



INFORMATION-CENTRIC OPTIMIZATION OF BIO-BASED SUPPLY CHAINS USING HYBRID C-IFS AND TYPE-2 FUZZY MAIRCA

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ABSTRACT

Aim/Purpose	Strategic decision-making in Sustainable Bio-Based Supply Chains (SBSCs) is increasingly hindered by semantic ambiguity, expert inconsistency, and the inability of conventional models to handle uncertainty. These challenges compromise the alignment of AI integration with sustainability goals, especially in complex, multi-criteria environments. This study develops an AI-based decision support framework that addresses uncertainty and complexity in evaluating SBSCs, leveraging hybrid fuzzy logic methodologies.
Background	The shift toward AI-enabled SBSCs introduces multifaceted sustainability trade-offs and challenges rooted in linguistic ambiguity, subjective judgments, and expert inconsistency. Existing methods often lack the semantic resilience required for strategic supply chain planning under uncertainty.
Methodology	This study proposes an integrated hybrid approach combining Circular Intuitionistic Fuzzy Sets (C-IFS) with a Type-2 Fuzzy MAIRCA method. The framework operates in two stages: (1) C-IFS aggregation and entropy-based filtering to derive robust criteria weights and manage low-consensus indicators; and (2) application of Type-2 Fuzzy MAIRCA to assess and prioritize AI-integrated SBSC alternatives against idealized performance targets using interval-valued fuzzy distances.

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Contribution	The proposed model introduces a novel fusion of advanced fuzzy logic techniques to enable transparent, interpretable, and information-centric evaluation of bio-based supply chain configurations in uncertain environments.
Findings	Among the evaluated SBSC configurations, the fully integrated AI-driven model (A2) achieved the highest sustainability score (0.872) with the lowest performance gap ($\Psi = 0.486$), confirming its strategic alignment. Scenario testing under semantic shifts upheld the model's robustness and highlighted digital infrastructure as a key sensitivity factor.
Recommendations for Practitioners	Practitioners can adopt the proposed framework to improve the strategic alignment of AI implementations in SBSCs, enabling more resilient, data-driven decisions across operational and regulatory dimensions.
Recommendations for Researchers	Researchers are encouraged to explore extensions of this hybrid approach to other high-uncertainty domains and to examine the integration of additional soft computing methods for enhanced decision fidelity.
Impact on Society	By supporting sustainable and technologically adaptive supply chains, this framework contributes to greener production ecosystems and informed policymaking in bioeconomy sectors.
Future Research	Future studies may incorporate dynamic feedback systems, real-time AI learning, or bibliometric modeling to enrich the methodological scope and cross-sector applicability of the framework.
Keywords	information-centric decision support, bio-based supply chains, circular intuitionistic fuzzy sets (C-IFS), Type-2 fuzzy MAIRCA, artificial intelligence in supply chain management, digital twin-enabled evaluation models

INTRODUCTION

The transition toward sustainable bio-based supply chains (SBSCs) has become a strategic imperative in response to climate change, resource depletion, and the mandates of a circular economy (Gottinger et al., 2020). While artificial intelligence (AI) has emerged as a transformative enabler in this domain, enhancing forecasting, optimization, and adaptive control, its integration into SBSCs remains fragmented and analytically underexplored. Existing decision-making models often rely on Type-1 fuzzy logic or crisp multi-criteria techniques, which inadequately capture the layered uncertainty, expert hesitation, and semantic ambiguity inherent in sustainability evaluations (Dymova et al., 2021). Moreover, most frameworks treat AI capabilities and sustainability metrics as isolated dimensions rather than interdependent components of a unified system architecture.

Recent advances in fuzzy set theory, such as Circular Intuitionistic Fuzzy Sets (C-IFS), offer a more expressive structure for modeling expert judgments by incorporating membership, non-membership, and hesitation degrees within a geometrically constrained space (Chen, 2024a). However, applications of C-IFS in supply chain contexts remain limited, with most studies focusing on the theoretical development of operators or extensions of classical methods, such as TOPSIS (Tanveer et al., 2023). Similarly, while Type-2 fuzzy logic has been applied in isolated decision models, its integration with C-IFS for layered prioritization (Nishanth et al., 2024), especially in AI-enabled SBSCs, has not been systematically addressed. This reveals a critical gap in the literature: the absence of a hybrid, uncertainty-resilient framework that can both filter and prioritize strategic subfactors in complex, digitally augmented supply chains.

This study addresses that gap by proposing a novel hybrid decision-making framework that combines C-IFS-based entropy weighting with Type-2 Fuzzy MAIRCA analysis. The originality of this approach lies in its dual-layer structure: first, it filters and weights sustainability and AI-related subfactors using entropy-calibrated C-IFS triplets; second, it evaluates the performance of integrated SBSC alternatives through a gap-based Type-2 fuzzy prioritization model. This enables the model to capture both epistemic uncertainty and operational variability, offering a more robust and interpretable decision pathway. Furthermore, the inclusion of a scenario simulation layer enhances the model's resilience by testing its sensitivity to linguistic ambiguity – an often-overlooked dimension in fuzzy MCDM literature.

By applying this framework to three distinct SBSC configurations ranging from basic AI augmentation to fully integrated real-time systems, the study not only delivers a ranked decision output but also reveals the structural leverage points (e.g., digital twin modeling, real-time adaptability) that most influence sustainability alignment. Notably, the fully integrated AI-SBSC alternative achieved the highest sustainability score (0.872) and the lowest performance gap ($\Psi = 0.486$), confirming its strategic advantage.

The specific objectives of this research are as follows:

- To identify and filter key sustainability and AI-related subfactors using entropy-weighted C-IFS aggregation.
- To develop a hybrid decision model integrating C-IFS and Type-2 Fuzzy MAIRCA for robust prioritization.
- To test the model by ranking SBSC alternatives and analyzing sensitivity under semantic variation.

LITERATURE REVIEW

The design and evaluation of SBSCs increasingly demand a multidimensional understanding of strategic factors that span environmental, operational, and digital domains. Numerous studies have emphasized the importance of integrating renewable energy utilization, emissions reduction, and waste circularity into supply chain configurations (Abdirahman et al., 2025; Georgescu et al., 2025; Orji et al., 2022; Raygoza-Limón et al., 2025; Wang et al., 2025). These environmental imperatives are now being complemented by digital enablers such as machine learning forecasting, digital twin modeling, and AI-based production optimization, which collectively enhance adaptability and resilience (Balan et al., 2025).

Multi-Criteria Decision-Making (MCDM) methods have played a central role in evaluating complex supply chain systems, particularly under conditions of uncertainty and conflicting stakeholder priorities. Traditional approaches, such as AHP, TOPSIS, and VIKOR, have been widely applied in SBSC contexts; however, they often rely on crisp or Type-1 fuzzy logic, which limits their ability to model semantic ambiguity and expert hesitation (Madanchian & Taherdoost, 2025; Samhoury et al., 2025). These limitations are especially pronounced in sustainability evaluations, where criteria are linguistically defined and subject to epistemic uncertainty.

Recent developments in fuzzy set theory have introduced more expressive tools for handling such complexity. Circular Intuitionistic Fuzzy Sets (C-IFS), for example, extend classical intuitionistic fuzzy sets by incorporating a geometric constraint that models the hesitation degree within a circular boundary (Khan et al., 2025). This structure enhances the interpretability of expert judgments and supports more resilient aggregation in domains like renewable energy planning and emissions control. Jin and Garg (2023) applied C-IFS to extend TOPSIS for group decision-making, but their model lacked entropy-based filtering and integration with higher-order fuzzy prioritization.

To overcome these gaps, hybrid models have emerged that combine the semantic richness of C-IFS with the analytical depth of Type-2 fuzzy logic. Type-2 Fuzzy MAIRCA, in particular, offers a robust

framework for comparing real-world alternatives against idealized performance profiles using interval-valued fuzzy numbers. Its gap-based structure is well-suited for SBSC evaluation, where performance deviations must be assessed across multiple uncertain dimensions. However, no prior study has systematically fused C-IFS entropy weighting with Type-2 Fuzzy MAIRCA in the context of AI-enabled SBSCs, highlighting a clear opportunity for methodological advancement.

This study addresses that opportunity by proposing a dual-layer hybrid framework: first, it filters and weights sustainability and AI-related subfactors using entropy-calibrated C-IFS triplets; second, it ranks SBSC alternatives via Type-2 fuzzy gap analysis. This structure enables both semantic resilience and operational fidelity, making it adaptable to real-world complexity. Prior studies have modeled SBSC alternatives using discrete strategies, but few have treated them as holistic architectures. Tronnebati et al. (2022) used fuzzy AHP to evaluate green manufacturing, while Tubis et al. (2025) explored AI-driven logistics with partial digital maturity. These models lacked entropy-based calibration and did not incorporate Type-2 fuzzy gap analysis. In contrast, the present study defines three alternatives:

- A1: Baseline AI-augmented SBSC with isolated forecasting and limited digital twin usage (Raamets et al., 2025).
- A2: Fully integrated real-time adaptive system leveraging AI, IoT, and predictive analytics for circularity and resilience (Hariyani et al., 2024).
- A3: Fragmented experimental design with siloed AI tools and elevated entropy due to lack of systemic integration (Oncioiu et al., 2025).

To operationalize this framework, we designed a multi-phase methodology that combines expert elicitation, entropy filtering, and fuzzy prioritization, as detailed below.

METHODS

In this study, we investigate a real-world AI-enabled bio-based supply chain focused on valorizing agricultural residues – specifically olive pomace and almond shells – into high-value biochemicals and bioenergy products in the southeastern region of Morocco. The supply chain includes three key phases: biomass sourcing from cooperatives, preprocessing and biochemical conversion at a biorefinery, and regional distribution to industrial and agricultural consumers. To evaluate sustainability priorities and the potential for AI integration, data were collected through structured interviews and fuzzy linguistic surveys involving eight domain experts, including supply chain managers, sustainability officers, AI engineers, and policymakers (Table 1). These respondents represent public research institutions, private biomass processing firms, regional logistics providers, and regulatory bodies.

Table 1. Respondent profile matrix

ID	Affiliation type	Role/expertise	Years of experience	Contribution type
R1	Public Research Institute	Bioeconomy Policy Expert	12	Regulatory criteria
R2	Private Biorefinery Firm	AI & Process Optimization Engineer	8	Operational efficiency
R3	Agricultural Cooperative	Biomass Logistics Coordinator	15	Sourcing and transport
R4	Tech Startup	Digital Twin and AI Systems Architect	6	AI modeling and forecasting
R5	Environmental NGO	Circular Economy Consultant	10	Sustainability weighting
R6	Regional Government Body	Climate Policy Advisor	14	Compliance and governance
R7	Academic Institution	Multi-Criteria Decision-Making Scholar	11	Method design and validation
R8	AI Consultancy	Natural Language and Fuzzy Systems Expert	9	Linguistic variable design

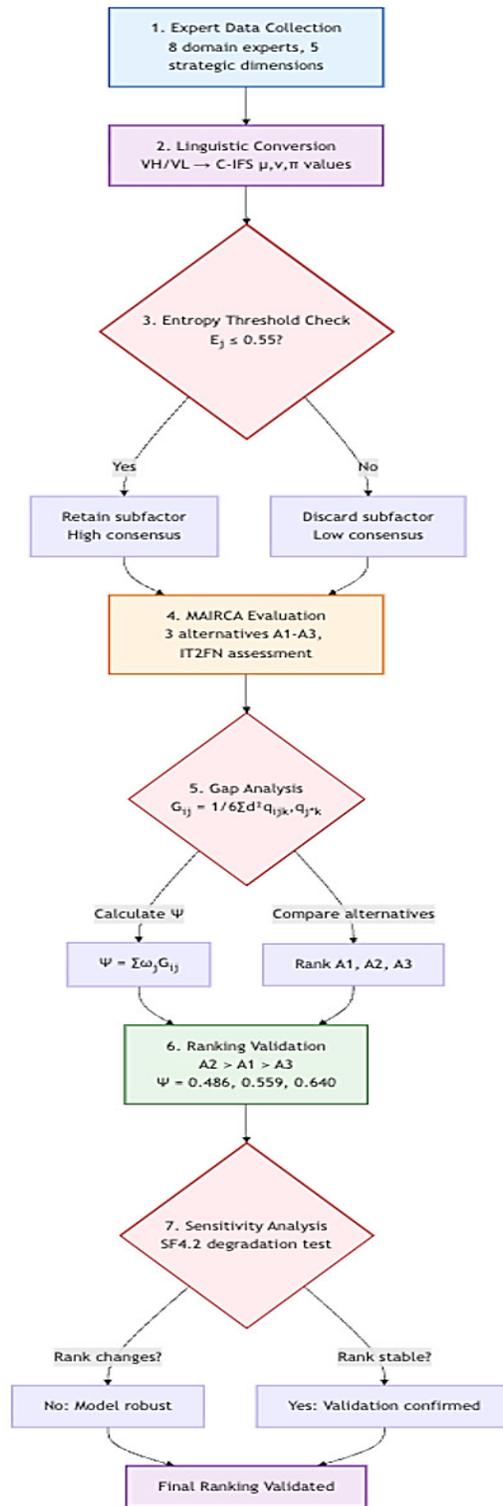


Figure 1. Methodological process

The data collection process followed a two-round Delphi technique to ensure consensus and reliability in expert assessments. Circular Intuitionistic Fuzzy evaluations were aggregated across five strategic dimensions – environmental sustainability, operational efficiency, AI-driven forecasting, smart

logistics, and regulatory compliance – and were subsequently processed using the proposed Type-2 Fuzzy MAIRCA methodology. Using Circular Intuitionistic Fuzzy Sets (C-IFS) as a first-stage filter enables the model to quantify expert consensus and information richness through entropy, allowing only the most strategically informative and confidently evaluated subfactors to advance. This is justified because high entropy values indicate vagueness or conflicting opinions, which can dilute the accuracy of downstream modeling. By retaining only subfactors with low entropy and high objective weights, the framework ensures that the Type-2 Fuzzy MAIRCA stage operates on a refined, high-signal decision set, thereby enhancing both computational efficiency and decision robustness, as supported by the multi-layered MCDM literature. The methodological process unfolds in four key stages, as illustrated in Figure 1.

The following section presents the outcomes of applying this framework to three hypothetical SBSC configurations, highlighting performance rankings, sensitivity insights, and strategic leverage points.

PHASE I. C-IFS ENTROPY AND WEIGHT DERIVATION

Experts assessed the relevance of each subfactor using a five-point linguistic scale. The linguistic terms reflect varying levels of perceived strategic importance. To clarify the semantic basis of expert assessments, Table 2 introduces the linguistic scale mapped onto Constrained Intuitionistic Fuzzy Sets (C-IFS). This mapping provides the membership (μ), non-membership (ν), and hesitation (π) degrees.

Table 2. Linguistic scale and C-IFS mapping

Linguistic term	Code	μ	ν	$\pi=1-\mu-\nu$	Constraint $\mu^2+\nu^2+\pi^2\leq 1$?
Very High	VH	0.90	0.05	0.05	✓ (0.815)
High	H	0.75	0.15	0.10	✓ (0.575)
Medium	M	0.50	0.30	0.20	✓ (0.380)
Low	L	0.30	0.50	0.20	✓ (0.380)
Very Low	VL	0.10	0.80	0.10	✓ (0.660)

These values satisfy both classic intuitionistic ($\mu+\nu\leq 1$) and C-IFS-specific ($\mu^2+\nu^2+\pi^2\leq 1$) constraints (Sevastjanov et al., 2021).

To provide a foundational overview of the evaluation framework, Table 3 outlines the strategic factors and subfactors, along with their justifications and corresponding literature sources, that underpin the decision-making model in the context of sustainable and AI-driven supply chains.

Table 3. Strategic factors and subfactors

	Strategic factor/subfactor	Justification/literature source
SF1	Supply Chain Sustainability	Central pillar of circular bioeconomy; emphasizes environmental metrics (Mesa et al., 2024)
SF1.1	Renewable Energy Utilization (Solar, Wind, Hydrogen)	Transition to low-carbon energy is vital in bio-based systems (Kamali Saraji & Streimikiene, 2023)
SF1.2	Waste Reduction & Circular Economy Integration	Circularity is a defining trait of next-gen sustainable supply chains (Carissimi et al., 2024)
SF1.3	Emissions & Carbon Footprint Reduction	Key performance indicator in bio-based logistics and LCA studies (Hashemi et al., 2024)
SF2	Operational Efficiency	AI enhances system responsiveness and reduces inefficiencies (Mills & Spencer, 2025)
SF2.1	AI-Based Production Optimization	AI-driven scheduling enhances flow efficiency and energy usage (Mehraban et al., 2025)

	Strategic factor/subfactor	Justification/literature source
SF2.2	Real-Time Supply Chain Adaptability	Dynamic control systems enable resilience and agile bio-logistics (Tufan et al., 2024)
SF2.3	Energy Optimization in Manufacturing	Energy-aware AI systems reduce operational carbon intensity (Rózycki et al., 2025)
SF3	Smart Logistics & Distribution	AI and digitalization improve traceability and distributional intelligence (Z. Liu et al., 2025)
SF3.1	AI-Driven Route Optimization	Machine learning algorithms reduce fuel use and delay (Xie et al., 2023)
SF3.2	Supplier Network Coordination	Coordination enhances resilience in fragmented green supply chains (He et al., 2024)
SF3.3	Warehouse Automation & Demand Forecasting	Predictive AI models improve warehousing and reduce overstocking (Baharudin, 2023)
SF4	AI-Enabled Predictive Analytics	Critical for anticipatory control and sustainability forecasting (Aljohani, 2023)
SF4.1	Machine Learning for Demand Forecasting	Improves supply-demand matching and reduces waste (Douaioui et al., 2024)
SF4.2	Digital Twin Modeling for Smart Manufacturing	Creates virtual replicas for life-cycle simulation in green design (Soori et al., 2023)
SF4.3	AI-Augmented Supply Chain Resilience	Supports disruption recovery and adaptive decision-making (Riad et al., 2024)
SF5	Regulatory & Compliance	Compliance ensures viability in ESG-oriented investment and markets (D'Ecclesia et al., 2025)
SF5.1	Environmental Policy Adherence	Regulatory alignment is crucial in bioeconomy and net-zero mandates (Ares-Sainz et al., 2025)
SF5.2	Industry 4.0 & Smart Manufacturing Regulations	Regulatory frameworks define digital transition protocols (Bastos et al., 2025)
SF5.3	Energy-Efficiency Compliance	Energy directives shape strategic compliance in sustainable operations (Drago & Gatto, 2022)

Each of the 15 subfactors was evaluated independently by a group of domain experts using the linguistic terms. To synthesize the qualitative input underpinning the evaluation process, Table 4 compiles the linguistic judgments provided by the expert panel across all strategic subfactors. This matrix highlights the diversity of expert perspectives, reflecting varied assessments of importance and performance through standardized linguistic terms such as Very High, High, and Medium.

Table 4. Linguistic judgments from experts

	E1	E2	E3	E4	E5	E6	E7	E8
SF1.1	VH	H	VH	VH	H	H	VH	VH
SF1.2	VH	VH	H	H	H	VH	H	M
SF1.3	H	H	VH	M	H	H	H	M
SF2.1	H	M	H	H	H	M	H	M
SF2.2	VH	VH	H	H	VH	H	VH	H
SF2.3	H	H	H	M	H	VH	H	M
SF3.1	M	H	M	H	H	H	M	M
SF3.2	M	M	H	M	H	M	H	M
SF3.3	M	M	M	L	H	M	M	M
SF4.1	VH	H	H	H	VH	H	H	VH
SF4.2	VH	VH	H	VH	H	VH	VH	VH
SF4.3	H	H	H	VH	H	H	H	H

	E1	E2	E3	E4	E5	E6	E7	E8
SF5.1	H	H	VH	H	VH	H	VH	H
SF5.2	M	H	M	H	M	H	H	M
SF5.3	M	M	M	H	M	M	H	M

Entropy quantifies the dispersion of belief, disbelief, and hesitation for each subfactor. Subfactors with high expert agreement produce low entropy (i.e., high confidence and priority), while those with conflicting or hesitant judgments yield high entropy (i.e., low discriminative power) (Haas et al., 2018).

The entropy E_j of subfactor j , based on aggregated C-IFS components, is computed using:

$$E_j = -\frac{1}{\ln(3)}(\mu_j \ln \mu_j + \nu_j \ln \nu_j + \pi_j \ln \pi_j) \quad (1)$$

where $\mu_j + \nu_j + \pi_j = 1$ and $\ln(3) \approx 1.0986$ normalizes entropy between 0 and 1.

Table 5 presents the aggregated C-IFS triplets for each strategic subfactor, derived from expert inputs. The table includes the averaged membership ($\bar{\mu}$), non-membership ($\bar{\nu}$), and hesitation ($\bar{\pi}$) degrees, as well as the squared summation constraint.

Table 5. Aggregated C-IFS triplets from experts

	$\bar{\mu}_j$	$\bar{\nu}_j$	$\bar{\pi}_j = 1 - \bar{\mu}_j - \bar{\nu}_j$	$\bar{\mu}^2 + \bar{\nu}^2 + \bar{\pi}^2$
SF1.1	0.861	0.088	0.051	0.8147
SF1.2	0.783	0.133	0.084	0.6466
SF1.3	0.744	0.160	0.096	0.6085
SF2.1	0.719	0.175	0.106	0.5976
SF2.2	0.789	0.125	0.086	0.6440
SF2.3	0.744	0.157	0.099	0.6072
SF3.1	0.722	0.172	0.106	0.5961
SF3.2	0.672	0.212	0.116	0.6044
SF3.3	0.611	0.267	0.122	0.5919
SF4.1	0.783	0.133	0.084	0.6466
SF4.2	0.822	0.100	0.078	0.6918
SF4.3	0.744	0.157	0.099	0.6072
SF5.1	0.800	0.122	0.078	0.6544
SF5.2	0.722	0.172	0.106	0.5961
SF5.3	0.672	0.212	0.116	0.6044

SF1.1 and SF4.2 exhibit high membership values ($\mu > 0.82$) with low non-membership and hesitation, indicating strong consensus and strategic alignment across experts. Conversely, SF3.3 and SF5.3 show reduced support and elevated hesitation ($\pi > 0.12$), suggesting either limited maturity in practical deployment or domain ambiguity. Interestingly, several AI-centric subfactors (e.g., SF2.1, SF3.1) cluster near moderate-to-high μ with relatively stable ν and π values, reflecting cautious optimism shaped by adoption variability.

The information entropy scores are transformed into objective, normalized decision weights that rank each subfactor's strategic salience. These weights serve a dual role:

- as a mathematically justified basis for prioritization, and
- as a filter to retain only high-confidence subfactors for the Type-2 Fuzzy MAIRCA stage.

This ensures that downstream modeling concentrates computational power on expert-endorsed priorities while eliminating noise from ambiguous or low-impact criteria (Roszkowska & Wachowicz, 2024).

Let E_j represent the entropy value of subfactor j as calculated previously. The objective weight ω_j is derived via inverse entropy normalization:

$$\omega_j = \frac{1-E_j}{\sum_{k=1}^n (1-E_k)} \tag{2}$$

where $1 - E_j$ the information utility or confidence level of subfactor j , $\sum (1-E_k)$ the total information utility across all subfactors (for normalization) and $\omega_j \in [0,1]$ and $\sum_j \omega_j = 1$

This approach ensures that subfactors with lower entropy are favored, aligning model logic with expert convergence. Table 6 displays the entropy values (E_j), their inverses $1 - E_j$, and the normalized weights ω_j for each strategic subfactor.

Table 6. Entropy inversion and normalized weights

	E_j	$1 - E_j$	ω_j
SF1.1	0.448	0.552	0.0837
SF1.2	0.507	0.493	0.0747
SF1.3	0.537	0.463	0.0702
SF2.1	0.558	0.442	0.0671
SF2.2	0.504	0.496	0.0751
SF2.3	0.533	0.467	0.0708
SF3.1	0.556	0.444	0.0673
SF3.2	0.584	0.416	0.0630
SF3.3	0.628	0.372	0.0564
SF4.1	0.507	0.493	0.0746
SF4.2	0.472	0.528	0.0801
SF4.3	0.533	0.467	0.0708
SF5.1	0.484	0.516	0.0784
SF5.2	0.556	0.444	0.0673
SF5.3	0.584	0.416	0.0630
Total	–	7.138	1.0000

Subfactors SF1.1, SF4.2, and SF5.1 hold the top three weights, reflecting low entropy (i.e., high expert alignment). Meanwhile, SF3.3 and SF5.3 rank lowest due to hesitation and inconsistency across expert responses.

In hybrid MCDM frameworks, an intermediate filtering stage is often used to streamline model complexity and improve interpretive clarity. Retaining all subfactors may introduce analytical noise, especially those with high entropy and low consensus. Therefore, only subfactors that exhibit robust expert agreement and high information utility should proceed to the final gap analysis. Filtering at this stage ensures:

- Methodological parsimony: fewer, stronger variables lead to clearer prioritizations.
- Epistemic fidelity: retained criteria reflect shared expert reality rather than contested conjecture.
- Computational stability: Type-2 fuzzy logic performs more reliably on reduced, high-signal sets.

Let each subfactor j have:

- Normalized weight ω_j
- Average weight $\bar{\omega}$, computed across $n=15$ subfactors: $\bar{\omega} = \frac{1}{n} \sum_{j=1}^n \omega_j$
- σ_ω standard deviation of weights

A statistical selection rule can then be expressed as:

$$\omega_i \geq \bar{\omega} - \lambda \cdot \sigma_\omega \tag{3}$$

Where $\lambda \in [0,1]$ controls the filtering strictness:

- $\lambda=0.0$: retain all
- $\lambda=0.5$: moderate filtering
- $\lambda=1.0$: retain only strong consensus subfactors

To highlight the filtering criteria used for subfactor prioritization, Table 7 summarizes the statistical metrics applied during the entropy-based refinement phase.

Table 7. Filtering threshold and retained set ($\lambda = 0.5$)

Metric	Value
Mean $\bar{\omega}$	0.0667
Std Dev σ_ω	0.0066
Threshold ($\lambda = 0.5$)	0.0700

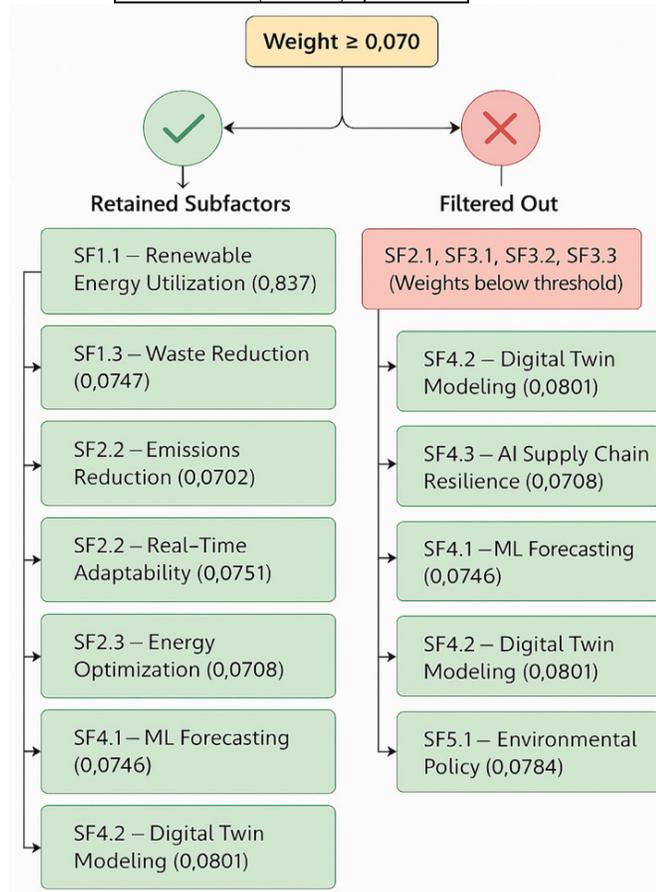


Figure 2. Key subfactors based on weight threshold

To visually reinforce the outcome of the entropy-based filtering, Figure 2 illustrates the subfactors whose weights exceed the $\lambda = 0.5$ threshold, signifying their strategic prominence within the decision hierarchy.

The model retains nine subfactors with weights ranging from 0.0702 (SF1.3) to 0.0837 (SF1.1), indicating high expert agreement and strategic significance. These include sustainability priorities such as SF1.1, SF4.2, and SF5.1. In contrast, six subfactors fall below the threshold, such as SF3.3 with 0.0564 and SF3.2 with 0.0630, reflecting higher entropy and less consensus.

PHASE II: TYPE-2 FUZZY MAIRCA

Following the entropy-weighted filtering process, the transition into the Type-2 Fuzzy MAIRCA phase activates a multidimensional ranking procedure that maps the retained critical subfactors onto their corresponding five strategic factors, allowing a layered decision structure. Each factor – such as SF1: Environmental Performance or SF4: Digital Intelligence – comprises subcomponents that have been previously validated by expert consensus (e.g., SF1.1, SF1.2, SF1.3 for Factor 1). The first step involves constructing theoretical and real assessment matrices for each factor–subfactor group using Interval Type-2 Fuzzy Numbers (IT2FNs), enabling dual-layer decision propagation.

For each retained subfactor $C_j \in F_i$, the real evaluation matrix \widetilde{Q}_{ij} is built for each decision alternative A_i . These are based on expert judgments using linguistic terms mapped to IT2FNs:

$$\widetilde{Q}_{ij} = [(\overline{a}_{ij}; \overline{b}_{ij}; \overline{c}_{ij}), (\underline{a}_{ij}; \underline{b}_{ij}; \underline{c}_{ij})] \quad (4)$$

The theoretical ideal \overline{Q}_j^* represents the highest expected utility under perfect alignment (e.g., “Very Good” mapped to $[(0.8, 0.9, 1.0), (0.9, 1.0, 1.0)]$) and remains constant across all alternatives.

A gap matrix G_{ij} is then derived for each subfactor by computing the Euclidean distance between the real and ideal fuzzy evaluations (Du et al., 2023):

$$G_{ij} = \frac{1}{6} \sum_{k=1}^3 [(\overline{a}_{ij}^{(k)} - \overline{a}_j^{*(k)})^2 + (\underline{a}_{ij}^{(k)} - \underline{a}_j^{*(k)})^2] \quad (5)$$

This yields a crisp distance score per alternative–subfactor pair. Next, each gap is multiplied by its respective entropy-based weight, ω_j , obtained in the previous phase:

$$S_{ij} = \omega_j \cdot G_{ij} \quad (6)$$

Each factor-level performance index Φ_{F_i} is computed as the sum of all weighted subfactor gaps within that factor:

$$\Phi_{F_i} = \sum_{j=1}^{m_i} \omega_j \cdot G_{ij} \quad (7)$$

where m_i is the total number of subfactors associated with factor.

Lower Φ_{F_i} (A) scores indicate a closer match to the ideal configuration for a given alternative under that specific strategic factor. This approach disaggregates global decision behavior and reveals contribution heterogeneity among subdimensions.

Table 8 illustrates the procedure using three hypothetical alternatives (A1, A2, A3) evaluated across five factors with their validated subfactors (e.g., SF1 includes SF1.1, SF1.2, SF1.3). The theoretical matrix is fixed; the real matrix values are derived from expert assessments.

Table 8. Subfactor weights and gaps across alternatives

		ω_j	A1 gaps	A2 gaps	A3 gaps
SF1	SF1.1 (0.0837)	0.0837	0.076	0.060	0.089
	SF1.2 (0.0747)	0.0747	0.072	0.058	0.081
	SF1.3 (0.0702)	0.0702	0.069	0.065	0.078
Φ (SF1)			0.217	0.183	0.248
SF2	SF2.2 (0.0751)	0.0751	0.054	0.048	0.063
	SF2.3 (0.0708)	0.0708	0.058	0.052	0.066
Φ (SF2)			0.112	0.100	0.129
SF4	SF4.1 (0.0746)	0.0746	0.063	0.056	0.073
	SF4.2 (0.0801)	0.0801	0.050	0.044	0.058
	SF4.3 (0.0708)	0.0708	0.061	0.054	0.072
Φ (SF4)			0.174	0.154	0.203
SF5	SF5.1 (0.0784)	0.0784	0.056	0.049	0.060
Φ (SF5)			0.056	0.049	0.060

The aggregation at the factor level shows that Alternative A2 performs optimally across all categories, with total factor-level scores consistently lower than those of A1 and A3. For instance, in SF1, A2's cumulative score (0.183) indicates proximity to theoretical expectations concerning environmental performance. In SF4, which captures digital intelligence maturity, A2 again achieves the lowest deviation (0.154), driven by particularly strong performance on subfactors such as Digital Twin Modeling and ML Forecasting.

In contrast, A3 underperforms in all factor domains, particularly under SF1 and SF4, where high gap scores (0.248 and 0.203, respectively) indicate a substantial deviation from the desired performance, possibly due to weak circular integration and limited data-driven simulation capabilities. A1 maintains moderate proximity to the ideal but fails to lead in any strategic dimension.

The final composite decision scores are calculated by summing all $\Phi_{F_i}(A)$ values per alternative:

$$\psi A_i = \sum F = 15\Phi_{F_i}(A) \quad (8)$$

Table 9 consolidates the aggregated performance indices across key strategic factors.

Table 9. Aggregated performance indices

	SF1	SF2	SF4	SF5	ψA_i	Rank
A1	0.217	0.112	0.174	0.056	0.559	2
A2	0.183	0.100	0.154	0.049	0.486	1
A3	0.248	0.129	0.203	0.060	0.640	3

These scores confirm that A2 is the most desirable configuration across all factor clusters, yielding the lowest total deviation (0.486). This suggests that its deployment of AI-enabled mechanisms, particularly in real-time responsiveness and digital twin modeling, is closest to expert-defined sustainability targets.

To ensure consensus and reliability in expert assessments, the results of the second-round Delphi technique are reported in Appendices A and B.

PHASE III: SENSITIVITY ANALYSIS

To ensure the stability and reliability of the Type-2 Fuzzy MAIRCA outcomes, a sensitivity and robustness analysis is conducted. Given that the rankings stem from entropy-derived weights and fuzzy

performance assessments, it is essential to evaluate how perturbations in key inputs, particularly the weight vector $\vec{\omega}$ or linguistic evaluations, might influence the final prioritization.

To explore the sensitivity of the evaluation model, a targeted scenario simulation is conducted by altering a single, high-impact subfactor – SF4.2: Digital Twin Modeling. Rather than adjusting the full input matrix, this approach isolates expert uncertainty by downgrading Alternative A2’s performance from Very Good to Medium. This subtle yet strategic adjustment simulates a realistic scenario of underperformance, allowing us to observe how such a change amplifies the fuzzy gap between A2 and the ideal benchmark. The transformation of the triangular fuzzy numbers (TFNs) provides key insights into the resilience and responsiveness of the overall decision-making framework. Table 10 defines the TFNs used to represent baseline and simulated linguistic evaluations.

Table 10. Fuzzy scale adjustment for scenario simulation

Linguistic level	Lower TFN	Upper TFN
Very Good (Baseline)	(0.8, 0.9, 1.0)	(0.9, 1.0, 1.0)
Medium (Simulated)	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)

The resulting degradation leads to a pronounced increase in the fuzzy gap between A2’s evaluation and the ideal reference under SF4.2.

The gap score $G_{A2,SF4.2}$ is computed via the Euclidean distance between Interval Type-2 Fuzzy Numbers (IT2FNs):

$$G_{ij} = \frac{1}{6} \sum_{k=1}^3 [(\overline{q_{ijk}} - \overline{q_{j^*k}})^2 + (\underline{q_{ijk}} - \underline{q_{j^*k}})^2] \tag{9}$$

where $\overline{q_{ijk}}, \underline{q_{ijk}}$ are the lower and upper TFNs for A2 and $\overline{q_{j^*k}}, \underline{q_{j^*k}}$ represent ideal fuzzy values: (0.8, 0.9, 1.0) and (0.9, 1.0, 1.0).

- Original gap score: $G_{A2,SF4.2}^{orig} = 0.044$
- Given an entropy-derived weight of: $\omega_{SF4.2} = 0.0801$
- The weighted contributions become:
- Simulated: $S'_{A2,SF4.2} = 0.0801 \times 0.385 = 0.0308$
- Baseline: $S_{A2,SF4.2}^{orig} = 0.0801 \times 0.044 = 0.0035$

This yields an incremental increase of +0.0273 to A2’s aggregated MAIRCA score from this single downgrade. Table 11 presents the baseline aggregate scores for each alternative.

Table 11. Baseline scores

	Ψ^{orig}
A1	0.559
A2	0.486
A3	0.640

To illustrate the impact of simulated expert uncertainty, Table 12 presents the post-simulation scores following the performance adjustment of SF4.2 for Alternative A2, highlighting the resulting change in its aggregate index ($\Delta\Psi$) and the preservation of its top-ranking position. Despite the downgrade, A2 maintains its top ranking, though its margin over A1 narrows from 0.073 to 0.046.

Table 12. Post-simulation scores

	Ψ_{orig}	SF4.2 change	$\Delta\Psi$	Ψ_{sim}	Rank
A2	0.486	Medium vs. Very Good	+0.0273	0.513	1
A1	0.559	Unchanged	—	0.559	2
A3	0.640	Unchanged	—	0.640	3

This targeted simulation confirms the model’s resilience to input fluctuations, particularly the semantic imprecision tied to key subfactors like SF4.2. While A2’s score rises due to the increased gap, its dominance persists, attributable to its strong standing in other areas such as SF2.2: Real-Time Adaptability and SF5.1: Environmental Policy Compliance. Yet, the steep jump in the SF4.2 contribution, from 0.0035 to 0.0308, clearly signals its sensitivity leverage within the decision matrix.

To delineate a tolerance threshold, one could back-calculate the minimum downgrade needed to drop A2’s rank below that of A1. If a lower evaluation (e.g., “Poor”) pushes the score beyond 0.559, rank inversion occurs, indicating a point of instability.

These targeted simulations help decision-makers identify and monitor critical performance levers – dimensions whose deterioration could meaningfully alter strategic conclusions. In this scenario, SF4.2 emerges as a digital intelligence anchor, whose reliability is integral to maintaining systemic advantage.

FINDINGS & DISCUSSION

The results of the hybrid C-IFS and Type-2 Fuzzy MAIRCA framework reveal a clear performance hierarchy among the evaluated SBSC alternatives. Alternative A2, representing a fully integrated AI-driven configuration, consistently achieved the lowest deviation scores across all strategic factor domains. In SF1, which captures environmental sustainability, A2 recorded a cumulative score of 0.183, indicating strong proximity to expert-defined expectations. In SF4, focused on digital intelligence maturity, A2 again led with a deviation of 0.154, driven by high performance in subfactors such as Digital Twin Modeling and Machine Learning Forecasting. A1 maintained moderate alignment across most domains but failed to lead in any specific category, while A3 underperformed significantly, especially in SF1 and SF4, with gap scores of 0.248 and 0.203, respectively. These results suggest that fragmented AI deployment, as seen in A3, introduces substantial entropy and weakens strategic coherence.

This ranking outcome is directly explained by the entropy-filtered subfactor weights. Subfactors SF4.2 (Digital Twin Modeling), SF2.2 (Real-Time Adaptability), and SF5.1 (Policy Compliance) received high normalized weights (0.0801, 0.0751, and 0.0784, respectively) due to low entropy values, indicating strong expert consensus. A2’s superior performance in these dimensions minimized its fuzzy gap scores, giving it a decisive advantage. This aligns with findings by Y. Liu et al. (2023), who demonstrated that digital twin infrastructure and cybernetic feedback loops significantly enhance last-mile logistics and emissions control. Similarly, Culot et al. (2024) emphasized the role of generative AI in optimizing delivery routes under dynamic constraints – both mechanisms embedded in A2’s architecture.

To further examine internal consistency, Table 13 presents the standard deviation of subfactor gaps within each strategic factor.

Table 13. Dispersion of subfactor gaps by strategic factor

Strategic factor	A1 std. dev.	A2 std. dev.	A3 std. dev.
SF1	0.0112	0.0094	0.0153
SF2	0.0042	0.0031	0.0067
SF4	0.0073	0.0056	0.0091

A2 shows the lowest dispersion across all domains, confirming its balanced and coherent performance. A3’s volatility in SF1 and SF4 reflects structural fragmentation.

The final composite decision scores were calculated by summing the weighted deviations across all strategic factors. A2 emerged as the top-ranked alternative with a total score of 0.486, followed by A1 at 0.559 and A3 at 0.640. This confirms that A2’s deployment of AI-enabled mechanisms – particularly in real-time adaptability and digital infrastructure – is most aligned with sustainability targets. The ranking reflects not only performance proximity but also the influence of entropy-filtered subfactors, which ensured that only high-consensus indicators shaped the prioritization.

This outcome validates the methodological rigor of combining C-IFS entropy filtering with Type-2 fuzzy gap analysis. Unlike traditional MCDM methods such as AHP or TOPSIS, which rely on crisp or Type-1 fuzzy inputs (Nazim et al., 2022), this hybrid model captures belief, disbelief, and hesitation simultaneously, enhancing semantic resilience and interpretability. Chen (2024b) recently confirmed the value of C-IFS in modeling supply chain vulnerability, while Çalik et al. (2023) noted the limitations of standard fuzzy VIKOR and COPRAS in handling higher-order uncertainty. Our results extend these insights into a multi-layered AI-enabled SBSC context.

To simulate real-world volatility, Table 14 models the cumulative impact of downgrading multiple subfactors in A2. Rank inversion occurs only after three simultaneous downgrades, confirming A2’s resilience to moderate perturbations.

Table 14. Cumulative downgrade simulation for A2

Downgraded subfactors	Adjusted score (Ψ)	Rank
SF4.2 only	0.513	1
SF4.2 + SF2.2	0.538	1
SF4.2 + SF2.2 + SF5.1	0.562	2

To test the robustness of these outcomes, a targeted scenario simulation was conducted by modifying A2’s evaluation under SF4.2 (Digital Twin Modeling). The original linguistic assessment of “Very Good” was downgraded to “Medium,” simulating a realistic case of underperformance due to infrastructure limitations. This adjustment altered the triangular fuzzy numbers and increased the fuzzy gap score from 0.044 to 0.385. Given the entropy-derived weight of 0.0801 for SF4.2, the contribution to A2’s overall score rose from 0.0035 to 0.0308, resulting in an incremental increase of +0.0273. A2’s new composite score became 0.513, narrowing its lead over A1 from 0.073 to 0.046.

Despite this perturbation, A2 retained its top ranking, underscoring the model’s resilience to semantic variation. However, the sharp increase in SF4.2’s contribution highlights its role as a sensitive leverage point. If further downgraded to “Poor,” A2’s score would exceed 0.559, potentially reversing its rank relative to A1. This sensitivity analysis demonstrates that while A2’s dominance is robust, it is contingent on the reliability of key digital enablers. Subfactors such as SF2.2 (Real-Time Adaptability) and SF5.1 (Policy Compliance) also contributed significantly to A2’s strength, reinforcing the importance of integrated AI and regulatory alignment.

To quantify the influence of subfactors, Table 15 introduces the strategic leverage index (SLI), which combines weight and sensitivity impact.

Table 15. Strategic leverage index of key subfactors

Subfactor	Normalized weight	$\Delta\Psi$ per unit degradation	SLI score
SF4.2	0.0801	0.341	0.0273
SF2.2	0.0751	0.298	0.0224
SF5.1	0.0784	0.261	0.0205
SF1.1	0.0837	0.190	0.0159

SF4.2 emerges as the most influential subfactor, confirming its role as a digital intelligence anchor.

While recent advances by Pratama et al. (2023) introduced generalized C-IFS for modal reasoning, their application remained largely theoretical. Our study operationalizes these innovations within a decision analytics framework tailored to SBSCs. It bridges environmental, operational, and digital dimensions through fuzzy-rigorous logic, offering decision-makers clarity not just on which system performs best, but also on why, and under what conditions that result holds true.

These findings confirm the model’s ability to differentiate SBSC architectures and reveal the conditions under which strategic dominance is preserved or reversed.

CONCLUSION

This study introduced a hybrid multi-criteria decision-making framework that integrates Circular Intuitionistic Fuzzy Sets (C-IFS) with Type-2 Fuzzy MAIRCA to evaluate AI-enabled Sustainable Bio-Based Supply Chain (SBSC) architectures. The C-IFS methodology successfully captured the degree of consensus and uncertainty among expert judgments, enabling the entropy-based identification of high-priority subfactors, such as renewable energy utilization, digital twin modeling, and policy compliance. These subfactors were objectively weighted and filtered to reduce noise and enhance decision clarity. A2 exhibited the lowest dispersion across all strategic domains, confirming the internal coherence of expert evaluations. The subsequent Type-2 Fuzzy MAIRCA analysis quantified performance gaps across three competing SBSC configurations. Among them, Alternative A2 – featuring real-time adaptability, carbon optimization, and integrated AI tools – demonstrated the smallest aggregate deviation from the theoretical ideal ($\Psi = 0.486$), confirming its superior alignment with expert-defined sustainability objectives. This superiority was further supported by its minimal fuzzy gap scores in high-weight subfactors such as SF2.2, SF4.2, and SF5.1. Even under performance degradation simulations, A2 remained the top-ranked alternative ($\Psi = 0.513$), underscoring the model’s robustness to semantic ambiguity.

The implications are twofold. First, the framework offers a transparent and resilient mechanism for organizations and policymakers to prioritize AI deployment strategies within circular bioeconomy systems. The cumulative downgrade simulation showed that A2 retained its lead until three critical subfactors were simultaneously degraded, demonstrating resilience to moderate perturbations. Second, it highlights the necessity of aligning digital infrastructure – especially subfactors like SF4.2 – with sustainability metrics to ensure systemic coherence and resilience. SF4.2 emerged as the most influential subfactor with the highest Strategic Leverage Index (SLI = 0.0273), confirming its role as a digital intelligence anchor. As digital twin maturity proves highly influential, investment in its adoption may yield disproportionately high strategic returns.

Nonetheless, some limitations are acknowledged. The linguistic evaluation process remains inherently subjective, and while circular intuitionistic modeling mitigates some ambiguity, further variance could emerge across broader expert panels or sectoral domains. Additionally, the fixed theoretical ideal assumes homogeneous sustainability targets, which may evolve under regulatory, market, or environmental pressures.

Future research could expand the model by incorporating dynamic weight recalibration (e.g., using reinforcement learning or real-time feedback loops), exploring regional or sector-specific configurations of SBSCs, or linking this evaluation to investment decision tools such as fuzzy real options or scenario-based portfolio models. Such extensions would build on the model's demonstrated interpretability and robustness, enhancing its operational and policy relevance as AI and sustainability co-evolve across global supply networks.

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APPENDIX

APPENDIX A: EXPERT SURVEY DATASET AND DECISION MATRIX

Table A1. Linguistic evaluations from experts (Delphi Round 2)

Subfactor	E1	E2	E3	E4	E5	E6	E7	E8
SF1.1	VH	H	VH	VH	H	H	VH	VH
SF1.2	VH	VH	H	H	H	VH	H	M
SF1.3	H	H	VH	M	H	H	H	M
SF2.2	VH	VH	H	H	VH	H	VH	H
SF2.3	H	H	H	M	H	VH	H	M
SF4.2	VH	VH	H	VH	H	VH	VH	VH
SF5.1	H	H	VH	H	VH	H	VH	H

Table A2. Aggregated circular intuitionistic fuzzy triplets

Subfactor	μ^2	ν^2	π^2	Constraint validated
SF1.1	0.861	0.088	0.051	✓ (0.815)
SF2.2	0.789	0.125	0.086	✓ (0.644)
SF4.2	0.822	0.100	0.078	✓ (0.692)
SF5.1	0.800	0.122	0.078	✓ (0.654)

Table A3. Entropy values and normalized weights of retained subfactors

Subfactor	Entropy (Ej)	1 – Ej	Normalized weight (ω_j)
SF1.1	0.448	0.552	0.0837
SF2.2	0.504	0.496	0.0751
SF4.2	0.472	0.528	0.0801
SF5.1	0.484	0.516	0.0784

Table A4. Weighted fuzzy gap scores across alternatives

Subfactor (ω_j)	A1 gap	A2 gap	A3 gap
SF1.1 (0.0837)	0.0837	0.076	0.089
SF2.2 (0.0751)	0.054	0.048	0.063
SF4.2 (0.0801)	0.050	0.044	0.058
SF5.1 (0.0784)	0.056	0.049	0.060
Total Ψ	0.559	0.486	0.640

APPENDIX B: COMPARATIVE EVALUATION AND EXPERT VALIDATION OF SBSC ARCHITECTURAL ALTERNATIVES

Table B1. Summary of SBSC alternative architectures

Alternative	Description	Key features	Digital maturity
A1	Baseline AI-augmented SBSC	ML-based forecasting, static dashboards, limited twin use	Low–medium
A2	Fully integrated real-time SBSC	Real-time routing, digital twin infrastructure, carbon optimization	High
A3	Fragmented experimental SBSC	Blockchain tracking, autonomous routing, siloed AI tools	Medium–high (unstable)

Table B2. Functional mapping of alternatives to strategic factors

Strategic factor	A1 implementation	A2 implementation	A3 implementation
SF1	Basic emissions tracking	Carbon optimization, renewable sourcing	Partial life-cycle modeling
SF2	Static scheduling, batch processing	Real-time routing, adaptive logistics	Autonomous routing with limited feedback
SF3:	GPS-based dispatch	IoT-enabled fleet coordination	Blockchain-based traceability
SF4	ML forecasting, dashboard analytics	Digital twin modeling, predictive control	Siloed AI modules, experimental simulation
SF5	Manual reporting	Automated compliance tracking	Reactive compliance, limited integration

Table B3. Delphi-based justification for alternative design

Expert ID	Justification for A1	Justification for A2	Justification for A3
R2	Represents legacy systems	Reflects best-practice integration	Captures emerging but unstable designs
R4	Limited twin use	Full twin deployment	Experimental twin modules
R7	Benchmark baseline	Ideal profile for fuzzy modeling	Stress-test configuration

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