International Journal of Mathematical, Engineering and Management Sciences
Vol. 11, No. 4, 1560-1589, 2026
https://doi.org/10.33889/IJMEMS.2026.11.4.064

A Swarm Intelligence-Driven Decision Support Framework for Adaptive Threshold Optimization in Integrated BWM-DEMATEL-ISM Models

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(Received on April 7, 2026; Revised on May 9, 2026 & June 6, 2026 & June 15, 2026; Accepted on June 24, 2026)

Abstract
Evaluating barriers in complex decision contexts requires analyzing causal interdependencies. The integration of the Best-Worst Method (BWM), Decision-Making Trial and Evaluation Laboratory (DEMATEL), and Interpretive Structural Modeling (ISM) provides a logically complete paradigm. Yet its reliability is persistently compromised by subjective or statistically flawed threshold determinations used to construct the ISM hierarchy. To address this gap, this study proposes the SI-BDI framework, which mathematically embeds BWM weights to establish a weighted causal network, and couples Swarm Intelligence (SI) metaheuristics with a newly formulated, parameter-free Causal Structure Index (CSI) that jointly maximizes causal clarity and structural depth. Applied to organic rice farming barriers in Vietnam's Mekong Delta, three independent SI metaheuristics converge to an identical optimal threshold of 0.156, corresponding to a CSI of 0.852. This optimal threshold yields a four-level hierarchy that exhibits exceptional robustness under both leave-one-out and leave-two-out expert exclusions. Furthermore, as evaluated using the proposed Industrial Adaptability-Structural Stability Reliability (IA-SSR) composite metric, the framework demonstrates superior structural resilience under Monte Carlo weight perturbations of up to 10% compared with conventional mean-plus-standard-deviation and Maximum Mean De-Entropy (MMDE) benchmarks. Practically, the framework reveals that institutional deficiencies, specifically the Inadequate Support Policy Framework as the singular Level-4 root cause, propagate through fragmented zoning and absent enterprise leadership to manifest as weak market control. Crucially, the optimal threshold structurally decouples consumer demand from these upstream policy drivers, providing Multi-Criteria Decision-Making-derived empirical grounding for re-sequencing institutional reforms while concurrently deploying independent demand-side interventions.

Keywords- BWM-DEMATEL-ISM, Causal structure index, Organic rice farming, Swarm intelligence, Threshold optimization.

1. Introduction

Barriers to decision-making are broadly understood as obstacles that hinder the rational, timely decision-making process and often undermine strategic goals (Gkrimpizi et al., 2023; Mahroum, 2015). Merely identifying the existence of such obstacles is insufficient for meaningful intervention. To effectively mitigate their impact, it is critical to analyze their deeper structural characteristics, specifically the weights of the criteria, their causal interrelationships, hierarchical influence, and root causes. Multi-Criteria Decision Making (MCDM) is explicitly designed for such complex structural evaluations. Within this domain, the integration of the Best-Worst Method (BWM), Decision Making Trial and Evaluation Laboratory (DEMATEL), and Interpretive Structural Modeling (ISM) has emerged as a robust paradigm (hereafter, the BWM-DEMATEL-ISM or BDI approach). BWM efficiently derives criterion weights; DEMATEL captures causal interdependencies; and ISM constructs a clear hierarchical structure (Hien et al., 2024; Qian and Wang, 2023; Sheykhan et al., 2024).

Despite its logical completeness, a persistent methodological challenge in the integrated BWM-DEMATEL-ISM approach is determining the threshold value (α) used to dichotomize the DEMATEL total-relation matrix T (hereafter the T-matrix) into the binary reachability matrix M that ISM requires as its input. A critical review of recent literature (2018-2025) reveals that current integrations are often fragmented, sequential, or highly sensitive to subjective thresholding. Many studies treat BWM and DEMATEL as separate modules, failing to mathematically embed priority weights into the causal matrix (Agrawal et al., 2025; Chirra and Raut, 2025; Choudhary et al., 2020; Dhingra et al., 2025; Kavre et al., 2024; Kumar et al., 2023; Li and Fei, 2025; Moktadir et al., 2020), or they evaluate ISM and DEMATEL sequentially without robust linkage (Ahmad et al., 2024; Chi et al., 2025; He et al., 2025; Kumar and Dixit, 2018; Wang et al., 2024). Furthermore, when constructing the ISM hierarchy, threshold determination frequently relies on arbitrary expert judgment (Ou et al., 2022; Wang et al., 2024) or rigid statistical measures such as Mean + SD (Alqahtani and Makki, 2023; Ebrahimi et al., 2024; Meng et al., 2022; Shi et al., 2024) and Maximum Mean De-Entropy (Chen, 2021; Ojha et al., 2024; Singh and Bhanot, 2019; Zhang et al., 2026; Zheng et al., 2023). Synthesizing these limitations, the BWM-DEMATEL-ISM literature exhibits three specific research gaps that motivate the present study:(i) the absence of a parameter-free objective function for continuous threshold optimization at the DEMATEL-ISM bridge; (ii) the mathematical incompatibility between the embedding of BWM priority weights into the DEMATEL T-matrix and traditional entropy-based threshold selection methods; and (iii) the absence of resilience-based validation protocols that benchmark threshold-selection methods against both expert-panel uncertainty and weight perturbations. These conventional methods can yield overly dense or sparse networks, thereby distorting the structural clarity of the causal system and compromising the framework's objectivity (Chen et al., 2022).

To overcome this methodological bottleneck, this study proposes an optimized threshold selection approach by introducing the Swarm Intelligence-driven BWM-DEMATEL-ISM (SI-BDI) framework. In computational mathematics, metaheuristics are advanced optimization algorithms explicitly designed to efficiently resolve complex, non-convex problems with infinite search spaces where traditional exact methods fail. Leveraging this capability, SI is integrated into this framework to autonomously navigate the continuous threshold search space and pinpoint the optimal value, thereby eliminating the reliance on subjective human judgment or rigid statistical assumptions. To guide this algorithmic optimization, a novel objective function, the Causal Structure Index (CSI), is formulated to systematically evaluate the fitness of each candidate threshold. Unlike conventional metrics such as Maximum Mean De-Entropy (MMDE) or Mean + SD, which rely on rigid statistical or entropy-based properties, the CSI operates on a fundamentally different mathematical logic. It dynamically balances causal clarity (maximizing net influence) with structural simplicity (managing the number of retained relationships) to identify the global optimum. Because the threshold α is a continuous variable on $[0, max(T)]$ and the resulting CSI landscape is non-convex with multiple local optima generated by step changes in the binary reachability matrix M, conventional discrete grid-search approaches are fundamentally constrained by their predefined step sizes; this structural property motivates the use of population-based SI metaheuristics specifically designed for continuous optimization in non-smooth landscapes. Rather than relying on a single predefined algorithm, this study benchmarks four heterogeneous SI metaheuristics, including Secretary Bird (SB), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO), to automate threshold discovery, with cross-algorithm consensus on the global optimum providing empirical evidence of the CSI's well-posedness.

To validate the proposed framework, this research applies it to a highly complex and fragmented real-world system: the adoption of organic rice farming in Vietnam's Mekong Delta. Vietnam is the world's third-largest rice exporter, with the Mekong Delta accounting for approximately 50% of national rice output and over 90% of rice exports (Dao et al., 2020). However, decades of conventional intensive cultivation have degraded soil quality, increased methane emissions, and compromised the long-term sustainability of this strategically critical sector. Organic rice transition offers a pathway to environmental restoration and access to high-value export markets. However, adoption remains below 2% of cultivated area despite sustained policy support since 2018, indicating that supply-side promotion strategies have failed to address the underlying structural barriers (Dinh et al., 2023). Despite extensive literature on Vietnamese rice production, comprehensive structural causal analyses that apply integrated MCDM methodologies to organic rice barriers remain limited.

2. Literature Review

2.1 Theoretical Foundations of the Integrated BWM-DEMATEL-ISM Paradigm

Evaluating complex decision-making barriers requires analyzing deeply embedded causal interdependencies rather than merely identifying isolated factors. To achieve this, integrating the BWM, DEMATEL, and ISM provides a logically complete paradigm. The foundation of this integration relies on three distinct yet complementary methodologies. First, BWM, originally proposed by Rezaei (2015), is a robust technique designed to derive the relative importance weights of criteria (Rezaei, 2015). BWM distinguishes itself from traditional pairwise comparison methods, such as AHP, by employing a structured vector-based comparison that significantly reduces data requirements and enhances consistency (Rezaei, 2015). Second, the DEMATEL method, originally developed by Gabus and Fontela (1972) at the Battelle Memorial Institute, is a sophisticated structural modeling technique for visualizing complex causal relationships (Gabus and Fontela, 1972; Quayson et al., 2024). Unlike traditional methods that assume independence among criteria, DEMATEL explicitly accounts for interdependencies by using matrix operations to classify factors into cause-effect groups (Quayson et al., 2024). Third, ISM, first proposed by Warfield (1974), is an interactive learning process that transforms vaguely articulated mental models into well-defined hierarchical structural models (Warfield, 1974). While the theoretical synergy of these three methods is evident, BWM provides strategic priority weights, DEMATEL captures causal intensity, and ISM maps the hierarchy. Recent literature reveals a critical lack of deep mathematical engagement in their integration. Existing studies often adopt fragmented or sequential workflows (Qian and Wang, 2023; Sheykhan et al., 2024). For instance, fragmented integrations frequently operate BWM independently from the structural insights of DEMATEL, meaning the derived weights do not mathematically influence the causal network (Agrawal et al., 2025; Chirra and Raut, 2025; Choudhary et al., 2020; Dhingra et al., 2025; Kavre et al., 2024; Li and Fei, 2025; Moktadir et al., 2020). Similarly, sequential ISM-DEMATEL workflows often fail to mathematically link the ISM binary reachability matrix to DEMATEL's influence intensity (Ahmad et al., 2024; Chi et al., 2025; He et al., 2025; Kumar and Dixit, 2018; Wang et al., 2024).

Table 1 summarizes the comparative taxonomy of dominant MCDM methods, highlighting their strengths, drawbacks, and methodological constraints in barrier evaluation.

Table 1. Comparative taxonomy of dominant MCDM methods in barrier evaluation.

Method	Type	Strength	Drawbacks	Combinations
AHP	Pairwise comparison	- Assess the importance of the problem (Khasawneh and Dweiri, 2024; Kustiyahningsih et al., 2021; Munier and Hontoria, 2021). - Prioritize/Rank barriers (Agarwal et al., 2022; Batwara et al., 2024; Cao and Solangi, 2023; Das et al., 2023; Lalita et al., 2025; Nigam et al., 2023; Pandey et al., 2025; Percin, 2023; Uddin et al., 2019; Xue et al., 2024; Zhao et al., 2024).	- Not showing the relationship of barriers. The AHP is impractical for complex scenarios because it was not designed to address complexity (Munier and Hontoria, 2021). In complex problems, factors often have interdependencies or complex interactions that a hierarchical structure cannot accurately describe (Munier and Hontoria, 2021). AHP assumes that factors are independent of each other. However, in complex problems, factors rarely operate independently; they often have interconnected relationships and influence one another (Taherdoost and Madanchian, 2023).	- Ranking-focused integrations: AHP is primarily combined with distance-based methods to derive weights for alternative ranking, ignoring causal network analysis: AHP-TOPSIS: AHP for Weights, TOPSIS for Ranking (Khasawneh and Dweiri, 2024; Kustiyahningsih et al., 2021; Solangi et al., 2021). - Applying AHP and DEMATEL in parallel (Das et al., 2021; Singh et al., 2025).
BWM	Pairwise comparison	- New method for prioritizing/Ranking barriers (Gholipoor, 2021; Gupta and Barua, 2018; Kumar et al., 2023; Madaan et al., 2023; Mahdiyar et al., 2020; Malek and Desai, 2019; Mohammadpour et al., 2024; Mostafaeipour et al., 2021; Shahedi et al., 2023; Shahin et al., 2024; Wei et al., 2023).	- BWM is like AHP in that both rely on pairwise comparisons and typically work with the opinions of a Single person or a unified group. Like AHP, BWM lacks a direct mechanism to combine evaluations from multiple decision-makers. Using arithmetic or geometric mean to aggregate opinions can lead to information loss (Mohammadi and Rezaei, 2020).	- Ranking-focused integrations: BWM is typically combined with distance-based or outranking methods purely for prioritization without causal structural analysis: BWM-FTOPSIS (Gholipoor, 2021; Gupta and Barua, 2018) BWM & IR-MABAC (Shahedi et al., 2023); IT2F-PROMETHE II (Wei et al., 2023). - Fragmented BWM-DEMATEL: BWM weights operate independently as a separate module and do not mathematically influence the DEMATEL causal (Agrawal et al., 2025; Chirra and Raut, 2025; Choudhary et al., 2020; Dhingra et al., 2025; Kavre et al., 2024; Li and Fei, 2025; Moktadir et al., 2020).
TOP-SIS	Distance based	- Prioritize/Rank barriers. TOPSIS then ranks the barriers based on the criteria's weights (e.g., determined by AHP, ANP, or BWM). (Gholipoor, 2021; Gupta and Barua, 2018; Lalita et al., 2025; Nguyen et al., 2024).	- TOPSIS primarily focuses on the disparity (distances) of the plans (alternatives) from the ideal and anti-ideal solutions (Song and Tong, 2022). - The traditional TOPSIS method is its reliance on crisp (precise) numerical data, which often fails to account for the inherent uncertainty and ambiguity present in real-world information (Pandey et al., 2025).	- TOPSIS relies entirely on exogenous weights (e.g., from AHP, ANP, or BWM) to rank barriers based on geometric distances, offering zero insights into the causal mechanisms or hierarchical transmission structures among them: AHP-TOPSIS: AHP for Weights, TOPSIS for Ranking (Khasawneh and Dweiri, 2024; Kustiyahningsih et al., 2021; Solangi et al., 2021). Others: ANP-TOPSIS (Nguyen et al., 2024), BWM-TOPSIS (Gholipoor, 2021; Gupta and Barua, 2018).
ISM	Hierarchy	- Interrelationships between the barriers (root cause barriers through the hierarchical structure) (Chanchaichujit et al., 2024; Dixit et al., 2024; Jena and Dwivedi, 2021; Lalita et al., 2025; Narkhede et al., 2020; Raut and Gardas, 2018; Singh and Bhanot, 2019; Wu et al., 2022).	- ISM does not distinguish between the level of influence (strong or weak), because it only uses 0 and 1 (Chen, 2021).	- Sequential ISM-DEMATEL: Independent workflows that fail to mathematically link the ISM binary reachability matrix to DEMATEL's influence intensity, often utilizing separated calculation modules (Ahmad et al., 2024; Chi et al., 2025; He et al., 2025; Jena and Dwivedi, 2021; Kumar and Dixit, 2018; Lalita et al., 2025; Narkhede et al., 2020; Raut and Gardas, 2018; Wu et al., 2022).

Table 1 continued...

DEM-ATEL	Graph-based	- Interrelationships between the barriers (degree of influence between factors) (Dixit et al., 2024; Jena and Dwivedi, 2021; Khan et al., 2018; Kumar et al., 2023; Narkhede et al., 2020; Nguyen et al., 2024; Nigam et al., 2023; Quayson et al., 2024; Singh and Bhanot, 2019; Wu et al., 2022).	- DEMATEL outputs a continuous total-relation matrix; integrating with ISM requires choosing a threshold α to binarize T, but no scientific method for this binarization is provided (Chen, 2021).	- Filters the DEMATEL matrix to generate the ISM structure, but critically relies on subjective expert opinions, rigid statistical filters (Mean + SD), or mathematically distorted entropy-based methods (MMDE): DEMATEL-ISM (Alqahtani and Makki, 2023; Chen, 2021; Meng et al., 2022; Ojha et al., 2024; Ou et al., 2022; Shi et al., 2024; Singh and Bhanot, 2019; Trivedi et al., 2021; Yadav et al., 2022; Zhang et al., 2026; Zheng et al., 2023).

2.2 Critical Review of Threshold Optimization Methods in DEMATEL

The most severe methodological bottleneck in the DEMATEL-ISM bridge is the determination of the threshold value (α) used to dichotomize the continuous T-matrix into the binary reachability matrix M required by ISM (Chen et al., 2022). This filtering directly dictates the structure of the final ISM hierarchy. A critical review of existing literature reveals three dominant yet flawed, approaches to threshold determination:

- Subjective Expert Opinion: Historically, the threshold has been set arbitrarily based on expert consensus. This subjectivity compromises the framework's objectivity, leading to inconsistent causal networks and unstable hierarchical structures (Ou et al., 2022).
- Density-Based/Statistical Methods (Mean + SD): To introduce objectivity, many studies rely on statistical density measures, predominantly the Mean plus Standard Deviation (Mean + SD) approach (Alqahtani and Makki, 2023; Ebrahimi et al., 2024; Meng et al., 2022; Shi et al., 2024). However, these are rigid statistical filters. They blindly evaluate the matrix's numerical distribution, neglecting the network's structural integrity, often yielding overly sparse matrices that discard critical secondary interdependencies.
- Entropy-Based Methods: The Maximum Mean De-Entropy (MMDE) algorithm represents a significant improvement by framing threshold selection as an entropy minimization problem (Chen, 2021; Ojha et al., 2024; Singh and Bhanot, 2019; Zhang et al., 2026; Zheng et al., 2023). Theoretically, maximizing MMDE results in a network with concentrated influence, thereby reducing structural noise (Li and Tzeng, 2009).
- However, a critical vulnerability emerges when BWM priority weights are mathematically integrated into the DEMATEL matrix. Multiplying fractional weights significantly reduces the absolute values of the influence coefficients. In this weighted-causality environment, the probability distribution changes fundamentally, distorting entropy-based algorithms such as MMDE. Consequently, they lose their discriminative power, fail to filter stochastic noise, and leave the causal network saturated.

2.3 Positioning the Causal Structure Index (CSI) within the Literature

The failure of subjective, density-based, and entropy-based thresholding methods in a fully integrated, weighted BWM-DEMATEL-ISM environment exposes a critical research gap. Existing methods treat the threshold determination as either a discrete statistical calculation or a subjective assumption. Identifying the optimal threshold α is a continuous optimization problem that balances network clarity with structural complexity (Fu et al., 2024; Sanjalawe et al., 2025).

To fill this gap, this study introduces the Causal Structure Index (CSI). Unlike conventional metrics that rely on rigid mathematical distributions (e.g., MMDE or Mean + SD), the CSI is explicitly designed as an objective function for metaheuristic algorithmic optimization. The CSI operates on a distinctly different mathematical logic: it evaluates the fitness of a candidate threshold by dynamically balancing the maximization of net causal influence (the clarity of the cause-effect separation) with the minimization of retained relationships (to prevent network saturation).

Because navigating the infinite search space of a continuous variable (α) is computationally intensive, the CSI is positioned to be optimized via SI metaheuristics, which have been proven highly effective for continuous variable optimization in MCDM contexts (Akbari and Henteh, 2019; Rishabh and Das, 2024; Wang et al., 2021). Specifically, this framework benchmarks four heterogeneous SI metaheuristics: SB, PSO, ABC, and ACO to assess cross-algorithm consensus on the CSI global optimum, with consensus serving as empirical evidence of the objective's well-posedness rather than positioning any single algorithm as superior. The recently proposed SB (Fu et al., 2024), with its two-stage hunt-escape architecture combining Lévy-flight exploration and exponential-stomping exploitation, is included among the four candidate optimizers due to its demonstrated performance on continuous, non-convex objectives.

3. Method

3.1 Research Framework

The conceptual framework outlined in this study (**Figure 1**) provides a structured approach to evaluating barriers by transitioning from expert inputs to actionable outputs through well-defined stages. The integrated methodology combines the complementary strengths of BWM, DEMATEL, the SI algorithm, and ISM into a cohesive, goal-oriented pipeline.

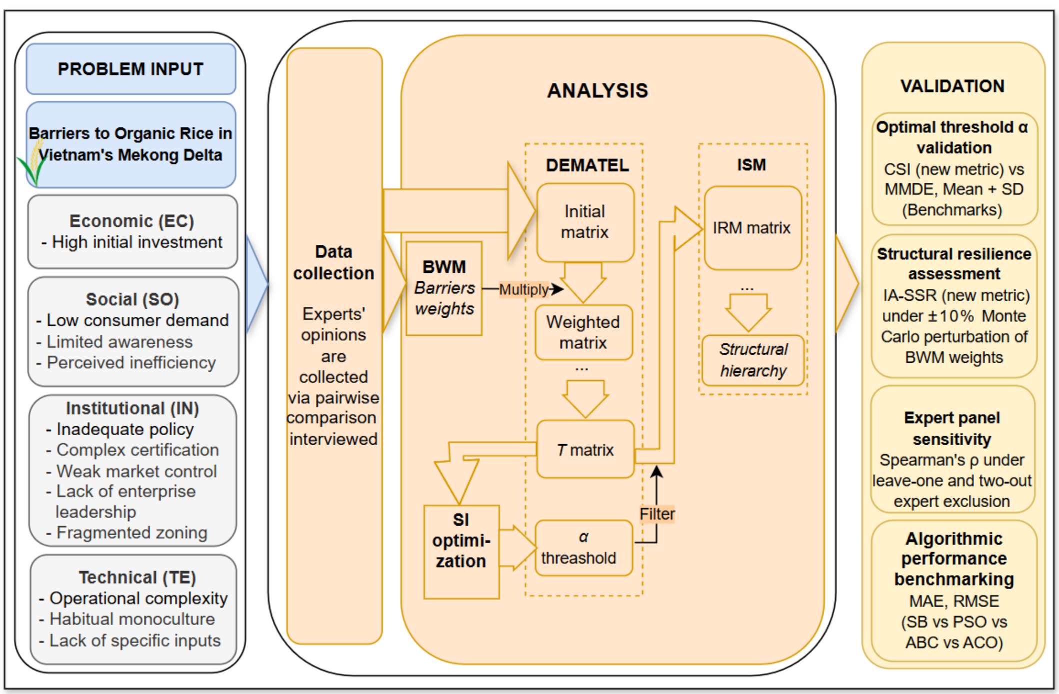

Figure 1. Conceptual framework of the proposed SI-BDI methodology integrating BWM, DEMATEL, SI-CSI optimization, and ISM.

The DEMATEL step conducts a causal analysis. To address the modular separation gap in previous studies, this step explicitly integrates BWM priority weights into the DEMATEL computational process. Specifically, the optimal weight vector (*W*) derived from BWM is mathematically multiplied with the initial direct-influence matrix (*Z*) to yield a strategically weighted matrix ($Z_{weighted} = W \times Z$).This integration ensures that the resulting Total Relation Matrix (*T*) accurately reflects not only the raw causal interdependencies but also the strategic priority of each barrier. Following the DEMATEL computations, a critical optimization problem arises, determining the threshold (α) to filter the normalized *T*-matrix. Rather than relying on arbitrary manual selection, this framework introduces the SI algorithm step. To evaluate the fitness of each candidate threshold during the SI algorithm's search phase, we propose the Causal Structure Index (CSI). This parameter-free objective function aggregates two complementary structural utilities through a geometric mean.

First, the causal strength $CS(\alpha)$ measures the average net causal influence retained at threshold α:

$$CS(\alpha) = \frac{(\overline{R-C})_{cause} + |\overline{R-C}|_{effect}}{N_{arrows}(\alpha)} \tag{1}$$

where,
$R_i = \sum_j T_{ij}$: row sum of the weighted *T*-matrix.
$C_i = \sum_j T_{ji}$: column sum of the weighted *T*-matrix.
Cause group: Barriers with $R_i - C_i > 0$.
Effect group: Barriers with $R_i - C_i < 0$.

$N_{Arrows}(\alpha) = \{(i, j): T_{ij} \geq \alpha, i \neq j\}$ is the number of retained directed influences.

Second component, hierarchical depth $L(\alpha) \in \{1,2, \dots, n\}$ is the number of levels in the ISM hierarchy obtained by Warshall transitive closure, followed by Warfield's level partitioning (Warfield, 1974) of the binary reachability matrix $M(\alpha) = [T_{ij} \geq \alpha]$. Higher $L(\alpha)$ indicates greater structural depth and finer causal stratification. To ensure unit incommensurability does not bias the aggregation, both components are rescaled to $[0,1]$ via min-max normalization (Jahan and Edwards, 2015):

$$\widetilde{CS}(\alpha) = \frac{CS(\alpha) - CS_{min}}{CS_{max} - CS_{min}}, \tilde{L}(\alpha) = \frac{L(\alpha) - L_{min}}{L_{max} - L_{min}} \tag{2}$$

where,

- CS_{min}, CS_{max}: minimum and maximum values of $\mathrm{CS}(\alpha)$.
- L_{min}, L_{max}: minimum and maximum values of $L(\alpha)$.
- Across the feasible threshold range $\alpha \in [0, max(T)]$.

The CSI is then defined as the geometric mean of the two normalized components (Aczél and Saaty, 1983; Tofallis, 2014):

$$CSI(\alpha) = \sqrt{\widetilde{CS}(\alpha) \cdot \tilde{L}(\alpha)} \tag{3}$$

The optimal threshold α^* is the global maximizer of CSI:

$$\alpha^* = arg \underbrace{max}_{\alpha \in [0, max(T)]} CSI(\alpha) \tag{4}$$

First, by virtue of the geometric-mean (Aczél and Saaty, 1983; Tofallis, 2014), CSI is bounded in [0,1], weakly increasing in both components, and invariant under positive affine rescaling of either component, ensuring that the aggregation is unaffected by the unit incommensurability between CS and integer L. Second, when either component attains its minimum, $CSI(\alpha) = 0$, regardless of the other, so a high CS cannot compensate for a collapsing hierarchy. This embeds an intrinsic anti-sparsity mechanism into the objective itself, eliminating the need for the ad hoc elbow-selection procedure required by purely density-based criteria, a property of non-substitutability formally established by Tofallis (2014) for multiplicative MCDM aggregation. Third, the maximizer of CSI coincides with the unique Nash bargaining solution over (CS, L) with disagreement point (0,0) (Nash, 1950); equivalently, log CSI is the equally-weighted log-utility average, the maximum-entropy choice when no exogenous criterion-importance information is available (Tang and Lin, 2025). The complete flowchart of the proposed SI-CSI optimization procedure is illustrated in **Figure 2**.

- Anti-bias safeguards in the CSI construction

To ensure mathematical rigor and address potential structural biases, the CSI is designed with three critical justifications:

- Preventing circular dependency: A common flaw in dynamic thresholding is the circular dependency between the chosen threshold α and the classification of Cause/Effect groups. To eliminate this, the Prominence (R+C) and Relation (R−C) indices used to classify barriers into Cause (R−C>0) and Effect (R−C<0) groups are calculated solely from the original, unthresholded T-matrix. Consequently, the group classifications remain structurally constant, and α only dictates the active causal connections in the final diagram.
- Numerator justification: The numerator aggregates the average net driving power $(\overline{R - C})_{cause}$ and the average net perceived influence ($|\overline{R - C}|_{effect}$). Using averages rather than absolute sums mitigates cardinality bias, ensuring that a group with a disproportionately large number of criteria does not mathematically dominate the objective function.
- Denominator and sparsity penalty: $N_{Arrows}(\alpha)$ represents the total number of retained relationships. To prevent the algorithm's bias toward generating overly sparse networks (where critical secondary pathways are lost), a strict constraint $N_{Arrows} > n$ (where n is the total number of criteria) is enforced. This constraint prevents the algorithm from generating an excessively fragmented model while allowing the SI metaheuristic to identify the most significant causal backbone. Under this optimized threshold α, while global connectivity is maintained, specific barriers with low interaction intensities may emerge as autonomous elements, reflecting their high functional specificity in the system.

- Optimization of the continuous threshold variable α.

- Determining the optimal threshold requires maximizing the CSI. However, this optimization process poses a significant mathematical challenge: the threshold α is a continuous variable ($\alpha \in [0, max(T)]$), resulting in an infinite search space. While traditional discrete approaches (e.g., mathematical grid search) could technically be employed, their accuracy is fundamentally constrained by predefined step sizes, and achieving high precision requires computationally exhaustive loops. Moreover, the CSI function is non-convex and multi-modal due to the discrete step changes in $N_{Arrows}(\alpha)$ when α crosses values in T, combined with the integer nature of $L(\alpha)$, producing a piecewise-constant landscape with multiple plateaus and local optima that conventional grid-search approaches cannot navigate without committing to an arbitrarily fine resolution (Helton and Davis, 2003; Saltelli et al., 2008). Population-based metaheuristics designed for non-smooth continuous landscapes are therefore the appropriate optimization paradigm (Fu et al., 2024).

- To overcome this, SI metaheuristics are utilized, as they are explicitly designed for continuous optimization problems. Specifically, this framework embeds the SB algorithm to navigate this infinite search space. By balancing broad Lévy-flight exploration with targeted exponential-stamping exploitation, the SB algorithm efficiently pinpoints the exact global optimum α^* without being constrained by the structural limitations of discrete resolution. Although the CSI function only changes at discrete points corresponding to off-diagonal values of T, the optimal α is not restricted to these discrete values. In practice, any α between two consecutive off-diagonal values yields the same CSI, but choosing a slightly larger α than necessary may discard meaningful relationships. Therefore, the optimization must precisely identify the threshold value itself, not just the index of a sorted list. Furthermore, when extending this framework to dynamic or uncertain environments where T is not fixed, the discrete nature disappears, and continuous optimization becomes essential. Thus, adopting metaheuristics provides both theoretical rigor and practical extensibility.

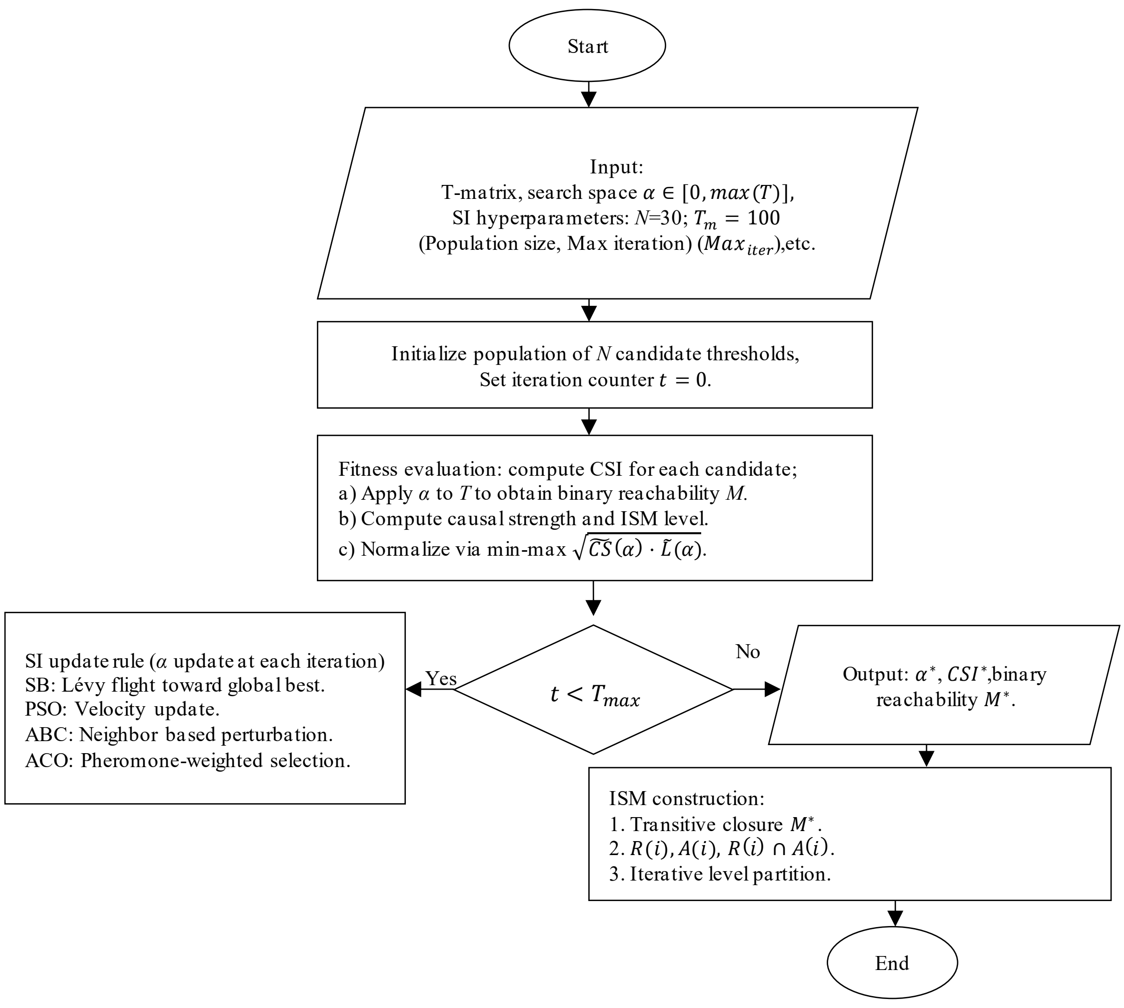

Figure 2. Proposed SI-CSI optimization procedure.

Once the optimal threshold α^* has been identified, the binary reachability matrix M is constructed as $M_{ij} = 1$, if $T_{ij} \geq \alpha^*$, and 0 otherwise; with $M_{ii} = 1$ by convention. The transitive closure M^* is then computed via the Warshall algorithm to capture all direct and indirect reachable relationships among barriers (Warfield, 1974). For each barrier i, two sets are defined: the reachability set $R(i) = \{j: M_{ij} = 1\}$ comprising all barriers that can be reached from ii; and the antecedent set $A(i) = \{j: M_{ji} = 1\}$, comprising all barriers from which ii can be reached. The intersection $R(i) \cap A(i)$ identifies barriers mutually connected to i. Level partitioning proceeds iteratively. At iteration k, all barriers satisfying $R(i) \cap A(i) = R(i)$ are assigned to level k and removed from further consideration. The procedure terminates when all barriers have been assigned. Following Warfield's convention, Level 1 (the top of the hierarchy) contains terminal outcome barriers, those that cannot transmit influence to any remaining unassigned barriers. In contrast, the bottom level contains root-cause drivers from which all others are reachable. The resulting hierarchy provides a topological decomposition of the causal network into successive layers of causation, enabling the downstream identification of intervention leverage points.

3.2 Dataset

Synthesizing the theoretical insights from the comprehensive literature review, this study identifies a finalized set of critical barriers hindering organic rice adoption. To ensure these criteria are suitable for Vietnam's Mekong Delta context and actionable for decision-making, the initial raw list was screened, refined, and thematically categorized into four distinct dimensions: Economic, Social-Cognitive, Institutional-Policy, and Technical. In the next step, the expert panel will evaluate the identified barriers to determine their impact on organic rice adoption. To ensure high information density and relevance, this study focuses on the Mekong Delta, Vietnam's rice bowl. Therefore, targeting experts within this network ensures access to in-depth, context-specific knowledge that is crucial for identifying structural barriers. Unlike statistical methods (e.g., SEM, regression) that require large sample sizes for generalization, structural MCDM methodologies prioritize the quality and depth of expert opinion over quantity (Shahid and Ali, 2025). The mathematical validity of these methods relies on the transitivity and consistency of judgments derived from individuals with specialized domain expertise. Accordingly, this study employs a purposive sampling strategy, involving a panel of 10 experts (**Table 2**), to ensure robustness and cross-sectoral representation. These experts are selected based on a rigorous 'Expertise Score' framework, ensuring they possess significant authority and experience. The expert panel (**Table 2**) is strategically composed to ensure cross-sectoral representation, capturing the rice supply chain's complexity through three critical lenses:

(1) Academic/Research: Experts from universities and institutes ensure evaluation is grounded in scientific rigor and theoretical principles; (2) Government/Management: Officials assess barriers through institutional capacity and policy implementation; (3) Practical Application: Experienced organic rice farming and cooperative leaders provide insights into operational efficiency and resource utilization. This diverse composition ensures the final model integrates theoretical, institutional, and operational perspectives into a cohesive framework.

Experts were requested to convene and re-evaluate the 10 barriers identified in previous studies (Dinh et al., 2023; Hoang, 2021; Tien et al., 2022) to ensure their relevance to Vietnam's context. Following the meeting, a consensus was reached on the following barriers:

- Economic Dimension

High Initial Investment (EC1): The transition phase demands substantial upfront costs for organic fertilizers and labor. Furthermore, initial yield drops pose a significant financial risk for smallholder farmers.

- Social-Cognitive Dimension

Low Consumer Demand (SO1): Difficulty distinguishing organic from conventional products reduces consumer trust and market demand.

Limited Awareness (SO2): Farmers often lack a comprehensive understanding of organic principles and the long-term environmental benefits of organic farming.

Perceived Inefficiency vs. Conventional (SO3): The ingrained belief that organic farming is more labor-intensive yet less productive than chemical-based methods create a negative perception of its viability.

- Institutional & Policy Dimension

Inadequate Support Policy Framework (IN1): There is a lack of consistent government incentives and subsidies to protect organic farmers from market volatility.

Complex Certification Standards (IN2): Documentation and procedural requirements for international standards (e.g., EU, USDA, JAS) are too complex and costly for individual farmers to navigate.

Weak Input-Output Market Control (IN3): Unstable output linkages, often caused by contract breaking by traders or intermediaries, discourage long-term commitment.

Lack of Enterprise Leadership (IN4): The absence of leading enterprises capable of aggregating farmers' output hinders participation in the value chain.

Fragmented Production Zoning (IN5): Organic rice areas are often spontaneous and small-scale, lacking systematic government planning for specialized, concentrated production zones.

- Technical Dimension

Operational Complexity (TE1): Organic cultivation requires precise water control, biological pest regulation, and labor-intensive weed management, increasing production uncertainty.

Habitual Monoculture Practices (TE2): The long-standing tradition of intensive triple-cropping has degraded soil health, making it technically challenging to restore the ecosystem for organic farming.

Lack of Specific Organic Inputs (TE3): Currently available organic fertilizers do not fully meet the specific agronomic requirements of large-scale organic rice production.

Table 2. Profile and competence assessment of the expert panel.

Role	Education (score)	Experience (score)	Position level (score)	Total expertise score
Vice Director, Southern Inst. of Ag. Science & Tech.	PhD (3)	26 years (4)	Director Level (3)	10/10 (High)
Lecturer, Faculty of Agronomy, Can Tho University.	PhD (3)	18 years (3)	Senior Expert (2)	8/10 (High)
Deputy Director, Ben Tre Plant Seed Center.	MSc (2)	22 years (4)	Director Level (3)	9/10 (High)
Head, Ag. Extension Station (Chau Thanh Dist., Tien Giang province).	MSc (2)	15 years (3)	Manager Level (3)	8/10 (High)
Senior Researcher, Southern Rice Institute.	PhD (3)	12 years (3)	Senior Expert (2)	8/10 (High)
Staff, Southern Rice Institute.	Bachelor (1)	24 years (4)	Senior Official (2)	7/10 (Med-High)
Official, Ben Tre Dept. of Agriculture .	MSc (2)	20 years (4)	Senior Official (2)	8/10 (High)
Head, Organic Farming Cooperative (Regional).	High school (1)	30 years (4)	Leader (3)	8/10 (High)
Lead Farmer, Model Organic Farm.	High school (1)	25 years (4)	Practitioner (2)	7/10 (Med-High)
Lead Farmer, Clean Rice Production Group.	High school (1)	20 years (4)	Practitioner (2)	7/10 (Med-High)

***Note: The Expertise Score (Max = 10) is calculated based on: (1) Education (PhD=3, MSc=2, BSc/Lower BSc=1); (2) Experience (> 20 years(y)=4, 10-20y=3, 5-10y=2, less than 10y =1); (3) Current Position (Director/Head=3, Senior/Practitioner=2).*

3.3 Validation Plan

To ensure the robustness and reliability of the proposed SI-BDI framework, a comprehensive three-tier validation plan was implemented:

a) Optimal Threshold Validation: The optimization performance of the proposed CSI objective function (Equation 3) is cross-validated against conventional thresholding techniques. Specifically, the optimal threshold (α*) identified by the SB algorithm is compared with the Maximum Mean De-Entropy (MMDE) approach and the statistical Mean + SD benchmark. This comparison evaluates the balance between structural interpretability (filtering out noise) and information retention within the causal network.

b) Structural Robustness Assessment: The resilience of the proposed model against input uncertainties is evaluated through Monte Carlo simulation, a stochastic technique that quantifies output uncertainty by repeatedly evaluating a deterministic model under randomized input perturbations (Hamby, 1994; Helton and Davis, 2003; Saltelli et al., 2008). Specifically, $a\ \pm 10\%$ uniform random perturbation is applied to the initial BWM weights, following the local sensitivity protocols established by Saltelli et al. (2008) and recently applied in MCDM contexts (Boukrouh et al., 2024; Cui et al., 2023). This stochastic process is executed via $N\ =\ 100$ independent simulations, using the sample-size benchmark validated by Helton and Davis (2003), who demonstrated that an $m \times n$ configuration with 100 sample elements is mathematically sufficient to generate highly stable distribution estimates and minimize sampling variability in uncertainty propagation. For each perturbed weight vector, the entire DEMATEL-ISM pipeline is re-executed and the resulting structural metrics are aggregated to characterize the empirical distribution of outcomes under input uncertainty. To quantify structural resilience under perturbation, this study proposes a novel composite metric, the Industrial Adaptability-Structural Stability Reliability (IA-SSR), which simultaneously captures three distinct aspects of structural robustness through the multiplicative product of three normalized components:

$$IA - SSR(\alpha) = S(\alpha) \cdot H_{n(\alpha)} \cdot Sp(\alpha) \tag{5}$$

where, each component is justified independently by established literature, and multiplicative aggregation is chosen to enforce non-substitutability among the three resilience dimensions (Aczél and Saaty, 1983; Tofallis, 2014):

(i) Hierarchical Stability $S(\alpha) \in [0,1]$: The proportion of ISM hierarchical layers preserved after perturbation, operationalizing the engineering-resilience concept (return to structural equilibrium under perturbation) formalized by Holling (1973) and Pimm (1984), and recently applied to network robustness by Zheng et al. (2024) and Lou et al. (2023).

(ii) Information Content $H_{\mathrm{n}}(\alpha) \in [0,1]$: The normalized Shannon entropy $H_{\mathrm{n}}(\alpha) = H(\alpha)/log_2(n)$ of the layer-distribution probability mass, where $H(\alpha) = -\Sigma p_{\mathrm{i}} log_2 p_{\mathrm{i}}$ measures the uniformity of barrier distribution across hierarchical levels (Shannon, 1948). The normalization by $\log_2(n)$ ensures $H_{\mathrm{n}} \in [0,1]$ regardless of network size, with $H_{\mathrm{n}} = 0$ indicating degenerate single-layer collapse and $H_{\mathrm{n}} = 1$ indicating maximally informative multi-layer distribution. This entropy-based interpretation of structural informativeness has recently precedent in network analysis (Huang et al., 2024; Yu et al., 2022; Zeng et al., 2024).

(iii) Network Parsimony $Sp(\alpha) \in [0,1]$: the sparsity measure $Sp(\alpha) = 1 - N_{Arrows}/n(n-1)$, penalizing structural saturation. Sparsity-based parsimony measures are theoretically established by Hurley and Rickard (2009). $Sp = 1$ indicates a maximally parsimonious network (ideal for hierarchical interpretability); $Sp \to 0$ indicates network saturation that obscures the causal hierarchy.

c) Algorithmic Performance Benchmarking: The structural reliability and reconstruction accuracy of the SB algorithm are benchmarked against other established SI metaheuristics (PSO, ABC, and ACO). The precision of each algorithm in preserving the original expert-based influence matrix is comprehensively evaluated using Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

3.4 Computational Environment

To ensure reproducibility, all algorithmic simulations (SB, PSO, ABC, ACO) were executed in Python 3.12.4 on AMD Ryzen 5 5500U with Radeon Graphics. To guarantee statistical reliability and eliminate stochastic bias, convergence times and performance metrics were recorded as the mean ± standard deviation across 30 independent runs for each algorithm.

3.5 Hyperparameter Configuration

To ensure full reproducibility, all four SI algorithms (SB, PSO, ABC, ACO) were configured with the parameter settings reported in **Table 3**. Common settings, population size $N = 30$ and maximum iterations $I = 100$ were fixed across all algorithms to enable a fair comparison. Algorithm-specific parameters were chosen following the recommendations of their respective seminal references and held constant across all 30 independent runs.

Table 3. Hyperparameter configuration of SI algorithms.

Algorithm	Parameter	Value	Reference
SB	Stage 1 phase boundaries (hunting)	I/3, 2I/3	Fu et al. (2024)
	Lévy flight exponent β	1.5	
	Stage 2 escape mode probability	0.5	
	Boundary handling	Reflection on [0.01, 0.30]	
PSO	Inertia weight w	0.7	Kennedy and Eberhart (1995)
	Cognitive coefficient c_1	1.5	
	Social coefficient c_2	1.5	
ABC	Number of employed bees/onlookers	N/2 each	Karaboga (2005)
	Scout abandonment limit	20	
ACO	Pheromone evaporation rate ρ	0.9	Dorigo and Stützle (2004)
	Heuristic exponent β	2.0	
	Discretization grid (continuous α)	100 nodes on [0.01, 0.30]	
ALL	Population size N	30	
	Maximum iterations T	100	
	Independent runs	30	

4. Empirical Study

4.1 Priority Weights of Barriers (BWM Results)

Following the establishment of the expert panel, BWM was applied to ascertain the relative priority weights of the 12 identified barriers (**Table 4**). Utilizing the Aggregate Weights Later (AWL) approach (Van De Kaa et al., 2018), the optimal weight vectors were computed individually for each expert and subsequently aggregated. The Consistency Ratio (CR) for all 10 expert assessments remained below 0.1, confirming a high degree of reliability in the comparative judgments. The aggregated results reveal that Weak Input-Output Market Control (IN3) is universally perceived as the most critical barrier, holding the highest priority weight (0.212). This is followed by Operational Complexity in Organic Rice Farming (TE1, 0.093) and Fragmented Production Zoning (IN5, 0.085). Conversely, Limited Awareness (SO2) ranked as the least significant constraint (0.022). These optimal BWM weights were then integrated into the initial DEMATEL direct-influence matrix to formulate a strategically weighted causal network.

Table 4. Aggregated BWM weights and ranking of barriers.

Code	Barrier	Name	Average weight
IN3	Weak Input-Output Market Control	0.212	1
TE1	Operational Complexity in Organic Rice Farming	0.093	2
IN5	Fragmented Production Zoning	0.085	3
SO3	Perceived Inefficiency vs. Conventional	0.082	4
TE3	Lack of Specific Organic Inputs for Rice	0.079	5

Table 4 continued…

IN1	Inadequate Support Policy Framework	0.078	6
IN4	Lack of Enterprise Leadership in the Value Chain	0.076	7
IN2	Complex Certification Standards	0.073	8
TE2	Habitual Monoculture Practices	0.071	9
SO1	Low Consumer Demand	0.067	10
EC1	High Initial Investment	0.062	11
SO2	Limited Awareness	0.022	12

4.2 Performance Validation of the Framework

A critical objective of this study is to overcome the subjective thresholding bottleneck in traditional BDI applications. The proposed SI-BDI framework automates this process by maximizing CSI. The validation landscape cross-validated the CSI approach against standard statistical benchmarks, including MMDE and Mean + SD. The traditional MMDE benchmark ($\alpha = 0.0110$) failed to adequately filter the network, retaining an excessive 132 relationships that saturated the causal structure. This failure stems from directly multiplying BWM-derived fractional weights into the DEMATEL matrix, which significantly reduces the absolute values of the influence coefficients. Consequently, traditional entropy-based algorithms like MMDE become mathematically distorted in this weighted environment, rendering them incapable of distinguishing core causal links from stochastic noise.

To assess the influence of the threshold parameter α on the causal structure, a discrete grid search was conducted over the set $\alpha = \{0.085, 0.110, 0.145, 0.150, 0.155, 0.160, 0.165\}$. As reported in **Table 5**, the CSI value exhibits a clear increasing trend from 0.315 at $\alpha = 0.085$ to a peak value of 0.822 at $\alpha = 0.155$, while maintaining a stable four-level ISM structure within the interval [0.145, 0.155]. Beyond this point, a slight increase in the threshold to $\alpha = 0.160$ results in structural degradation, with the ISM hierarchy collapsing from four levels to three and CSI declining to 0.750. This behavior confirms that the optimal threshold lies within a narrow region around $\alpha = 0.155$. However, due to the inherently discrete nature of manual grid search, the exact optimum may not be captured within the predefined candidate set. In contrast, the SB algorithm, operating over a continuous search domain $\alpha \in [0.01, 0.30]$, identifies a more precise optimal threshold at $\alpha^* = 0.156$, achieving $CSI^* = 0.852$ while preserving the four-level ISM hierarchy. The 3.6% relative improvement in CSI (from 0.822 to 0.852) over the best discrete grid point demonstrates the advantage of metaheuristic approaches in continuous parameter spaces, where conventional discrete search strategies may overlook near-optimal solutions falling between predefined grid points.

Table 5. Comparative threshold selection results for CSI optimization.

α	N_{Arrows}	ISM Levels	CSI
0.085	53	3	0.315
0.110	34	3	0.438
0.145	20	4	0.748
0.150	18	4	0.796
0.155	17	4	0.822
0.156	16	4	0.852
0.160	14	3	0.750
0.165	13	3	0.781

***Note*: *The optimal threshold identified by the SB algorithm* ($\alpha = 0.156$) *is highlighted in a shaded background and marked with an asterisk. A grid search was conducted across* $\alpha \in [0.085, 0.165]$, *evaluating seven discrete candidate thresholds, augmented by the SB-optimized continuous solution* $\alpha^* = 0.156$ (*which lies between adjacent grid points* 0.155 *and* 0.160).

Table 6 demonstrates three findings. First, the four SI-BDI variants are statistically indistinguishable in IASSR ($p > 0.4$ for all SI pairs), confirming that the proposed CSI objective is well-defined: independent metaheuristics with disparate search dynamics, SB's two-stage hunt-escape, PSO's velocity-based search, ABC's three-bee phases, and ACO's pheromone trails, converge to equivalent global optima. Second, all SI-BDI variants significantly outperform both non-SI baselines (Mean + SD and MMDE, $p < 0.001$). Third, BDI-MMDE attains nominal stability ($S = 1$) but IA-SSR=0 due to joint degeneracy between the entropy and sparsity components. Its single-level hierarchy ($H_n = 0$) saturates the network with all 132 arrows ($S_p = 0$), confirming that conventional entropy-based thresholding produces structurally vacuous solutions under uncertainty. The multiplicative construction of IA-SSR is essential: an additive aggregation would award MMDE a misleadingly high score by exchanging zero entropy for unit stability, whereas the multiplicative form correctly identifies the structural failure.

Table 6. Resilience analysis under ±10% Monte Carlo perturbation of BWM weights ($N = 100$).

Method	α^*	L	S	H_n	S_p	IA-SSR [95% CI]	p
SB-BDI	0.156	4	0.881	0.391	0.892	0.306 [0.296, 0.315]	-
PSO-BDI	0.157	4	0.881	0.387	0.893	0.304 [0.294, 0.313]	0.876
ABC-BDI	0.155	4	0.882	0.387	0.893	0.304 [0.295, 0.313]	0.703
ACO-BDI	0.154	4	0.878	0.381	0.894	0.298 [0.289, 0.307]	0.424
BDI(MEAN + SD)	0.163	3	0.824	0.355	0.899	0.259 [0.255, 0.262]	<0.001
BDI(MMDE)	0.011	1	1.000	0.000	0.000	0.000 [0.000, 0.000]	<0.001

***Notes*: α^*, *optimal threshold; L, number of ISM levels; S* (*stability rate*), *barrier-level stability* (*mean*); H_n (*information content*), *normalized Shannon entropy of layer distribution* (*mean*); S_p *(network parsimony), sparsity* $1-N_{Arrows}/n(n-1)$, *mean); IA-SSR* (*composite score*)=$S \cdot H_n \cdot S_p$ *with 95% bootstrap CI* (*confidence intervals*) (1,000 *resamples*). *p-value of Wilcoxon rank-sum test against SB-BDI; pairwise comparisons among SI-BDI variants are non-significant* (*p*>0.4), *reflecting joint convergence to the CSI global optimum, while both non-SI baselines differ significantly* (*p*<0.001). *N=100 following Helton and Davis* (2003).

Table 7. Algorithmic performance benchmarking.

Algorithm	α	MAE	RMSE
SB	0.156	0.060	0.072
PSO	0.156	0.060	0.072
ABC	0.156	0.060	0.072
ACO	0.154	0.058	0.071

Table 7 presents detailed algorithmic performance benchmarks, evaluated using MAE and RMSE. First, three of four algorithms converge to the identical global optimum. SB, PSO, and ABC all identify $\alpha^* = 0.156$; Resulting reconstruction errors ($MAE = 0.060$, $RMSE = 0.072$) are mathematically identical across these three algorithms, not as a redundant artifact of the benchmark, but as direct evidence that the proposed CSI objective admits a well-defined global maximum recoverable by independent metaheuristics with disparate search dynamics: SB's two-stage hunt-escape architecture, PSO's velocity-based swarm dynamics, and ABC's three-bee employed-onlooker-scout phases. This convergence pattern empirically supports Proposition 1 of Section 2.3 (boundedness and Pareto-monotonicity of CSI).

Second, ACO converges to a suboptimal local plateau at $\alpha^* = 0.154$, with marginally lower MAE (0.058) and RMSE (0.071). This apparent error advantage, however, is an artifact of insufficient filtering rather than superior optimization quality: ACO discards fewer cells from T, mechanically yielding lower reconstruction error while sacrificing the CSI-balanced trade-off between causal clarity and structural parsimony.

Third, MAPE was deliberately excluded from the benchmark. The T-matrix contains entries near zero that produce division-by-zero singularities under MAPE (Hyndman and Koehler, 2006), and thresholding generates structural under-prediction that MAPE asymmetrically penalizes (Tofallis, 2014). Furthermore, DEMATEL causal influence intensities lack the absolute measurement scale that gives MAPE its interpretability in forecasting contexts; MAE and RMSE, both unit-preserving and symmetric, are the methodologically appropriate choices for reconstruction error in a thresholding context.

As shown in **Figure 3** Panel A, the function exhibits a sharp discontinuity at $\alpha \approx 0.157$, where CSI drops from 0.8515 to 0.7211 in a single threshold step (continuous landscape values; **Table 5** reports only the discrete grid points). This non-smoothness is methodologically significant rather than incidental: it reflects the structural collapse of the ISM hierarchy from four levels to three levels when a critical inter-level edge is severed. Because CSI is defined as the geometric mean of normalized causal strength (CS_{norm}) and normalized hierarchical depth (L_{norm}), a one-unit reduction in L from 4 to 3 produces an immediate one-third drop in L_{norm} that cannot be compensated by any concurrent gain in CS_{norm}. This empirical behavior directly validates Proposition 2 (non-substitutability): an additive aggregation would smooth across the transition of L from 4 to 3 and select a threshold that destroys hierarchical structure, whereas the multiplicative CSI penalizes such collapse and steers the optimizer back to the depth-preserving plateau.

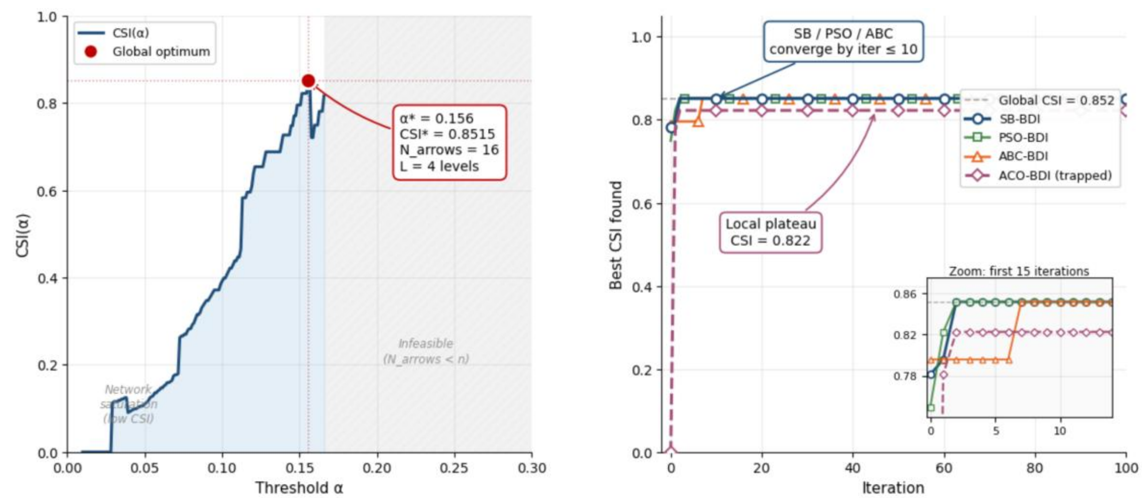

Figure 3. CSI landscape & convergence trajectories.

***Note*: (*A-left image*) *CSI*(*α*) *profile across the feasible threshold range α* ∈ [0.01, 0.30], *showing the global maximum at α** = 0.156 (*CSI** = 0.852). (*B-right image*) *Convergence behavior of four SI metaheuristics* (*SB, PSO, ABC, ACO*) *over 100 iterations, averaged across* 30 *independent runs.*

Panel B traces the best CSI value located by each metaheuristic across 100 iterations (population size = 30). Three patterns emerge. SB-BDI, PSO-BDI, and ABC-BDI all reach the global optimum $CSI = 0.852$ within ten iterations, with SB and PSO converging by iteration 5 and ABC by iteration 7. The mutual convergence of three algorithms with disparate search dynamics, SB's two-stage hunt-and-escape architecture, particle swarm's velocity-based dynamics, and artificial bee colony's three-bee employed-onlooker-scout phases, provides empirical evidence that the CSI landscape contains a single attractor reachable by gradient-free search. This pattern complements the topological observation in Panel A: the unique peak in the CSI(α) profile is recovered from arbitrary initializations by independent optimization principles. ACO-BDI converges prematurely to a suboptimal local plateau at $CSI = 0.822$ ($\alpha = 0.154$)

within five iterations and remains trapped throughout the remaining 95 iterations. This stagnation is consistent with documented limitations of ant colony optimization on continuous, piecewise-constant landscapes (López-Ibáñez et al., 2018): pheromone deposition reinforces early-discovered solutions, and the discrete nature of CSI's transitions does not provide the gradient-like information that ACO's heuristic exploitation relies upon.

Three of four SI methods reaching the same optimum suggest that algorithm choice is not the primary lever for performance on this 12-criterion problem; the framework's success rests instead on the well-posed CSI objective itself. This observation tempers any claim that a particular metaheuristic is essential. Conversely, the failure mode exhibited by ACO illustrates that not all gradient-free algorithms are equally suited to step-function landscapes, providing practical guidance for analysts adopting this framework: pheromone-based search should be avoided in favor of swarm-based or hunting-based dynamics that explicitly model exploration-exploitation transitions.

Table 8. Leave-one-out (LOO) and leave-two-out (L2O) sensitivity analysis of BWM weights.

Removed	Spearman ρ	Top-3 preserved	$Max\lvert\Delta w\rvert$
E1	1.000	YES	0.0014
E2	0.993	YES	0.0034
E3	0.993	YES	0.0033
E4	0.972	YES	0.0042
E5	0.979	YES	0.0035
E6	0.979	YES	0.0040
E7	0.993	YES	0.0039
E8	0.979	YES	0.0025
E9	0.979	YES	0.0024
E10	1.000	YES	0.0014
Mean	0.9867	10/10	0.0030
Min	0.9720	-	-
L2O Mean	0.9859	45/45	-
L2O	0.9650	-	-

***Note: E1-E10 denote the ten experts in the panel; their order corresponds to the rows of **Table** 2.*

The results presented in **Table 8** provide three convergent pieces of evidence for robustness. First, Spearman's ρ remained between 0.972 and 1.000 (mean = 0.9867) in all ten LOO trials and at or above 0.965 (mean = 0.9859) across all 45 L2O combinations, comfortably exceeding the 0.95 threshold for high robustness (Mohammadi and Rezaei, 2020). Second, the top-3 critical barriers IN3, IN5, and TE1, were preserved without exception in 100% of both LOO and L2O trials. Third, the maximum absolute weight change in LOO trials was $|\Delta w| = 0.0042$ (mean = 0.0030), an order of magnitude smaller than the smallest baseline weight $w(SO2) = 0.022$ (**Table 4**).

4.3 Causal Hierarchy and Impact Relations Analysis

Applying the optimized threshold ($\alpha = 0.156$), the causal hierarchy was delineated based on the Prominence (R+C) and Relation ($R-C$) indices (**Table 9**). The barriers were systematically classified into Cause-and-Effect groups:

The DEMATEL classification (**Figure 4**) and the ISM (**Figure 5**) yield convergent yet complementary insights into how the twelve barriers to organic rice farming propagate through Vietnam's Mekong Delta system. Read together, the two diagrams expose a four-tier causal architecture with a clear leverage point.

Table 9. Prominence (*R*+*C*) and relation (*R*−*C*) indices of barriers.

Barrier	R	C	R+C	R−C	Group
EC1	0.843	0.972	1.815	-0.129	Effect
SO1	0.910	1.005	1.915	-0.095	Effect
SO2	0.837	0.238	1.075	0.599	Cause
SO3	0.827	1.235	2.062	-0.408	Effect
IN1	1.997	0.258	2.255	1.739	Cause
IN2	1.062	0.652	1.714	0.410	Cause
IN3	1.055	3.091	4.146	-2.036	Effect
IN4	1.277	0.964	2.241	0.313	Cause
IN5	1.177	0.862	2.039	0.315	Cause
TE1	0.869	1.424	2.293	-0.556	Effect
TE2	0.748	0.712	1.460	0.036	Cause
TE3	0.795	0.985	1.780	-0.190	Effect

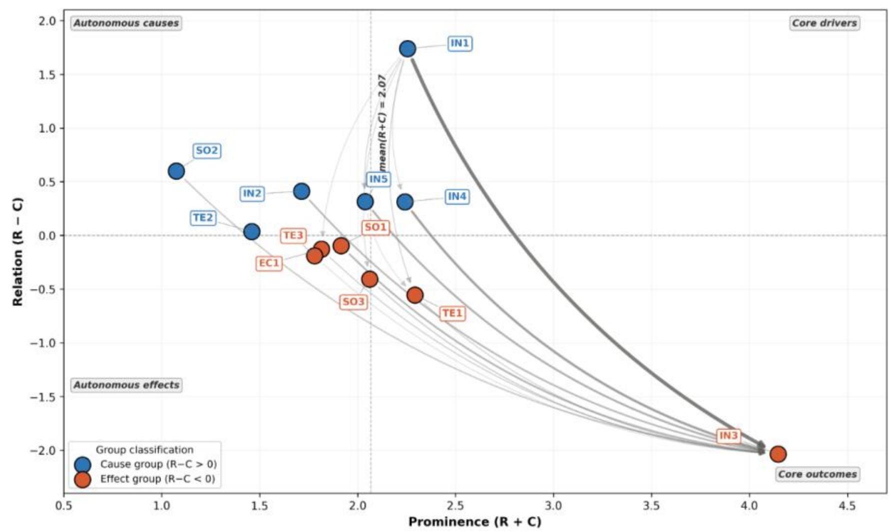

Figure 4. DEMATEL causal relationship diagram: prominence (R+C) versus relation (R − C) of the twelve barriers ($\alpha^* = 0.156$).

While the diagram (**Figure 4**) reveals the horizontal positioning of barriers along the prominence-relation plane, the ISM hierarchy (**Figure 5**) provides the complementary vertical decomposition of how these barriers transmit influence across the system. Read together, the two diagrams expose a coherent four-tier architecture for how barriers to organic rice farming propagate. ISM places IN1 alone at Level 4, the deepest tier from which the upstream causal chain originates, transitively reaching six downstream barriers (EC1, SO3, IN3, IN4, IN5, TE1), while DEMATEL positions it firmly in the *Core driver's* quadrant ($R - C = +1.739$, the strongest net causality in the system). Its moderate prominence ($R + C = 2.255$) signals that IN1 does not participate in many bidirectional exchanges but rather initiates the causal chain unidirectionally. In the Mekong Delta context, this finding aligns with field realities: without coherent state policy on certification subsidies, land-use planning, and price stabilization, farmers cannot meaningfully transition to organic practices regardless of consumer demand or technical knowledge.

Standing alone at Level 3, IN5 functions as the sole intermediate bridging node within the hierarchical structure, mediating the transmission of influence from IN1 toward Operational Complexity (TE1) and, to a lesser extent, the terminal node IN3. Its DEMATEL profile ($R + C = 2.039$; $R - C = +0.315$) aligns with this intermediary role, reflecting moderate prominence and a modest net causal effect. These findings suggest that zoning consolidation operates as a complementary intervention capable of mitigating the transmission pathway linking IN1, IN5, and TE1. Nevertheless, because IN1 also exerts direct influence on EC1, SO3, and IN4, policy reform alone appears sufficient to address the majority of operational barriers without reliance on the mediating role of IN5. This identifies zoning consolidation as a necessary second-stage intervention. The structural pathway from IN1 (Inadequate Support Policy Framework) to EC1 (High Initial Investment) reveals an institutional mechanism that DEMATEL alone obscures. Although EC1 sits at Level 2 with a moderately negative net relation ($R - C = -0.129$, Effect group), the transitive closure (Appendix C) shows that EC1's antecedent set $A(EC1) = \{EC1, IN1\}$ contains IN1 as its sole upstream driver, while no other Level 2 barrier (SO1, SO2, IN2, IN4) reaches EC1. This isolated dependency is structurally meaningful: in the Mekong Delta context, the high upfront capital required for organic transition, covering certification fees, soil-restoration inputs, and 2-3 years of yield depression during conversion, does not arise from market dynamics or farmer preferences but from the absence of policy instruments that would otherwise socialize this risk. Specifically, the linking IN1 → EC1 channel operates through three institutional mechanisms: (i) the absence of certification-cost subsidies forces farmers to internalize fees that, in mature organic markets, are typically borne by public extension programs or collective certification schemes; (ii) the lack of long-term land-tenure guarantees deters bank lending against farmland during the multi-year conversion period, raising the effective cost of capital; and (iii) the absence of price-stabilization mechanisms or purchase guarantees during conversion eliminates the bridging income that would otherwise offset transitional yield losses. These three mechanisms collectively explain why EC1 cannot be addressed through farmer-targeted financial literacy programs or microcredit schemes alone; the investment barrier is downstream of policy gaps and dissolves only when IN1 is reformed. The same logic links IN1 to IN5 through fragmented zoning (preventing economies of scale for conversion) and to IN4 through the absence of value-chain anchor enterprises that could provide forward contracts.

This layer splits cleanly into two functional groups along the DEMATEL axis. Three net transmitters-Limited Awareness (SO2), Complex Certification Standards (IN2), and Lack of Enterprise Leadership (IN4), propagate influence upward, with IN4 being the most consequential ($R + C = 2.241$, $R - C = +0.313$). Five net receivers, High Initial Investment (EC1), Low Consumer Demand (SO1), Perceived Inefficiency (SO3), Operational Complexity (TE1), and Lack of Specific Organic Inputs (TE3), absorb influence and translate it into operational obstacles experienced by farmers. Among the receivers, TE1 stands out as the most prominent ($R + C = 2.293$) yet contributes minimal net direction ($R - C = -0.556$), indicating it functions less as a discrete barrier and more as a clearing house through which multiple upstream pressures manifest as day-to-day farming difficulties. The dual positioning of the Social-Cognitive cluster (SO1, SO2, SO3) carries a counterintuitive but actionable implication for extension policy. Two of the three social-cognitive barriers, SO1 (Low Consumer Demand, $R - C = -0.095$) and SO3 (Perceived Inefficiency vs. Conventional, $R - C = -0.408$), emerge in the Effect group, indicating that consumer skepticism and farmer-perceived unviability are not autonomous attitudes but downstream symptoms of upstream institutional failures. Specifically, $A(SO3) = \{SO3, IN1\}$, meaning that the only upstream barrier transitively reaching SO3 is IN1. SO1's antecedent set $A(SO1) = \{SO1\}$ indicates structural isolation in the receiving network, its effect-group classification reflects weak overall causal influence rather than transitive dependence on a specific upstream driver. The third barrier, SO2 (Limited Awareness, $R - C = +0.599$), appears in the Cause group and behaves as a transmitter, but with the lowest BWM weight ($w = 0.022$, ranked 12 of 12) and a constrained reach $R(SO2) = \{SO2, IN3\}$, indicating that SO2's causal role is structurally minor. Taken together, this pattern poses a direct challenge to extension strategies that prioritize awareness-raising campaigns, consumer education, farmer training on organic principles, or media outreach as primary policy levers. Such programs, when deployed without simultaneous reform of IN1, address the symptoms while the upstream policy vacuum continues to regenerate them: farmer perceptions of inefficiency persist because conversion remains genuinely unprofitable in the absence of subsidies and price guarantees; consumer demand remains low because the verified-organic supply chain remains underdeveloped without enterprise leadership and certification infrastructure. The framework, therefore, suggests that awareness-raising should be sequenced after, or jointly with, the institutional reforms identified at Levels 3 and 4, operating as an amplifier of substantive policy change rather than a substitute for it.

At Level 1, with extreme prominence ($R + C = 4.146$, nearly twice the second-highest value), IN3 absorbs the cumulative influence of nearly the entire upstream network. Its near-symbiotic relationship with TE1 ($R + C = 2.293$, the second-most prominent barrier) reveals that operational complexity at the farm level and market dysfunction at the value chain level are two faces of the same systemic failure. Critically, IN3's high prominence is symptomatic rather than causal: targeting market interventions without addressing the underlying policy vacuum (IN1) and zoning fragmentation (IN5) would yield only superficial improvement.

TE2 also resides at Level 1, but with a structurally distinct role, at $\alpha^* = 0.156$, it exhibits zero in-degree and zero out-degree, operating outside the causal network. Its DEMATEL position near the origin ($R + C = 1.460$, $R - C = +0.036$) confirms the marginal directional role. The framework's separation of TE2 from the main hierarchy carries an important practical message: monoculture habits are not a downstream consequence of policy or market failures, but a path-dependent cultural inertia rooted in decades of conventional rice farming practice in the Delta. This implies that conventional top-down interventions targeting IN1 will not automatically dissolve TE2; addressing it requires distinct, behavior-focused interventions such as participatory farmer schools or peer-learning networks. DEMATEL alone identifies IN3 as the most prominent barrier and might suggest market reforms as the priority. ISM corrects this interpretation: IN3's prominence is the accumulated effect of upstream barriers, not a leverage point. The integrated CSI-optimized framework instead reveals a clear policy sequence: (i) reform IN1 to provide coherent organic-farming policy infrastructure (certification subsidies, land-tenure guarantees, price stabilization); (ii) deploy targeted financial instruments to dissolve EC1 (concessional credit, conversion subsidies, public-private risk-sharing schemes), these become viable only after IN1 is reformed; (iii) consolidate IN5 to enable zoning that supports organic value chains; (iv) reinforce IN4 (enterprise leadership) and IN2 (certification simplification) as transmission accelerators; (v) address TE2 separately through cultural and behavioural programs; and (vi) integrate awareness-raising on SO1, SO2, and SO3 as amplifiers of the structural reforms above, rather than as standalone interventions. Only at the final stage do market-side interventions on IN3 and TE1 become effective, as the upstream prerequisites are already in place. This reframing, from fixing what's most prominent to fixing what propagates, is the principal practical contribution of integrating DEMATEL with ISM through the proposed CSI optimization.

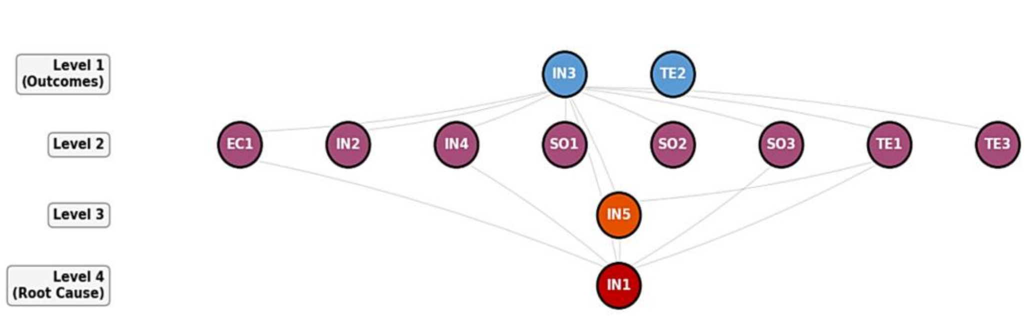

Figure 5. ISM hierarchical structure of barriers at the optimal threshold $\alpha^* = 0.156$.

5. Conclusion

This study addressed a persistent methodological bottleneck in the integrated BWM-DEMATEL-ISM (BDI) paradigm: the subjective or statistically rigid selection of the threshold (α) that dichotomizes the DEMATEL total-relation matrix into the binary reachability matrix required by ISM. To resolve it, the study proposed the Swarm Intelligence-driven BDI (SI-BDI) framework, which embeds BWM priority weights directly into the DEMATEL matrix and couples a newly formulated, parameter-free Causal Structure Index (CSI) with swarm-intelligence metaheuristics to locate the threshold that jointly maximizes causal clarity and hierarchical depth. Applied to the barriers hindering organic rice adoption in Vietnam's Mekong Delta, the framework converged to a stable optimal threshold ($\alpha^* = 0.156$, $CSI^* = 0.852$) and a four-level causal hierarchy that remained robust under both leave-one-out and leave-two-out expert exclusions and under ±10% Monte Carlo perturbations of the BWM weights.

Methodologically, the study advances the MCDM literature on three fronts. First, it resolves the longstanding problem of subjective threshold selection in DEMATEL by formulating the CSI as a parameter-free objective optimized through metaheuristic search, and in doing so it uncovers a critical mathematical incompatibility between the MMDE algorithm and the BWM-weighted DEMATEL matrix. Because priority weights are embedded by multiplication, the absolute values and probability distribution of the influence coefficients are fundamentally altered, distorting the entropy-based logic on which MMDE depends; this was empirically confirmed when the MMDE benchmark generated an excessively low threshold ($\alpha = 0.0110$) that failed to filter stochastic noise and retained 132 relationships, saturating the network. The proposed CSI optimization is therefore not merely an alternative but a mathematical necessity for integrating priority weights into DEMATEL. The point is reinforced by the newly proposed Industrial Adaptability-Structural Stability Reliability (IA-SSR) composite metric, under which the SI-BDI framework demonstrated markedly superior structural resilience to weight perturbation relative to the Mean + SD and MMDE benchmarks, both of which exhibited significant structural degradation.

Second, the study empirically establishes the well-posedness of the CSI objective by benchmarking four SI metaheuristics against grid search. Three population-based methods, Secretary Bird (SB), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC), converge with a 100% success rate to an identical global optimum ($\alpha^* = 0.156, CSI^* = 0.852$), confirming that the CSI landscape is reliably navigable by gradient-free continuous-search algorithms, whereas Ant Colony Optimization (ACO), constrained by its discretization mechanism, becomes trapped in a sub-optimal plateau ($CSI = 0.822$, 0% success). Although the absolute runtime advantage of any single variant is modest in this twelve-criterion case study, the framework's value rests on the consensus across heterogeneous heuristics, which provides strong evidence that the optimum is genuine rather than algorithm-specific. This consensus, together with a clear deployment pathway to higher-dimensional problems where grid enumeration becomes intractable, positions SI-CSI optimization as a methodologically scalable contribution rather than a claim of runtime efficiency. Third, the study introduces the concept of weighted causality into the integrated BWM-DEMATEL-ISM framework: by embedding BWM-derived importance weights directly into the DEMATEL initial direct-influence matrix, the resulting causal network inherently reflects strategic dominance, offering a logically consistent paradigm for structural evaluation.

Beyond these methodological contributions, the framework yields a coherent practical reading of the barriers to organic rice adoption in the Mekong Delta. BWM identifies Weak Input-Output Market Control (IN3) as the most critical barrier, yet DEMATEL shows that its high prominence is primarily symptomatic rather than causal, and the ISM hierarchy reveals the Inadequate Support Policy Framework (IN1) as the singular Level-4 root cause with the strongest net causal influence. Major downstream obstacles, including high investment costs, operational complexity, and market instability, are thus largely dependent on upstream institutional deficiencies, while Low Consumer Demand (SO1) remains structurally decoupled from the policy-driven causal chain. Accordingly, policymakers should move beyond symptom-oriented measures by prioritizing institutional reform and zoning consolidation to stabilize market coordination, while concurrently deploying separate demand-side interventions to stimulate consumer adoption.

Notwithstanding these contributions, three limitations merit acknowledgment and define avenues for future research. First, although the CSI is parameter-free and penalizes both over-densification (via the causal-strength term) and over-sparsity (via the ISM-level term coupled through a geometric mean), its calibration against alternative compositional logics such as harmonic-mean or Tchebycheff aggregation has not been explored; a multi-objective formulation returning a Pareto frontier of trade-offs between causal clarity and structural depth could offer decision-makers a richer set of structural alternatives than a single optimum. Second, the empirical validation rests on a twelve-barrier case study, and while the SI-CSI framework remains formally identical for higher-dimensional problems, its behavioral guarantees (convergence rate, plateau navigation) under $n \geq 30$ require dedicated computational benchmarking. Third, the BWM expert panel of ten reflects a domain-bounded consensus on Vietnamese organic-rice barriers; integrating fuzzy or Bayesian extensions, such as the Bayesian BWM of Mohammadi and Rezaei (2020), could accommodate cognitive ambiguity and enable cross-regional generalization. Finally, the present framework treats the BWM-derived weight vector as a deterministic input; modeling the propagation of weight uncertainty through the SI-CSI optimization to obtain confidence intervals on α^* is a natural extension and a focus of ongoing work.

Appendix

Appendix A. Aggregated initial direct-influence matrix.

Z	EC1	SO1	SO2	SO3	IN1	IN2	IN3	IN4	IN5	TE1	TE2	TE3
EC1	0	1.2	0.8	1.5	0.5	1.1	1.4	0.7	0.6	2.1	0.9	1.3
SO1	1.1	0	1.4	1.8	0.4	0.6	2.5	1.3	0.7	0.8	0.5	0.6
SO2	0.7	2.1	0	2.4	0.3	0.5	1.8	0.9	0.4	0.6	1.1	0.5
SO3	1.4	1.7	1.2	0	0.2	0.4	1.6	0.8	0.5	1.9	1.5	1.2
IN1	3.2	2.5	2.1	1.9	0	3.4	3.6	2.8	3.5	2.1	1.8	2.4
IN2	1.8	1.1	0.9	0.7	0.6	0	2.1	1.5	1.2	2.4	0.8	1.6
IN3	2.5	3.4	2.2	2.8	0.4	1.2	0	2.6	1.5	1.4	0.9	1.1
IN4	1.9	2.2	1.4	1.6	0.5	1.8	2.9	0	2.1	1.3	0.7	1.2
IN5	1.5	1.3	0.8	1.1	0.4	1.2	2.4	1.9	0	2.6	1.4	1.8
TE1	2.1	0.8	0.6	1.9	0.3	0.7	1.2	1.1	0.9	0	1.6	2.5
TE2	1.3	0.6	0.5	1.4	0.2	0.4	0.8	0.7	1.1	2.4	0	2.1
TE3	1.6	0.7	0.5	1.3	0.3	0.6	0.9	1.1	0.8	2.7	1.8	0

Appendix B. BWM-weighted total relation matrix *T*.

T	EC1	SO1	SO2	SO3	IN1	IN2	IN3	IN4	IN5	TE1	TE2	TE3
EC1	0.036	0.068	0.016	0.092	0.024	0.052	0.206	0.056	0.049	0.121	0.050	0.073
SO1	0.066	0.046	0.022	0.107	0.022	0.042	0.297	0.078	0.056	0.080	0.040	0.054
SO2	0.052	0.093	0.010	0.119	0.018	0.035	0.237	0.062	0.043	0.068	0.053	0.047
SO3	0.068	0.080	0.019	0.047	0.015	0.033	0.217	0.058	0.045	0.112	0.064	0.069
IN1	0.159	0.155	0.039	0.165	0.023	0.146	0.515	0.166	0.182	0.191	0.105	0.151
IN2	0.088	0.077	0.019	0.081	0.029	0.029	0.285	0.089	0.077	0.144	0.053	0.091
IN3	0.100	0.128	0.029	0.138	0.024	0.060	0.140	0.113	0.083	0.110	0.055	0.075
IN4	0.099	0.116	0.026	0.120	0.029	0.083	0.372	0.058	0.112	0.120	0.056	0.086
IN5	0.086	0.087	0.020	0.099	0.025	0.064	0.319	0.104	0.043	0.157	0.072	0.101
TE1	0.085	0.058	0.014	0.103	0.018	0.041	0.193	0.067	0.059	0.055	0.068	0.108
TE2	0.062	0.046	0.011	0.082	0.014	0.030	0.148	0.050	0.060	0.127	0.024	0.094
TE3	0.071	0.051	0.012	0.082	0.017	0.037	0.162	0.063	0.053	0.139	0.072	0.036

Appendix C. Binary reachability matrix M at the optimal threshold $\alpha^* = 0.156$.

M	EC1	SO1	SO2	SO3	IN1	IN2	IN3	IN4	IN5	TE1	TE2	TE3
EC1	1	0	0	0	0	0	1	0	0	0	0	0
SO1	0	1	0	0	0	0	1	0	0	0	0	0
SO2	0	0	1	0	0	0	1	0	0	0	0	0
SO3	0	0	0	1	0	0	1	0	0	0	0	0
IN1	1	0	0	1	1	0	1	1	1	1	0	0
IN2	0	0	0	0	0	1	1	0	0	0	0	0
IN3	0	0	0	0	0	0	1	0	0	0	0	0
IN4	0	0	0	0	0	0	1	1	0	0	0	0
IN5	0	0	0	0	0	0	1	0	1	1	0	0
TE1	0	0	0	0	0	0	1	0	0	1	0	0
TE2	0	0	0	0	0	0	0	0	0	0	1	0
TE3	0	0	0	0	0	0	1	0	0	0	0	1

Appendix D. Level partition of barriers for ISM hierarchy.

Barrier	Reachability Set R(i)	Antecedent Set A(i)	Iteration	Level
IN3	{IN3}	{EC1, SO1, SO2, SO3, IN1, IN2, IN3, IN4, IN5, TE1, TE3}	1	1
TE2	{TE2}	{TE2}	1	1
EC1	{EC1, IN3}	{EC1, IN1}	2	2
IN2	{IN2, IN3}	{IN2}	2	2
IN4	{IN3, IN4}	{IN1, IN4}	2	2
SO1	{SO1, IN3}	{SO1}	2	2
SO2	{SO2, IN3}	{SO2}	2	2
SO3	{SO3, IN3}	{SO3, IN1}	2	2
TE1	{IN3, TE1}	{IN1, IN5, TE1}	2	2
TE3	{IN3, TE3}	{TE3}	2	2
IN5	{IN3, IN5, TE1}	{IN1, IN5}	3	3
IN1	{EC1, SO3, IN1, IN3, IN4, IN5, TE1}	{IN1}	4	4

Conflicts of Interest
The authors declare no conflicts of interest.

Acknowledgments
The authors wish to express their sincere gratitude to the anonymous reviewers, whose valuable comments and constructive suggestions have significantly enhanced the quality and rigor of this paper. We are equally thankful to all those who generously shared their feedback and thoughtful insights during the course of this research; their contributions have been instrumental in refining and completing the work.

AI Disclosure
The author(s) declare that no assistance is taken from generative AI to write this article.

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