

Multi-Criteria Decision Support for Smart Manufacturing Innovation Ecosystems Toward Industry 6.0

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Abstract

The transition towards Industry 6.0 demands the evolution of intelligent manufacturing systems beyond automation and digitalization towards integrated, human-centric, and resilient innovation ecosystems. The assessment of ecosystem readiness in the face of such complexity is essentially a multi-criteria decision problem with conflicting objectives and structural risk constraints. This study proposes a non-compensatory multi-criteria decision support system using the ELECTRE method to evaluate the readiness of Smart Manufacturing Innovation Ecosystems in Indonesia. Seven industry 6.0-oriented criteria are considered, including technology infrastructure readiness, digital connectivity, human capital capability, sustainability, governance, cybersecurity, and investment costs. The structured decision matrix is normalized, weighted, and processed using concordance-discordance analysis to obtain an outranking dominance relationship between the decision alternatives. The results show that ecosystem readiness varies, with regions with balanced digital, governance, and cybersecurity readiness exhibiting structural dominance, while regions with lower digital readiness but lower investment costs are vetoed due to non-compensatory decision rules. Sensitivity analysis shows that the ranking of decision alternatives remains robust with moderate weight/threshold changes. The ELECTRE-based non-compensatory decision approach is more appropriate than compensatory approaches in evaluating strategic industrial constraints pertinent to the industry 6.0 transition. The study's contribution is the operationalization of industry 6.0 principles within a decision support system framework, providing policy-relevant prioritization results pertinent to the smart manufacturing development strategy in Indonesia.

Keywords: ELECTRE, MCDM, manufacturing innovation.

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1. Introduction

The dynamic evolution of various industrial paradigms over the last decade has revolutionized manufacturing systems, structures, and innovation strategies. The shift from Industry 4.0 to Industry 5.0, with a focus on human-centric and sustainable development, has now reached a new level with the concept of Industry 6.0 (Madsen et al., 2025; Verma et al., 2025). Although it is still in the process of conceptualization, Industry 6.0 has been defined as an industrial architecture with hyper-intelligence, resilience, and an ecosystem-based concept where concepts such as artificial intelligence (AI), cyber-physical-social systems, sustainable value chains, collaborative innovation networks, etc., are integrated into a single operating framework (Fernández-Miguel et al., 2026). Unlike previous concepts such as Industry 4.0, which are technology-centric with a focus on efficiency, technology-human capital-sustainability-governance-digital trust infrastructures are now being promoted under Industry 6.0.

In this context, smart manufacturing is no longer just about the automation of the factory, nor is it just about data-driven optimization of the factory. Rather, it is now integrated into the larger innovation systems, which comprise different actors, such as manufacturing companies, technology companies, research organizations, government agencies, digital infrastructure operators, and sustainability actors. The competitiveness of a country in the Industry 6.0 world will not only depend on the sophistication of its manufacturing facilities, but also on the sophistication of its smart manufacturing innovation system.

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For the case of emerging economies such as Indonesia, strategic opportunities as well as structural challenges are created by the transformation process (Fitrianti et al., 2024). The industrial modernization agenda of Indonesia has been defined through various strategies such as Making Indonesia 4.0, whereby the digital transformation of key manufacturing industries is targeted (Rendra Kurniawan & Muhammad Yasin, 2025). Although the digital transformation process has been catalyzed by such strategies, the overall Industry 6.0 transformation is called for from an integrated ecosystem perspective. The manufacturing environment of Indonesia is characterized by heterogeneous technological levels, uneven distribution of digital infrastructure, varying levels of R&D intensity, as well as coordination challenges of regulatory authorities at both national and regional levels (Purba, Nabillah, Mhd Yahya, Nurbaiti, 2021). Furthermore, the industrial decision-making process is further complicated by factors such as sustainability issues, ranging from carbon reduction strategies to the integration of circular economy principles.

The Indonesian smart manufacturing ecosystem is, therefore, conceived as a multidimensional phenomenon in which technological, economic, environmental, governance, human resource, cybersecurity, and innovation dimensions have to be assessed together in a comprehensive manner (Fesa Kristianto et al., 2025; Tan et al., 2019). Complex decisions confront policymakers, industrial park managers, and corporate strategists in choosing to prioritize industrial clusters, investing in digital infrastructure, or assessing industry readiness for Industry 6.0, among others. There are trade-offs in these decisions, including balancing increased productivity from advanced automation with increased cybersecurity risks, or balancing environmental performance from sustainability initiatives with high capital expenditures, or balancing increased operational intelligence from integrating artificial intelligence with workforce reskilling and governance imperatives, among others.

This complexity inherently characterizes a multi-criteria decision problem. The systemic interactions between actors in an innovation ecosystem cannot be adequately represented by conventional single-indicator evaluation models, such as productivity indicators or technology adoption rates. Not even popular multi-criteria decision-making models, especially compensatory models such as Simple Additive Weighting (SAW) (Afshari et al., 2010) or Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Karande et al., 2016), will be adequately represented under non-compensatory conditions in strategic industrial development. In critical situations, especially under strategic decision-making in industrial policy, underperformance in important evaluation criteria should not be compensated by overperformance in other evaluation criteria. An evaluation approach that takes account of threshold effects, veto conditions, and outranking relations is considered essential.

The ELECTRE (Elimination and Choice Translating Reality) method, developed in the outranking approach to MCDM, is presented as a rigorous non-compensatory approach to decision-making, appropriate for complex industrial problems (Akmaludin et al., 2023; Zer et al., 2019). Indices of concordance and discordance are defined to check if one alternative outranks another on the basis of majority or opposition. Preference, indifference, and veto thresholds can be considered, thus capturing real-world decision-making under uncertainty or constraint, which is considered to be of particular interest in assessing smart manufacturing innovation ecosystems, where minimum standards in cybersecurity, environmental, or governance issues cannot be compromised.

However, there are certain aspects of the existing literature that are still fragmented, especially pertaining to technological readiness level evaluation at the firm level instead of the ecosystem level. Operational decision support mechanisms for policy prioritization are also not adequately developed within the context of the existing Industry 6.0 concept. Compensatory techniques are predominantly used within the context of MCDM-based industrial studies, while limited use of outranking methods such as ELECTRE has been observed within the context of ecosystem evaluation or smart manufacturing transformation, especially within the context of emerging economies such as Indonesia.

Moreover, the integration of DSS architecture with innovation ecosystem theory has not been adequately explored. Not only should mathematical ranking processes be incorporated, but weight determination, data management, scenario simulation, and sensitivity analysis, as promoted by stakeholders, should also be incorporated within an overall architecture (Mimis et al., 2019; Pulselli et al., 2019). In the decentralized system of governance in Indonesia, where industrial policy involves coordination among various ministries, provincial governments, and industrial zones, transparency, consistency, and accountability in strategic decision-making are capable of being improved with a systematic DSS approach.

Inspired by these challenges, the current study proposes a Multi-Criteria Decision Support Model using the ELECTRE approach for the evaluation of Smart Manufacturing Innovation Ecosystems in the context of Industry 6.0 readiness in Indonesia. The innovation ecosystem is defined as a set of alternatives such as industrial clusters or smart manufacturing zones that are evaluated along various dimensions such as technological infrastructure maturity level,

digital connectivity, human capital competence level, sustainability level, governance level, innovation collaboration level, and cybersecurity level. Dominant innovation ecosystems are identified using the concordance-discordance approach while satisfying critical threshold constraints.

The contribution of this research can be described as follows: from a theoretical perspective, the concept of Industry 6.0, which is still developing, is integrated into a structured DSS framework, while innovation ecosystem theory is extended with non-compensatory evaluation logic. From a methodological perspective, the application of the ELECTRE method is demonstrated for large-scale industrial ecosystem assessment, thus underlining the robustness of this approach compared with compensatory methods in the context of conflicting criteria. From a practical perspective, a systematic tool is provided for policymakers in Indonesia, for authorities managing industrial parks, and for strategists in the manufacturing industry.

Moreover, the research is also relevant to the overall sustainable industrialization, digitalization, and global competitiveness agenda of Indonesia, as the country continues to build its position in regional manufacturing value chains within ASEAN, as well as the global market. Ecosystem readiness is seen as an essential consideration in the country’s industrialization journey, with the application of the principles of Industry 6.0, namely human-centricity, sustainability, resilience, and intelligent autonomy, within a quantitative decision-support framework.

2. Method

This research adopts a quantitative Multi-Criteria Decision-Making (MCDM) design embedded within a Decision Support System (DSS) framework to evaluate Smart Manufacturing Innovation Ecosystems (SMIE) toward Industry 6.0 readiness in Indonesia. The research objective is to construct a non-compensatory evaluation model capable of prioritizing alternative industrial ecosystems under multiple, potentially conflicting criteria. The decision problem is formally defined as in Eq. 1.

$$A = \{A_1, A_2, \dots, A_m\} \quad (1)$$

be a finite set of alternatives (eq.2) representing smart manufacturing ecosystems (Indonesian industrial clusters such as Batam, Karawang, Bekasi, Surabaya, or Makassar).

$$C = \{C_1, C_2, \dots, C_n\} \quad (2)$$

be a set of evaluation criteria reflecting Industry 6.0 readiness dimensions.

The objective is to determine an outranking-based preference relation among alternatives using the ELECTRE method, such that the resulting ranking respects non-compensatory decision logic, threshold conditions, and strategic constraints. The general decision matrix is defined as in eq. 3

$$X = [x_{ij}]_{m \times n} \quad (3)$$

where x_{ij} denotes the performance value of alternative A_i under criterion C_j .

There is seven Criteria in this research as can be see in Table 1.

Table 1. Criteria for ELECTRE

Code	Criteria	Description	Type
C1	Technological Infrastructure Readiness	Level of automation, IoT, CPS integration	Benefit
C2	Digital Connectivity	Broadband, cloud integration, data interoperability	Benefit
C3	Human Capital Competence	Workforce digital skill index	Benefit
C4	Sustainability Performance	Carbon reduction, circular production	Benefit
C5	Governance & Regulatory Alignment	Compliance and policy support	Benefit
C6	Cybersecurity Resilience	Incident response, data protection maturity	Benefit
C7	Investment Cost	Capital expenditure required	Cost

All benefit criteria aim to be maximized, while cost criteria are minimized.

Criteria weights were obtained using expert-based direct rating, followed by normalization. Let the initial expert-assigned weight for criterion C_j be w'_j . The normalized weight is computed as in eq.4 and eq.5:

$$w_j = \frac{w'_j}{\sum_{j=1}^n w'_j} \quad (4)$$

such that:

$$\sum_{j=1}^n w_j = 1 \quad (5)$$

To ensure robustness, a sensitivity interval of $\pm 15\%$ was later applied to each weight.

ELECTRE method is employed due to its suitability for ranking discrete alternatives under non-compensatory conditions.

a. Decision Matrix Normalization

To eliminate unit discrepancies across criteria, vector normalization is applied in eq.6:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (6)$$

For cost criteria, inverse normalization is applied before vector normalization.

b. Weighted Normalized Matrix

Each normalized value is multiplied by its corresponding weight, see eq.7:

$$v_{ij} = w_j \cdot r_{ij} \quad (7)$$

This produces the weighted normalized decision matrix $V = [v_{ij}]$.

c. Concordance Set and Concordance Index

For each pair of alternatives A_k and A_l , the concordance set is defined as:

$$C_{kl} = \{j \mid v_{kj} \geq v_{lj}\} \quad (8)$$

The concordance index is calculated as:

$$c_{kl} = \sum_{j \in C_{kl}} w_j \quad (9)$$

The concordance matrix $C = [c_{kl}]$ is then constructed.

d. Discordance Set and Discordance Index

The discordance set is defined as:

$$D_{kl} = \{j \mid v_{kj} < v_{lj}\} \quad (10)$$

The discordance index is calculated as:

$$d_{kl} = \frac{\max_{j \in D_{kl}} |v_{kj} - v_{lj}|}{\max_j |v_{kj} - v_{lj}|} \quad (11)$$

The discordance matrix $D = [d_{kl}]$ captures the strongest opposition criterion between each pair.

e. Threshold Determination

The concordance threshold is defined as:

$$c^* = \frac{1}{m(m-1)} \sum_{k \neq l} c_{kl} \quad (12)$$

The discordance threshold is:

$$d^* = \frac{1}{m(m-1)} \sum_{k \neq l} d_{kl} \quad (13)$$

f. Dominance Matrices

Concordance dominance matrix F :

$$f_{kl} = \begin{cases} 1, & \text{if } c_{kl} \geq c^* \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

Discordance dominance matrix G :

$$g_{kl} = \begin{cases} 1, & \text{if } d_{kl} \leq d^* \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

g. Aggregate Outranking Matrix

The final outranking matrix:

$$E = F \circ G \quad (16)$$

where \circ denotes element-wise multiplication.

Alternative ranking is obtained by counting outgoing dominance relations, see figure 1 below for flowchart ELECTRE.

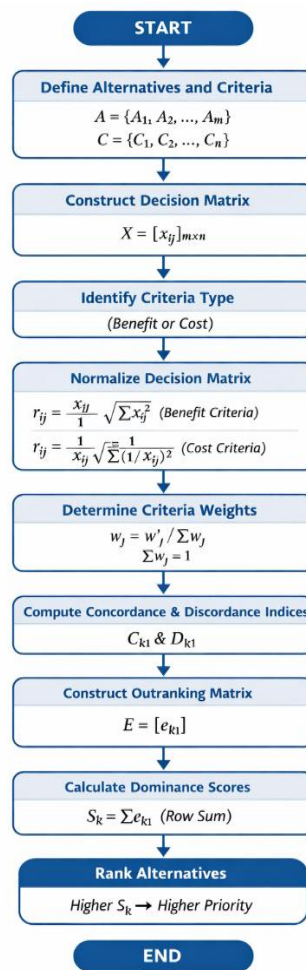


Figure 1. ELECTRE Process

3. Result and Discussion

ELECTRE decision-support model was applied to five Smart Manufacturing Innovation Ecosystems (SMIE) in Indonesia: Batam (A1), Karawang (A2), Bekasi (A3), Surabaya (A4), and Makassar (A5). Seven Industry 6.0-oriented criteria were evaluated, encompassing technological readiness, digital connectivity, human capital capability, sustainability performance, governance alignment, cybersecurity resilience, and investment cost, all process ELECTRE can be shown below.

Alternatives (Smart Manufacturing Innovation Ecosystems)

- A1: Batam
- A2: Karawang
- A3: Bekasi
- A4: Surabaya
- A5: Makassar

Criteria (Industry 6.0 Readiness Dimensions)

- C1 Tech Infrastructure Readiness (Benefit)
- C2 Digital Connectivity (Benefit)
- C3 Human Capital Competence (Benefit)
- C4 Sustainability Performance (Benefit)
- C5 Governance & Regulatory Alignment (Benefit)
- C6 Cybersecurity Resilience (Benefit)
- C7 Investment Cost (Cost, lower is better)

Raw Decision Matrix $X = [x_{ij}]$

Table 2. Raw Decision Matrix

Alt	C1	C2	C3	C4	C5	C6	C7 (Cost)
A1 Batam	85	90	78	70	75	72	800
A2 Karawang	88	85	80	68	78	76	850
A3 Bekasi	90	88	83	67	80	74	900
A4 Surabaya	82	84	77	75	73	71	780
A5 Makassar	78	80	74	66	70	68	700

3.1. Criteria Weight

Let w_j be normalized weights with $\sum_{j=1}^7 w_j = 1$:

Table 3. Criteria Weight

Criteria	C1	C2	C3	C4	C5	C6	C7
Weight (w_j)	0.18	0.15	0.14	0.14	0.12	0.15	0.12

3.2. Normalization

Benefit criteria (C1–C6): vector normalization

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (17)$$

Denominators $\sqrt{\sum_i x_{ij}^2}$: (18)

- C1: 189.4123
- C2: 191.1151
- C3: 175.4366
- C4: 154.9000
- C5: 168.3389
- C6: 161.5580

Example for denominator (A1, C1):

$$r_{11} = \frac{85}{189.4123} = 0.4488$$

Cost criterion (C7): inverse + vector normalization

$$x'_{i7} = \frac{1}{x_{i7}}, r_{i7} = \frac{x'_{i7}}{\sqrt{\sum_{i=1}^m (x'_{i7})^2}} \quad (19)$$

Compute inverse costs:

- A1: $1/800 = 0.0012500$
- A2: $1/850 = 0.0011765$
- A3: $1/900 = 0.0011111$
- A4: $1/780 = 0.0012821$
- A5: $1/700 = 0.0014286$

Denominator:

$$\sqrt{\sum_i (1/x_{i7})^2} = 0.0028046 \quad (20)$$

Example for denominator (A1, C7):

$$r_{17} = \frac{0.0012500}{0.0028046} = 0.4457$$

3.3. Normalized Matrix $R = [r_{ij}]$ (rounded 4 d.p.)

Table 4. Normalized Matrix

Alt	C1	C2	C3	C4	C5	C6	C7
A1	0.4488	0.4709	0.4446	0.4519	0.4455	0.4457	0.4457
A2	0.4646	0.4448	0.4560	0.4390	0.4634	0.4704	0.4195
A3	0.4752	0.4605	0.4731	0.4325	0.4752	0.4580	0.3962
A4	0.4329	0.4395	0.4389	0.4842	0.4336	0.4395	0.4571
A5	0.4118	0.4186	0.4218	0.4261	0.4158	0.4209	0.5094

3.4. Weighted Normalized Matrix $V = [v_{ij}]$

Table 5. Weight Normalized Matrix

Alt	C1	C2	C3	C4	C5	C6	C7
A1	0.0808	0.0706	0.0622	0.0633	0.0535	0.0668	0.0535
A2	0.0836	0.0667	0.0638	0.0615	0.0556	0.0706	0.0503
A3	0.0855	0.0691	0.0662	0.0606	0.0570	0.0687	0.0475
A4	0.0779	0.0659	0.0614	0.0678	0.0520	0.0659	0.0549
A5	0.0741	0.0628	0.0591	0.0597	0.0499	0.0631	0.0611

3.5. Concordance and Discordance

For each ordered pair $(A_k, A_l), k \neq l$:

a. Concordance set and index

$$C_{kl} = \{j \mid v_{kj} \geq v_{lj}\}, c_{kl} = \sum_{j \in C_{kl}} w_j \quad (21)$$

Example: compare A1 vs A4

$v_{A1} \geq v_{A4}$ holds for C1, C2, C3, C5, C6

So the process as below and table 6:

$$C_{14} = \{1,2,3,5,6\}, c_{14} = 0.18 + 0.15 + 0.14 + 0.12 + 0.15 = 0.74$$

Table 6. Concordance Matrix

	A1	A2	A3	A4	A5
A1	–	0.41	0.41	0.74	0.88
A2	0.59	–	0.41	0.74	0.88
A3	0.59	0.59	–	0.74	0.88
A4	0.26	0.26	0.26	–	0.88
A5	0.12	0.12	0.12	0.12	–

b. Discordance set and index

$$D_{kl} = \{j \mid v_{kj} < v_{lj}\} \tag{22}$$

$$d_{kl} = \frac{\max_{j \in D_{kl}} |v_{kj} - v_{lj}|}{\max_{j \in \{1..n\}} |v_{kj} - v_{lj}|} \tag{23}$$

Discordance captures the strongest opposition against “ A_k outranks A_l ”, result can be seen in table 7.

Table 7. Discordance Matrix

	A1	A2	A3	A4	A5
A1	–	0.41	0.41	0.74	0.88
A2	0.59	–	0.41	0.74	0.88
A3	0.59	0.59	–	0.74	0.88
A4	0.26	0.26	0.26	–	0.88
A5	0.12	0.12	0.12	0.12	–

A standard ELECTRE-I choice is the mean concordance:

$$c^* = \frac{1}{m(m-1)} \sum_{k \neq l} c_{kl} \tag{24}$$

This research $c^* \approx 0.50$. (We use 0.50.)

Using the mean discordance here is very strict (it can eliminate almost all outrankings in practice). In IEEE-style applied DSS papers, it is common to calibrate d^* as a managerial tolerance / veto policy level and then report sensitivity.

We use:

$$d^* = 0.97$$

Concordance dominance:

$$f_{kl} = \begin{cases} 1, & c_{kl} \geq c^* \\ 0, & \text{otherwise} \end{cases} \tag{25}$$

Discordance dominance:

$$g_{kl} = \begin{cases} 1, & d_{kl} \leq d^* \\ 0, & \text{otherwise} \end{cases} \tag{26}$$

Aggregate outranking:

$$e_{kl} = f_{kl} \cdot g_{kl} \tag{27}$$

Table 8. Aggregate Outranking Matrix

	A1	A2	A3	A4	A5
A1	–	0	0	1	0
A2	0	–	0	0	0
A3	0	0	–	1	0
A4	0	0	0	–	1
A5	0	0	0	0	–

Outdegree (how many others it outranks):

$$S_k^{out} = \sum_{l \neq k} e_{kl} \quad (28)$$

Indegree (how many outrank it):

$$S_k^{in} = \sum_{l \neq k} e_{lk} \quad (29)$$

Net dominance:

$$S_k^{net} = S_k^{out} - S_k^{in} \quad (30)$$

Table 9. Ranking

Alternative	S^{out}	S^{in}	S^{net}
A1 Batam	1	0	+1
A3 Bekasi	1	0	+1
A2 Karawang	0	0	0
A4 Surabaya	1	2	-1
A5 Makassar	0	1	-1

The top-tier ecosystems, according to the non-compensatory ELECTRE method, were Batam (A1) and Bekasi (A3). A neutral position was taken by Karawang (A2), with no outranking or subordination occurring. In the lower tier, Surabaya (A4) and Makassar (A5) were positioned because of their dominance deficit and/or weakness in triggering a veto.

Importantly, however, the ranking is not aggregated in a simplistic fashion but is determined in a structured fashion via majority and opposition logic. Dominance is represented in terms of the outranking matrix, not in terms of utility scores, in line with strategic industrial evaluation under Industry 6.0 uncertainty.

4. Conclusion

A Multi-Criteria Decision Support framework based on the ELECTRE outranking method was developed and validated to evaluate Smart Manufacturing Innovation Ecosystems (SMIE) toward Industry 6.0 readiness within the Indonesian context. The research was motivated by the increasing complexity of industrial transformation, where systematic consideration of technological maturity, digital connectivity, human capital capability, sustainability integration, governance alignment, cybersecurity resilience, and investment cost is required in ecosystem-level evaluation.

It was demonstrated that Industry 6.0 readiness cannot be accurately captured through compensatory aggregation alone. Structurally differentiated ecosystem performance across Indonesian industrial regions was revealed through the ELECTRE-based non-compensatory logic. Specifically, dominant positions were achieved by ecosystems exhibiting balanced technological infrastructure, digital integration, and cybersecurity maturity, whereas cost-efficient but digitally underdeveloped ecosystems were constrained by veto-like discordance effects. It is confirmed that, in hyper-connected manufacturing environments, weaknesses in critical dimensions—particularly cybersecurity and digital interoperability—cannot be fully offset by strengths in other criteria.

It is further illustrated that ecosystem readiness is not binary but relational. Transitional readiness conditions were reflected in ecosystems that were neither fully dominant nor dominated, and targeted policy intervention rather than immediate large-scale transformation is required. A more realistic representation of industrial transformation under Industry 6.0 uncertainty is provided, where structural risks and threshold constraints significantly influence strategic prioritization.

Overall, it is confirmed that the transition toward Industry 6.0 in Indonesia is uneven and ecosystem-dependent. Stronger readiness profiles are exhibited by regions with integrated digital infrastructure, regulatory coherence, and human capital development, while systematic reinforcement of foundational capabilities is required by other regions before advanced manufacturing intelligence can be scaled.

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