmatrix}(0.788,\\0.127),\\(-0.552,\\-0.364)\end{pmatrix}$

Step 4: The criteria weights are determined using the BWM. The computational procedure is summarized as follows.

Step 4.1: Let $\epsilon = (\epsilon_1, \epsilon_2, \cdots, \epsilon_5)$ denote the set of five evaluation criteria employed to assess the performance of the candidate alternatives within the proposed decision-making framework.

Step 4.2: Through consultation and consensus among the experts, Computational Performance ϵ_2 was identified as the most important (best) criterion, whereas Energy Efficiency ϵ_5 was identified as the least important (worst) criterion. Accordingly, these two criteria were designated as the best and worst criteria, respectively, for implementing BWM.

Step 4.3: The experts then expressed the preference of the best criterion over each of the other criteria using the standard 1–9 BWM scale. The resulting best-to-others preference vector is

$$\hbar_b = (3, 1, 4, 6, 7)$$

Step 4.4: The preference of each criterion over the worst criterion was determined using the same 1–9 scale. Accordingly, the others-to-worst preference vector is obtained as

$$\hbar_w = (6, 8, 4, 2, 1)^T$$

These preference vectors constitute the input information required for the BWM to derive the optimal criteria weight vector.

Step 4.5: Let $\mathfrak{w} = (\mathfrak{w}_1, \mathfrak{w}_2, \cdots, \mathfrak{w}_5)^T$ denote the unknown criterion weight vector, where $\mathfrak{w}_j \geq 0\ (1, 2, \cdots 5)$ and $\sum_{j=1}^{5} \mathfrak{w}_j = 1$. Based on the elicited preference information, the optimal criterion weights are obtained by solving the following BWM optimization model.

Min: $\mathfrak{q}$

Subject to:

$$\left|\frac{\mathfrak{w}_2}{\mathfrak{w}_1} - 3\right| \leq \mathfrak{q},\ \left|\frac{\mathfrak{w}_2}{\mathfrak{w}_2} - 1\right| \leq \mathfrak{q},\ \left|\frac{\mathfrak{w}_2}{\mathfrak{w}_3} - 4\right| \leq \mathfrak{q},\ \left|\frac{\mathfrak{w}_2}{\mathfrak{w}_4} - 6\right| \leq \mathfrak{q},\ \left|\frac{\mathfrak{w}_2}{\mathfrak{w}_5} - 7\right| \leq \mathfrak{q},$$

$$\left|\frac{\mathfrak{w}_1}{\mathfrak{w}_5} - 6\right| \leq \mathfrak{q},\quad \left|\frac{\mathfrak{w}_2}{\mathfrak{w}_5} - 8\right| \leq \mathfrak{q},\quad \left|\frac{\mathfrak{w}_3}{\mathfrak{w}_5} - 4\right| \leq \mathfrak{q},\left|\frac{\mathfrak{w}_4}{\mathfrak{w}_5} - 2\right| \leq \mathfrak{q},\left|\frac{\mathfrak{w}_5}{\mathfrak{w}_5} - 1\right| \leq \mathfrak{q},$$

$$\mathfrak{w}_j \geq 0\ \forall\ j = 1, 2, 3, 4, 5,$$

$$\sum_{j=1}^{5} \mathfrak{w}_j = 1.$$

Step 4.6: To improve computational tractability, the nonlinear model is approximated by its linear counterpart, which yields a unique optimal criterion weight vector.

Min: $\mathfrak{q}$

Subject to:

$$|\mathfrak{w}_2 - 3\mathfrak{w}_1| \leq \mathfrak{q},\quad |\mathfrak{w}_2 - \mathfrak{w}_2| \leq \mathfrak{q},\quad |\mathfrak{w}_2 - 4\mathfrak{w}_3| \leq \mathfrak{q},|\mathfrak{w}_2 - 6\mathfrak{w}_4| \leq \mathfrak{q},\ |\mathfrak{w}_2 - 7\mathfrak{w}_5| \leq \mathfrak{q},$$

$$|\mathfrak{w}_1 - 6\mathfrak{w}_5| \leq \mathfrak{q},\quad |\mathfrak{w}_2 - 8\mathfrak{w}_5| \leq \mathfrak{q},\quad |\mathfrak{w}_3 - 4\mathfrak{w}_5| \leq \mathfrak{q},\ |\mathfrak{w}_4 - 2\mathfrak{w}_5| \leq \mathfrak{q},|\mathfrak{w}_5 - \mathfrak{w}_5| \leq \mathfrak{q},$$

$$\mathfrak{w}_j \geq 0\ \forall\ j = 1, 2, 3, 4, 5,$$

$$\sum_{j=1}^{5} \mathfrak{w}_j = 1.$$

The linear optimization model was solved in Python to obtain the optimal criterion weights. The resulting weight vector is $\mathfrak{w} = (0.24242, 0.36364, 0.18181, 0.12121, 0.09091)^T$. The distribution and relative importance of the BWM-derived criterion weights are presented in Figure 3. To enhance the transparency and reproducibility of the proposed methodology, the Python implementation

used to solve the optimization model is available at the following link:

https://colab.research.google.com/drive/142oyCvj0Qt9LH31N0aFSkKhQPq53F2ZM#scrollTo=DbNlt5Xt_e9Q&line=108&uniqifier=1

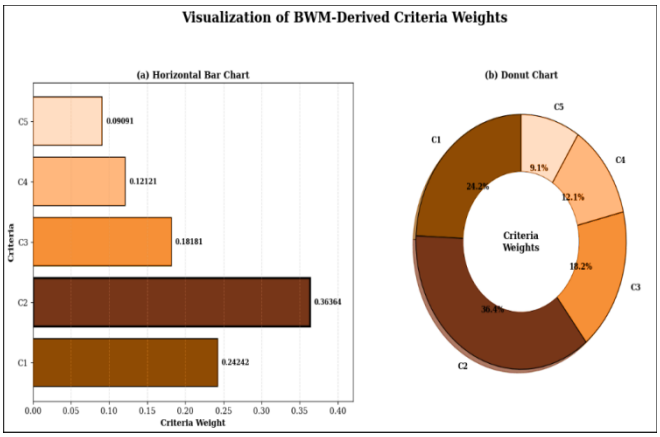


Fig. 2: Graphical representation of the criteria weights obtained using BWM.

Step 5: The theoretical preference matrix is constructed by assigning an equal initial preference to each of the eight alternatives, i.e.,

$$\dot{P}_{\breve{\alpha}_i} = \frac{1}{8}\ , i = 1, 2, \ldots 8$$

where $\sum_{i=1}^{8} \dot{P}_{\breve{\alpha}_i} = 1$. The theoretical preference matrix $\dot{T}_p = \left(\dot{t}_{ij}\right)_{8\times 5}$ is then obtained as

$$\dot{t}_{ij} = \dot{P}_{\breve{\alpha}_i} \times \omega_j$$

where ω_j denotes the BWM-derived weight of criterion ϵ_j. The theoretical preference matrix obtained from the BWM-derived criterion weights is shown in Table 8.

Table 7. Theoretical preference matrix.

	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
$\breve{\alpha}_1$	0.0303	0.0455	0.0227	0.0152	0.0114
$\breve{\alpha}_2$	0.0303	0.0455	0.0227	0.0152	0.0114
$\breve{\alpha}_3$	0.0303	0.0455	0.0227	0.0152	0.0114
$\breve{\alpha}_4$	0.0303	0.0455	0.0227	0.0152	0.0114
$\breve{\alpha}_5$	0.0303	0.0455	0.0227	0.0152	0.0114
$\breve{\alpha}_6$	0.0303	0.0455	0.0227	0.0152	0.0114
$\breve{\alpha}_7$	0.0303	0.0455	0.0227	0.0152	0.0114
$\breve{\alpha}_8$	0.0303	0.0455	0.0227	0.0152	0.0114

Step 6: The real BIF evaluation matrix $\bar{\dot{R}} = \left(\bar{\dot{r}}_{ij}\right)_{8\times 5}$ is obtained by applying the BIF scalar multiplication operator to the theoretical preference matrix and the collective BIF decision matrix, i.e.,

$$\bar{\dot{r}}_{ij} = \dot{t}_{ij} \odot \acute{K}_{ij}$$

where $\dot{t}_{ij}$ is the theoretical preference value and $\acute{K}_{ij}$ is the corresponding normalized collective BIFN. The real BIF evaluation matrix obtained from the aggregated assessments is presented in Table 9.

Table 8. Real BIF evaluation matrix.

	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
$\breve{\alpha}_1$	$\begin{pmatrix}(0.013,)\\0.976\end{pmatrix},\begin{pmatrix}(-0.971,)\\-0.017\end{pmatrix}$	$\begin{pmatrix}(0.054,)\\0.935\end{pmatrix},\begin{pmatrix}(-0.963,)\\-0.026\end{pmatrix}$	$\begin{pmatrix}(0.012,)\\0.980\end{pmatrix},\begin{pmatrix}(-0.986,)\\-0.004\end{pmatrix}$	$\begin{pmatrix}(0.006,)\\0.991\end{pmatrix},\begin{pmatrix}(-0.991,)\\-0.006\end{pmatrix}$	$\begin{pmatrix}(0.005,)\\0.992\end{pmatrix},\begin{pmatrix}(-0.990,)\\-0.007\end{pmatrix}$
$\breve{\alpha}_2$	$\begin{pmatrix}(0.032,)\\0.954\end{pmatrix},\begin{pmatrix}(-0.971,)\\-0.019\end{pmatrix}$	$\begin{pmatrix}(0.021,)\\0.971\end{pmatrix},\begin{pmatrix}(-0.979,)\\-0.018\end{pmatrix}$	$\begin{pmatrix}(0.022,)\\0.971\end{pmatrix},\begin{pmatrix}(-0.985,)\\-0.010\end{pmatrix}$	$\begin{pmatrix}(0.014,)\\0.983\end{pmatrix},\begin{pmatrix}(-0.987,)\\-0.011\end{pmatrix}$	$\begin{pmatrix}(0.008,)\\0.989\end{pmatrix},\begin{pmatrix}(-0.991,)\\-0.005\end{pmatrix}$
$\breve{\alpha}_3$	$\begin{pmatrix}(0.008,)\\0.985\end{pmatrix},\begin{pmatrix}(-0.971,)\\-0.012\end{pmatrix}$	$\begin{pmatrix}(0.006,)\\0.981\end{pmatrix},\begin{pmatrix}(-0.957,)\\-0.031\end{pmatrix}$	$\begin{pmatrix}(0.022,)\\0.964\end{pmatrix},\begin{pmatrix}(-0.990,)\\-0.006\end{pmatrix}$	$\begin{pmatrix}(0.009,)\\0.989\end{pmatrix},\begin{pmatrix}(-0.992,)\\-0.006\end{pmatrix}$	$\begin{pmatrix}(0.006,)\\0.989\end{pmatrix},\begin{pmatrix}(-0.980,)\\-0.012\end{pmatrix}$
$\breve{\alpha}_4$	$\begin{pmatrix}(0.018,)\\0.973\end{pmatrix},\begin{pmatrix}(-0.974,)\\-0.017\end{pmatrix}$	$\begin{pmatrix}(0.025,)\\0.963\end{pmatrix},\begin{pmatrix}(-0.967,)\\-0.018\end{pmatrix}$	$\begin{pmatrix}(0.007,)\\0.986\end{pmatrix},\begin{pmatrix}(-0.985,)\\-0.010\end{pmatrix}$	$\begin{pmatrix}(0.004,)\\0.992\end{pmatrix},\begin{pmatrix}(-0.988,)\\-0.008\end{pmatrix}$	$\begin{pmatrix}(0.010,)\\0.987\end{pmatrix},\begin{pmatrix}(-0.992,)\\-0.004\end{pmatrix}$
$\breve{\alpha}_5$	$\begin{pmatrix}(0.027,)\\0.963\end{pmatrix},\begin{pmatrix}(-0.968,)\\-0.019\end{pmatrix}$	$\begin{pmatrix}(0.084,)\\0.895\end{pmatrix},\begin{pmatrix}(-0.991,)\\-0.005\end{pmatrix}$	$\begin{pmatrix}(0.018,)\\0.973\end{pmatrix},\begin{pmatrix}(-0.975,)\\-0.017\end{pmatrix}$	$\begin{pmatrix}(0.018,)\\0.974\end{pmatrix},\begin{pmatrix}(-0.993,)\\-0.005\end{pmatrix}$	$\begin{pmatrix}(0.011,)\\0.986\end{pmatrix},\begin{pmatrix}(-0.995,)\\-0.002\end{pmatrix}$
$\breve{\alpha}_6$	$\begin{pmatrix}(0.015,)\\0.973\end{pmatrix},\begin{pmatrix}(-0.986,)\\-0.010\end{pmatrix}$	$\begin{pmatrix}(0.023,)\\0.958\end{pmatrix},\begin{pmatrix}(-0.964,)\\-0.025\end{pmatrix}$	$\begin{pmatrix}(0.009,)\\0.989\end{pmatrix},\begin{pmatrix}(-0.980,)\\-0.017\end{pmatrix}$	$\begin{pmatrix}(0.013,)\\0.980\end{pmatrix},\begin{pmatrix}(-0.974,)\\-0.022\end{pmatrix}$	$\begin{pmatrix}(0.005,)\\0.991\end{pmatrix},\begin{pmatrix}(-0.984,)\\-0.012\end{pmatrix}$

$\breve{\alpha}_7$	$\begin{pmatrix}(0.043,)\\0.943\\(-0.969,)\\-0.023\end{pmatrix}$	$\begin{pmatrix}(0.042,)\\0.946\\(-0.939,)\\-0.039\end{pmatrix}$	$\begin{pmatrix}(0.025,)\\0.972\\(-0.972,)\\-0.010\end{pmatrix}$	$\begin{pmatrix}(0.006,)\\0.991\\(-0.992,)\\-0.006\end{pmatrix}$	$\begin{pmatrix}(0.006,)\\0.989\\(-0.992,)\\-0.006\end{pmatrix}$
$\breve{\alpha}_8$	$\begin{pmatrix}(0.017,)\\0.967\\(-0.978,)\\-0.011\end{pmatrix}$	$\begin{pmatrix}(0.019,)\\0.963\\(-0.970,)\\-0.023\end{pmatrix}$	$\begin{pmatrix}(0.014,)\\0.979\\(-0.976,)\\-0.009\end{pmatrix}$	$\begin{pmatrix}(0.017,)\\0.973\\(-0.986,)\\-0.008\end{pmatrix}$	$\begin{pmatrix}(0.017,)\\0.977\\(-0.993,)\\-0.005\end{pmatrix}$

Step 7: The score values of the real BIF evaluation matrix are first computed using the score function in equation (1) and are presented in Table 10.

Table 9: Score values of the real BIF evaluation matrix.

	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
$\breve{\alpha}_1$	0.02091	0.04527	0.01277	0.00750	0.00740
$\breve{\alpha}_2$	0.03151	0.02230	0.01908	0.01380	0.00830
$\breve{\alpha}_3$	0.01614	0.02487	0.01845	0.00856	0.01243
$\breve{\alpha}_4$	0.02175	0.02815	0.01155	0.00805	0.00845
$\breve{\alpha}_5$	0.02872	0.05090	0.02169	0.01409	0.00807
$\breve{\alpha}_6$	0.01650	0.03133	0.01419	0.02044	0.01043
$\breve{\alpha}_7$	0.03857	0.04913	0.02249	0.00731	0.00764
$\breve{\alpha}_8$	0.02067	0.02742	0.01735	0.01645	0.01314

The corresponding gap values are then obtained as

$$\mathfrak{g}_{ij} = \left|\mathfrak{t}_{ij} - \delta\left(\breve{\mathfrak{r}}_{ij}\right)\right|$$

where $\mathfrak{t}_{ij}$ is the theoretical preference value and $\delta\left(\breve{\mathfrak{r}}_{ij}\right)$ denotes the score of the corresponding real BIF evaluation. The resulting gap matrix, $\mathfrak{G} = \left(\mathfrak{g}_{ij}\right)_{8\times5}$, is presented in Table 11.

Table 10: Gap matrix.

	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
$\breve{\alpha}_1$	0.009397	0.000187	0.009960	0.007649	0.003965
$\breve{\alpha}_2$	0.001207	0.023157	0.003644	0.001353	0.003063
$\breve{\alpha}_3$	0.014161	0.020590	0.004281	0.006589	0.001070
$\breve{\alpha}_4$	0.008549	0.017306	0.011181	0.007101	0.002911
$\breve{\alpha}_5$	0.001582	0.005442	0.001036	0.001061	0.003290
$\breve{\alpha}_6$	0.013806	0.014126	0.008540	0.005286	0.000939
$\breve{\alpha}_7$	0.008265	0.003670	0.000241	0.007842	0.003719
$\breve{\alpha}_8$	0.009631	0.018035	0.005382	0.001294	0.001775

Step 8: The overall utility value of each alternative is obtained by summing its corresponding gap values across all five evaluation criteria, i.e.,

$$\mathfrak{q}_i = \sum_{j=1}^{5} \mathfrak{g}_{ij} \ , i = 1, 2, \cdots, 8$$

The alternatives are then ranked in ascending order of their utility values, where the smallest value indicates the most preferred alternative. The computed utility values and the final ranking are presented in Table 12.

Table 11. Utility scores and final ranking of the alternatives.

Alternatives	Utility score
$\breve{\alpha}_1$	0.031158
$\breve{\alpha}_2$	0.032424
$\breve{\alpha}_3$	0.046691
$\breve{\alpha}_4$	0.047048
$\breve{\alpha}_5$	0.012411
$\breve{\alpha}_6$	0.042697
$\breve{\alpha}_7$	0.023737
$\breve{\alpha}_8$	0.036117
Ranking	$\breve{\alpha}_5 < \breve{\alpha}_7 < \breve{\alpha}_1 < \breve{\alpha}_2 < \breve{\alpha}_8 < \breve{\alpha}_6 < \breve{\alpha}_3 < \breve{\alpha}_4$

The utility scores and final ranking of the candidate neuromorphic AI chips obtained using the MAIRCA method are illustrated in Figure 4.

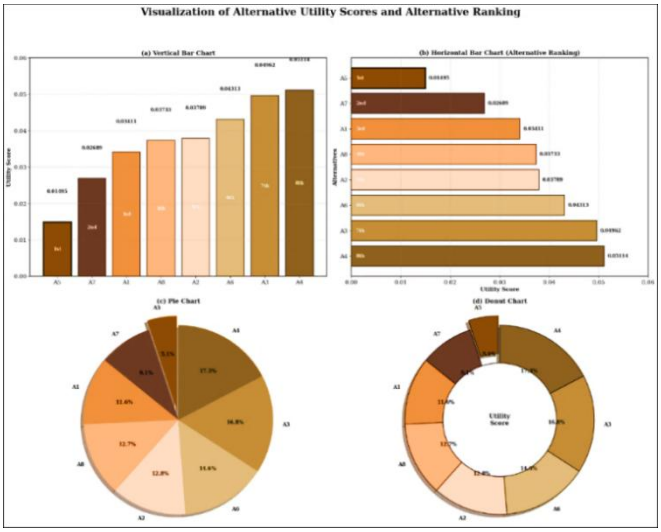


Fig.4: Multi-perspective visualization of the MAIRCA utility scores and the final ranking.

7. Sensitivity Analysis

Sensitivity analysis investigates the robustness of the proposed BIF-BWM-MAIRCA framework to changes in criterion importance. For this purpose, we construct an alternative weighting scenario by modifying the criterion weights while keeping all other computational procedures and decision parameters unchanged. The modified criterion weight vector is defined as $\omega = (0.18, 0.24, 0.27, 0.15, 0.16)^T$. The MAIRCA procedure is then repeated to determine the utility scores and corresponding rankings of the competing neuromorphic AI chips. Table 13 reports the utility scores and rankings obtained with the modified weights. Although the positions

of the intermediate alternatives ǎ1, ǎ2, and ǎ8 change, ǎ5 retains the first position and ǎ7 the second, while ǎ6, ǎ3, and ǎ4 retain the last three positions. This indicates that the best selection is robust with respect to the investigated weight variation and demonstrates the stability of the proposed framework against changes in criterion importance.

Table 12: Utility scores and rankings of the neuromorphic AI chip alternatives under the modified criterion weights.

Alternatives	Utility score
$\check{\alpha}_1$	0.038431
$\check{\alpha}_2$	0.028922
$\check{\alpha}_3$	0.040443
$\check{\alpha}_4$	0.048256
$\check{\alpha}_5$	0.014064
$\check{\alpha}_6$	0.040401
$\check{\alpha}_7$	0.025914
$\check{\alpha}_8$	0.031553
Ranking	$\check{\alpha}_5 < \check{\alpha}_7 < \check{\alpha}_2 < \check{\alpha}_8 < \check{\alpha}_1 < \check{\alpha}_6 < \check{\alpha}_3 < \check{\alpha}_4$

8. Comparative Analysis

The proposed BIF-BWM-MAIRCA framework is compared with representative MAIRCA-based methodologies to examine its methodological scope and decision-support capability. Since its introduction by Pamučar et al. [26], MAIRCA has proven effective in evaluating alternatives through the comparison of theoretical and real preference values. The original method was developed in a crisp decision-making environment and provided a computationally efficient mechanism for ranking alternatives in engineering applications. This pioneering study subsequently served as the basis for many methodological extensions to decision-making under uncertainty. As real-world decision problems have become more complex, researchers have sought to enhance MAIRCA by incorporating advanced uncertainty theories and hybrid MCDM methods. Can and Kıran [38] applied the classical MAIRCA method to evaluate the occupational health and safety performance of countries and demonstrated its applicability to comparative performance evaluation. Gul and Ak [39] combined fuzzy BWM with fuzzy MAIRCA for occupational risk assessment, coupling a structured criterion-weighting procedure with uncertainty-aware alternative evaluation, and their results confirmed the practical value of combining MAIRCA with complementary weighting mechanisms. Further methodological developments have focused on improving the representation of uncertain and imprecise assessment information. Mishra et al. [30] extended MAIRCA to an interval-valued intuitionistic fuzzy environment to evaluate sustainable wastewater treatment technologies, while Hezam et al. [40] introduced intuitionistic fuzzy modelling into a MAIRCA-based sustainability assessment framework for the biofuel industry. Subsequently, Karami and Mousavi [31] developed an interval-valued fuzzy group decision-making model by combining IVF-LBWA and IVF-MAIRCA, demonstrating the flexibility of MAIRCA in complex group decision-making problems involving uncertain expert judgments.

Although these studies have substantially broadened the applicability of MAIRCA, the associated decision frameworks rely primarily on crisp, fuzzy, intuitionistic fuzzy, or interval-valued fuzzy representations of uncertainty. In contrast, the proposed methodology uses BIFSs, in which both positive and negative preference information are represented within a single mathematical framework, enabling a more detailed description of expert evaluations. In addition, BWM determines consistent criterion weights through a structured optimization model that requires few pairwise comparisons, and the MAIRCA procedure ranks the candidate alternatives by quantifying the gaps between their theoretical and real performances. Therefore, the proposed framework extends the methodological capabilities of existing MAIRCA-based approaches by embedding bipolar uncertainty modelling, consistency-driven criterion weighting, and utility-based ranking within a single MCGDM framework. This integration offers a systematic and reliable decision-support methodology for neuromorphic AI chip selection, where diverse expert opinions, conflicting evaluation criteria, and imprecise assessment information must be handled simultaneously. The proposed framework is compared with representative MAIRCA-based approaches from a methodological perspective in Table 14. The comparison highlights the evolution of MAIRCA under different uncertainty environments and the distinguishing features of the proposed methodology.

Table 13: Comparative analysis of existing MAIRCA-based methodologies and the proposed BIF-BWM-MAIRCA framework.

Citation	Fuzziness	Intuitionistic	Bipolarity	MCGDM	Weight Determination	BIF	MAIRCA
Pamucar et al. [26]	No	No	No	No	Yes	No	Yes
Can and Kiran [38]	No	No	No	No	No	No	Yes
Gul and Ak [39]	Yes	No	No	No	Yes	No	Yes
Mishra et al. [30]	Yes	Yes	No	No	Yes	No	Yes
Hezam et al. [40]	Yes	Yes	No	No	Yes	No	Yes
Karami and Mousavi [31]	Yes	No	No	Yes	Yes	No	Yes
BIF-BWM-MAIRCA	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The comparative analysis matrix and feature coverage of representative MAIRCA-based methodologies, including the proposed framework, are illustrated in Figure 5.

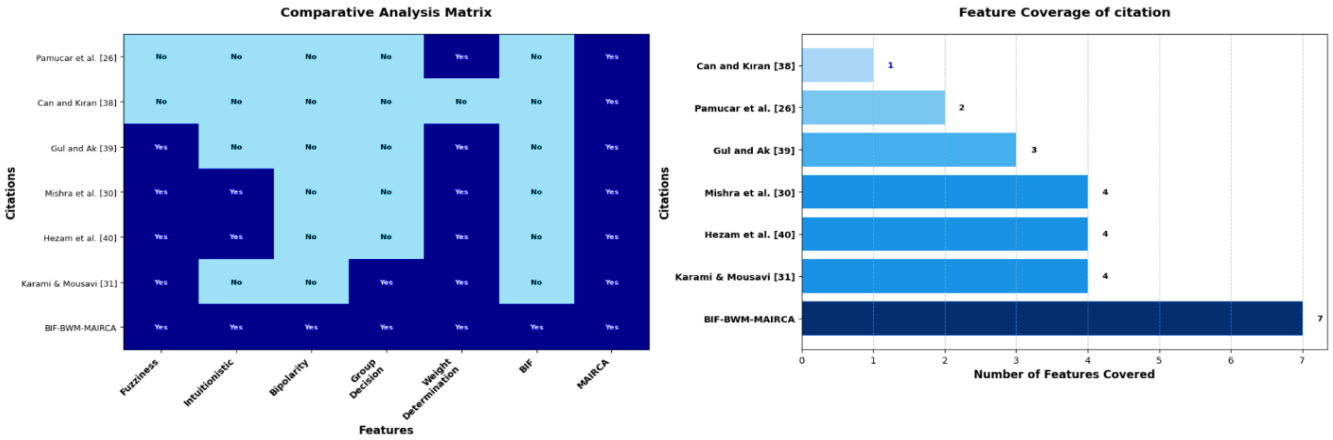


Fig. 3: Comparative analysis matrix and feature coverage of existing MAIRCA-based approaches and the proposed framework.

9. Conclusion

This study presented a novel BIF-BWM-MAIRCA framework for MCGDM under uncertainty. The proposed method combines the expressive power of BIFSs with the consistency-driven weighting of BWM and the utility-based ranking of MAIRCA, thereby providing integrated decision support that effectively addresses imprecise and conflicting expert evaluations. The resulting framework improves the reliability of criterion weighting and offers a systematic means of assessing competing alternatives in complex engineering decision settings. The applicability of the methodology was demonstrated through a neuromorphic AI chip selection case study involving eight alternatives and five benefit-type criteria. The BWM analysis identified Computational Performance (ϵ_2) as the most important criterion, with a weight of 0.36364, and Energy Efficiency (ϵ_5) as the least important criterion, with a weight of 0.09091, consistent with the best and worst criteria initially selected by the experts. Subsequently, the MAIRCA results showed that alternative $\ddot{\alpha}_5$ achieved the lowest utility value of 0.012411, securing the first position among the competing neuromorphic AI chips, followed by $\ddot{\alpha}_7$ and $\ddot{\alpha}_1$ in the second and third positions, respectively. The superior position of $\ddot{\alpha}_5$ highlights the suitability of its ultra-low-power architecture for continuous sensing, intelligent perception, and always-on edge AI applications. In contrast, alternative $\ddot{\alpha}_4$ obtained the highest utility value and was ranked as the least preferred alternative. The sensitivity analysis further confirmed that the top-ranked alternative remains unchanged under a modified criterion weight vector. The comparative analysis also showed that the proposed framework integrates bipolarity, intuitionistic uncertainty modelling, consistency-oriented criterion weighting, and MAIRCA-based MCGDM within a single computational framework, thereby extending existing MAIRCA-based methodologies. The proposed BIF-BWM-MAIRCA methodology, therefore, provides a complete, reliable, and practically applicable decision-support framework for selecting the most suitable neuromorphic AI chip and for other engineering evaluation problems that involve conflicting, imprecise, and uncertain assessment information.

Despite its contributions, the proposed framework has certain limitations. Its results depend on the consistency and reliability of expert judgments, which may introduce subjectivity into the evaluation process. Furthermore, the case study is based on a particular set of alternatives and criteria, and the priorities may change under different technological requirements or evaluation scenarios. The effectiveness of the framework also depends on the appropriate selection of the evaluation criteria. In addition, the framework was tested using an illustrative example, because reliable real-world datasets for neuromorphic AI chips were not available to validate it under actual operating conditions. Finally, the sensitivity analysis considered a single alternative weighting scenario, and a more extensive analysis is left for future work.

In future work, the proposed framework can be extended with bipolar intuitionistic fuzzy soft sets [41] to further strengthen the representation of uncertain evaluations. Further extensions may consider hesitant bipolar complex fuzzy structures and advanced Dombi aggregation operators [42]. Additionally, the framework could be adapted to sustainable waste-to-energy assessment and other complex engineering decision-making applications [43].

Table 15 summarizes the mathematical notation used throughout the proposed framework.

Table 14: Mathematical notations and their meanings.

Notation	Meaning	Notation	Meaning
Ụ	Universal set	Ÿⁿ	Non-membership function of IFS
Ÿ	Membership function of FS	Ÿᵖ	Positive membership function of BFS
ȟ	Hesitation degree of IFS	Ÿⁿ	Negative membership function of BFS

$\ddot{Y}^{m}$	Membership function of IFS	ω	Criteria weight set
$\ddot{Y}^{pm}$	Positive membership function of BIFS	$\ddot{Y}^{nm}$	Negative membership function of BIFS
$\ddot{Y}^{pn}$	Positive non-membership function of BIFS	$\ddot{Y}^{nn}$	Negative non-membership function of BIFS
$\check{h}^{p}$	Positive hesitation degree of BIFS	$\check{h}^{n}$	Negative hesitation degree of BIFS
$\check{\alpha}$	Set of alternatives	Φ	Set of experts
ϵ	Set of criteria	$\bar{\omega}$	Expert weight set

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