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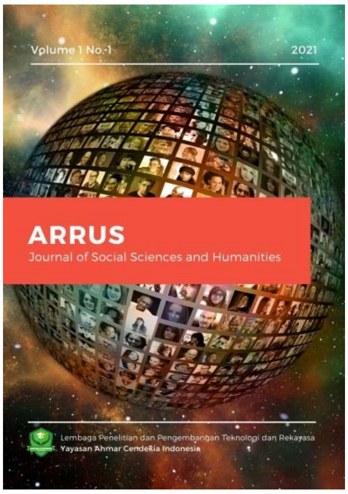

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RESEARCH ARTICLE

Beyond Compensatory Benchmarking: A Robust Multi-Criteria Decision Support Framework for Regional Digital Economy Performance

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Abstract: The multi-dimensional nature of the digital economy is such that there is a need to develop new methodologies to overcome the limitations of existing methods of measuring regional digital economy performance beyond composite indicators. The existing methods of benchmarking, which are based on compensatory aggregation, may mask structural problems in key governance areas. The research aims to develop an integrated multi-criteria decision support system to evaluate regional digital economy performance by applying the Analytical Hierarchy Process (AHP) with the geometric mean method for determining the weight of each criterion and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for ranking. The quantitative approach to multi-criteria decision-making (MCDM) has been used to develop the decision support system. The results of the research indicate that the digital economy's cybersecurity and digital trust are the most influential factors in determining digital economy performance. The results of the TOPSIS analysis indicate that there is a clear stratification of digital economy performance across regions, with the best-performing regions having well-developed digital infrastructure, human capital readiness, and cybersecurity. The results of the sensitivity analysis indicate that the ranking of digital economy performance is robust across all scenarios. The research contributes to theory by providing a new approach to measuring digital economy performance. The research contributes to the practical applications of digital economy research by providing an integrated approach to decision support. The research contributes to the methodological approach to multi-criteria decision-making by providing an integrated approach to decision support. The research contributes to the practical applications of digital economy research by providing an integrated approach to decision support. The research contributes to the practical applications of digital economy research by providing an integrated approach to decision support.

Keywords: Digital Economy Performance, Decision Support System (DSS), Multi-Criteria Decision Making (MCDM), Analytical Hierarchy Process (AHP), TOPSIS

1. Introduction

What was initially considered to be a peripheral technological feature of the economy is now regarded as one of the core drivers of structural change, productivity, and institutional modernization. It is always stressed that digital technologies should be viewed not only as supportive factors, but also as foundational infrastructures that underpin economic competitiveness and capacity to govern(Luo et al., 2026; Vaezinejad et al., 2025). In this

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regard, the concept of the digital economy is built around the idea of an ecosystem that is underpinned by digital technologies, digital infrastructure, and data-driven innovation, which is pervasive in all sectors of the economy. In the same vein, the concept of digital development is built around the idea of digital infrastructure, digital platforms, digital financial services, and digital entrepreneurship, and the interdependence with institutional and human capital is emphasized(Zeng et al., 2025; Zhang et al., 2026). In addition, the heterogeneity of digital capabilities is emphasized, and it is warned that disparities in connectivity, skills, and regulatory environments could further widen global inequality.

Although consensus exists on the revolutionary impact of the digital economy, its multidimensional character is also acknowledged with reference to its analytical complexity. Thus, instead of focusing on the volume of internet penetration or electronic commerce transactions in the measurement of digital economy performance, reference is made to the existence of a set of interconnected dimensions of the digital economy, such as the strength of digital infrastructure, the quality of broadband infrastructure, cloud computing adoption, cybersecurity strength, the development of digital skills, innovation potential, the adaptability of the regulatory environment, digital inclusion, and the maturity of institutional governance. Thus, an integrative approach is called for in order to address the structural interdependencies existing in the measurement of the digital economy(Ali et al., 2025; Mariana et al., 2025; Riesgo Gómez et al., 2025; Tian & Ma, 2026).

In response to this need, various global indices were created to measure digital competitiveness and readiness. Indicators of digital connectivity, human capital, digital public services, and business digitalization are aggregated. Technological adoption, governance, impacts, and inclusiveness are assessed. Knowledge, technology, and future readiness are prioritized. Even though useful insights are offered, methodological flaws are highlighted, which need to be further explored.

Firstly, compensatory aggregation methods are mostly employed, normally through the use of weighted averages. Under this system, poor performance can be compensated for by a strong performance in another area. Although this makes composite scoring easy, underlying vulnerabilities can be hidden(Krivý, 2023). For example, a high composite score can be attained even with underlying systemic risk exposure, as a result of poor cybersecurity governance. In a hyperconnected digital ecosystem, some underlying vulnerabilities, such as those concerning cybersecurity, data governance, and regulatory enforcement, can have veto effects, which can hardly be compensated for by positive performance in other areas. Secondly, there is normally a concern regarding the weights employed, particularly whether they have been established through expert opinion or statistical normalization without underlying robustness analysis. Questions about transparency, subjectivity, and sensitivity to small changes to weights for underlying criteria have also emerged. Thirdly, there is a concern that a number of global indices have mostly been developed for use as benchmarks, but have limited use for policy prioritization.

These are identified as highlighting the need for more structured and analytically rigorous approaches to performance assessment. An alternative is provided that is theoretically founded on Multi-Criteria Decision-Making (MCDM) theory. Criteria hierarchies, weighting logic, preference models, and dominance relationships are explicitly represented, unlike simple composite indices(Chen et al., 2019; Vidal et al., 2011). Quantitative information and expert judgment are both permitted to be included in an transparent and replicable fashion. Most significantly, unrealistic trade-offs are avoided, especially through non-compensatory outranking approaches that recognize the impossibility of compensating for poor performance on key dimensions with good performance on other dimensions.

From a theoretical perspective, the difference between compensatory and non-compensatory logic is seen as a key issue in digital economy evaluation. Continuous trade-offs are assumed between criteria, which implies substitutability between dimensions. Threshold effects and veto power are also recognized. However, in digital transformation, this difference is not trivial. Cyber security resilience, regulatory compliance, and digital trust are seen as systemic enablers, and digital sustainability would be at risk without them, regardless of progress in digital infrastructure and innovation. Realism and applicability are thus improved with the introduction of non-compensatory logic in digital economy evaluation(Du et al., 2025; Javaid et al., 2024).

Moreover, structured architectures for integrating data repositories, analytical models, and user interfaces will be provided, going beyond methodological computation. In the context of the digital economy, there will be the identification of priority intervention areas, simulation of scenarios, and evaluation of alternative policy configurations(Adu-Gyamfi, 2026). Instead of ranking, there will be refinement of policies in an iterative manner. Alignment with adaptive regulation, digital resilience, and data-driven public administration will be achieved.

In the context of emerging or developing economies, such a model of assessment is particularly necessary. Differences can emerge between urban and rural areas, larger enterprises and MSMEs, as well as tech-savvy sectors and traditional industries. Without a proper assessment model, investments in physical infrastructure could receive more attention, while institutional development, digital literacy, or cybersecurity could receive inadequate attention. Imbalances can be highlighted, thus facilitating a more balanced digital development strategy.

In such an environment, the development and utilization of a framework of Multi-Criteria Decision Support for measuring digital economy performance is being pursued. The development of an MCDM structured model, incorporating well-defined criteria, transparent weighting procedures, and robust ranking techniques, is considered to be the main methodological objective. The digital performance of regions or countries under consideration is being evaluated and compared through standardized measures, using secondary data sources. The stability of the ranking results is being tested through sensitivity analysis, thus strengthening the credibility of the methodology.

The contributions of this research have been identified to be threefold. Firstly, the discourse on digital economy measurement is advanced by challenging the traditional compensatory composite index approach, providing a more structured decision-analytic perspective. Secondly, the operationalization of MCDM-based Decision Support Systems for digital performance assessment is illustrated, with a focus on weighting, normalization, ranking, and robustness. Thirdly, a transparent and flexible evaluation tool is offered to support strategic bottleneck identification for digital transformation initiatives.

In brief, it is necessary to have analytically rigorous, transparent, and policy-oriented decision frameworks to support the assessment of digital economy performance beyond descriptive benchmarking. The need to capture the multidimensional complexity of digital economy while avoiding unrealistic compensatory trade-offs is addressed by the integration of Multi-Criteria Decision Support methodologies in digital economy evaluation. The development of more reliable, structured, and actionable digital governance assessment models is supported.

2. Research Method and Materials

An applied quantitative approach to a Multi-Criteria Decision-Making (MCDM) problem, within a Decision Support System (DSS) framework, is used to evaluate the performance of the digital economy for specific regional units. The evaluative and comparative nature of the applied MCDM model aims to produce a systematic and reproducible process for ranking alternatives according to a range of digital economy performance indicators. The applied methodology for the MCDM problem can be characterized by the application of the Analytical Hierarchy Process (AHP)(Mian et al., 2020; Rezaei, 2015; Suganthi et al., 2015) with geometric means for weight calculation and TOPSIS(Karande et al., 2016; Lestari et al., 2018; Xu et al., 2018) for alternative selection.

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This selection of both techniques is supported by decision science theory. The systematic structuring of complex decision-making problems is facilitated, and a formal consistency check is enabled through the Consistency Ratio (CR). The transparency of the compensatory ranking process is ensured, as alternatives are ranked according to their respective distances from both ideal and anti-ideal solutions. The rigor, transparency, and policy relevance of both methodological approaches in digital economy performance evaluation are enhanced.

A sequential modeling process is followed: (1) formulation of the decision hierarchy, (2) expert-based pairwise comparison for criteria weighting using AHP, (3) consistency validation, (4) construction of the decision matrix from quantitative indicators, (5) normalization and weighted scoring, (6) computation of ideal solutions, and (7) final ranking through TOPSIS.

The decision problem is formulated as follows: given a set of regional alternatives, determine their relative digital economy performance based on a structured multi-criteria evaluation model.

Let:

(1). $A = \{A_1, A_2, \ldots, A_m\}$denote the set of alternatives (regions or provinces).
(2). $C = \{C_1, C_2, \ldots, C_n\}$denote the set of evaluation criteria.

Based on digital economy measurement frameworks proposed by the Organisation for Economic Co-operation and Development and the World Bank, six criteria are defined as in table 1.

Table 1. Criteria

Code	Criterion	Indicator Examples	Type
C1	Digital Infrastructure	Broadband penetration, fiber coverage	Benefit
C2	Digital Skills & Human Capital	ICT literacy rate, STEM graduates	Benefit
C3	Innovation & Technology Adoption	Startup density, cloud adoption	Benefit
C4	Cybersecurity & Digital Trust	Incident response readiness, data protection compliance	Benefit
C5	Regulatory & Institutional Readiness	Digital policy framework, SPBE index	Benefit
C6	Digital Inclusion & Accessibility	Rural connectivity, digital service access	Benefit

All criteria are treated as benefit criteria, where higher values indicate stronger digital economy performance. The quantitative performance of each alternative under each criterion forms the decision matrix:

$$X = [x_{ij}], i = 1, \ldots, m; j = 1, \ldots n$$

where x_{ij}represents the performance score of alternative $A_i$under criterion C_j.

2.1 Criteria Weight Determination Using AHP

2.1.1. Hierarchical Structure

The AHP model consists of three levels:

a. Level 1: Goal (Digital Economy Performance Assessment)
b. Level 2: Criteria (C1–C6)
c. Level 3: Alternatives (A1–Am)

2.1.2. Pairwise Comparison Matrix

Perform pairwise comparisons among criteria using Saaty's 1–9 scale. The pairwise comparison matrix is defined as:

$$A = [a_{ij}]$$

where a_{ij}indicates the relative importance of criterion $C_i$over C_j, satisfying:

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$$a_{ij} = \frac{1}{a_{ji}}, a_{ii} = 1$$

2.1.3. Geometric Mean Method

weight of each criterion is obtained using the geometric mean method:

$$GM_i = \left(\prod_{j=1}^{n} a_{ij} \right)^{\frac{1}{n}}$$

The normalized weight vector is:

$$w_i = \frac{GM_i}{\sum_{k=1}^{n} GM_k}$$

with:

$$\sum_{i=1}^{n} w_i = 1$$

The geometric mean method is selected because it provides a consistent approximation of eigenvector-based weights and is computationally stable for aggregated expert judgments.

Consistency Test

To ensure reliability of expert judgments, consistency analysis is conducted. The maximum eigenvalue approximation is calculated as:

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(Aw)_i}{w_i}$$

The Consistency Index (CI) is: $CI = \frac{\lambda_{\max} - n}{n-1}$

The Consistency Ratio (CR) is: $CR = \frac{CI}{RI}$

where RI is the Random Index corresponding to matrix size n.

A judgment matrix is considered acceptable if: $CR < 0.10$

This threshold ensures logical coherence in expert comparisons and strengthens methodological validity.

2.1.4. Construction of Decision Matrix

Once weights have been established, quantitative data for each alternative is gathered from secondary sources, including national ICT data, digital governance reports, and innovation indices for regions. All data is standardized to make it comparable. The structure of the decision matrix is as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

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2.1.5. Ranking Alternatives Using TOPSIS

2.1.5.1. Normalization

Normalization equation is below:

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

2.1.5.2. Weighted Normalized Matrix

$$v_{ij} = w_j \cdot r_{ij}$$

where $w_j$is the AHP-derived weight.

2.1.5.3. Determine Ideal Solutions

Since all criteria is benefit:

$$A^+ = \{\max (v_{ij})\}$$

$$A^- = \{\min (v_{ij})\}$$

Positive ideal solution presents optimal digital performance profile and negative ideal reflects the weakest profile.

2.1.5.4. Distance Measures

Euclidean distances are calculated:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}$$

2.1.5.5. Closeness Coefficient

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

The alternative with the highest $CC_i$is ranked first.

2.1.6. Sensitivity Analysis

For assessing robustness, a one-at-a-time weight variation approach is carried out by varying each criterion weight by ±10%, i.e., increasing and decreasing each weight while keeping normalization at 100% in total. Ranking stability is computed using Spearman's rank correlation coefficient:

$$\rho = 1 - \frac{6\sum d_i^2}{m(m^2 - 1)}$$

High correlation values ($\rho > 0.80$) indicate stable rankings under weight perturbation.

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3. Result And Discussion

The results of the empirical analysis using the AHP-TOPSIS approach will be presented in this section, along with an analytical discussion on the results for the six alternatives in terms of the digital economy. In particular, the results will be presented in the following sequence: AHP results on weighting and consistency check, TOPSIS results on ranking, and finally an analytical discussion on the results along with policy considerations.

Geometric mean method was applied to calculate the criteria weights with expert pairwise comparison as the base. The calculation process is discussed in detail in the methodology section. However, the final normalized weights are as follows:

Table 2. Criteria Weights

Criterion	Description	Weight (w)	Relative Importance
C1	Digital Infrastructure	0.1686	Moderate
C2	Digital Skills & Human Capital	0.1686	Moderate
C3	Innovation & Adoption	0.0884	Low–Moderate
C4	Cybersecurity & Digital Trust	**0.3214**	**Highest**
C5	Regulatory Readiness	0.0843	Low
C6	Digital Inclusion	0.1686	Moderate
Total	—	**1.0000**	—

The AHP consistency test produced:

(a). $\lambda_{\max} = 6.0092$
(b). $CI = 0.00184$
(c). $CR = 0.00149$

Since $CR < 0.10$, the pairwise comparison matrix is considered highly consistent. This indicates strong logical coherence in expert judgments.

Using the normalized and weighted matrix derived earlier, the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) were determined.

Table 3. Ideal Solutions

Criterion	Positive Ideal (A^+)	Negative Ideal (A^-)
C1	0.081496	0.057576
C2	0.081690	0.057552
C3	0.043539	0.029705
C4	0.163068	0.102354
C5	0.040505	0.028570
C6	0.080724	0.058710

Distances from ideal solutions were computed using Euclidean metrics as in table 4.

Table 4. Separation Measures and Closeness Coefficient

Alternative	D^+	D^-	Closeness Coefficient (CC)	Rank
A1 Jakarta	0.000000	0.075657	**1.000000**	**1**
A2 West Java	0.024129	0.051652	**0.681595**	**2**
A4 East Java	0.038405	0.037316	**0.492811**	**3**
A5 North Sumatra	0.050896	0.024815	0.327758	4
A3 Central Java	0.062226	0.013680	0.180224	5
A6 South Sulawesi	0.075657	0.000000	0.000000	6

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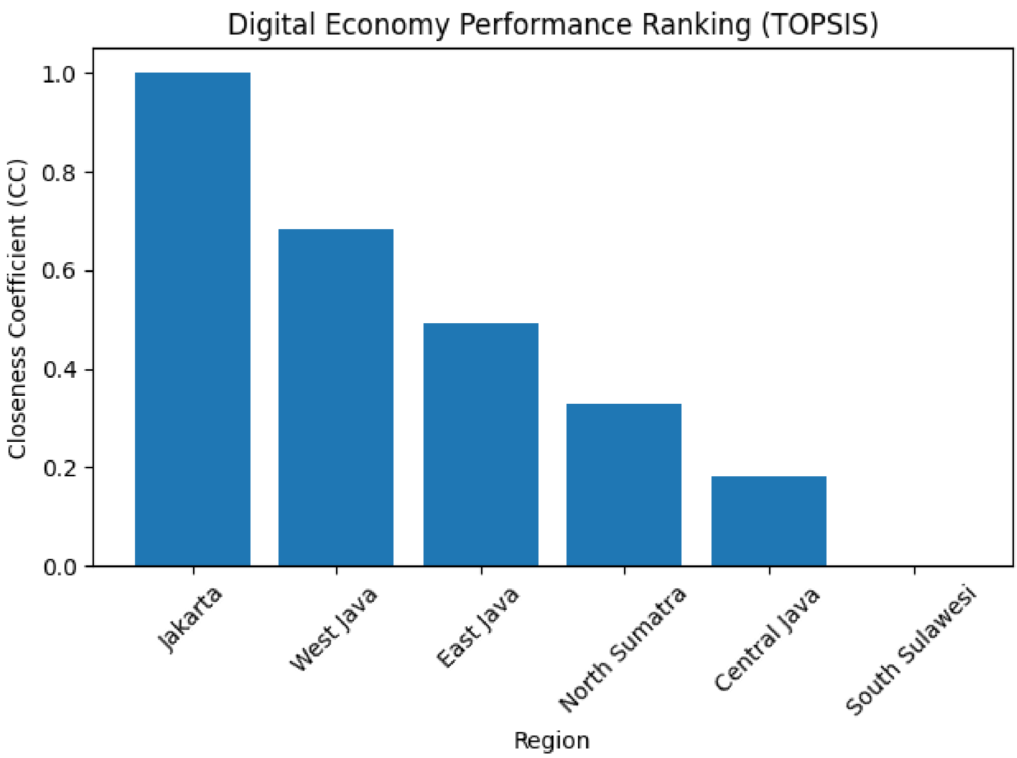

Figure 1. Digital Economy Performance

For Jakarta, a closeness coefficient of 1.000 is recorded, implying a perfect proximity to the ideal digital performance profile. This is not surprising, considering its strong infrastructural capacity (92), digital skillset (88), and cybersecurity readiness (80). The significant weight of criterion C4 adds to Jakarta's relative competitive advantage.

West Java, on the other hand, reports a closeness coefficient of 0.6816, reflecting a balanced performance across all criteria except for a relative weakness in cybersecurity readiness (70). Considering the significant weight of criterion C4, this weakness slightly impacts West Java's closeness coefficient.

East Java reports a closeness coefficient of 0.4928, reflecting moderate infrastructural capacity and innovation readiness while falling short of the relative strength of cybersecurity readiness reported by Jakarta and West Java. The relative parity of D^+ and D^- values may indicate a transitional phase of digital economy development.

From a regional perspective, there are relative weaknesses reported across all regions, including innovation and regulatory readiness. The lower closeness coefficients reported by West Java (0.3278) and East Java (0.1802) reflect limited digital economy systemic integration.

A6 reports the lowest closeness coefficient of 0.000, implying that it is closest to the negative ideal solution. Its low relative performance across all criteria reflects significant distance from the positive ideal solution, affirming relative challenges faced by A6 in terms of digital readiness.

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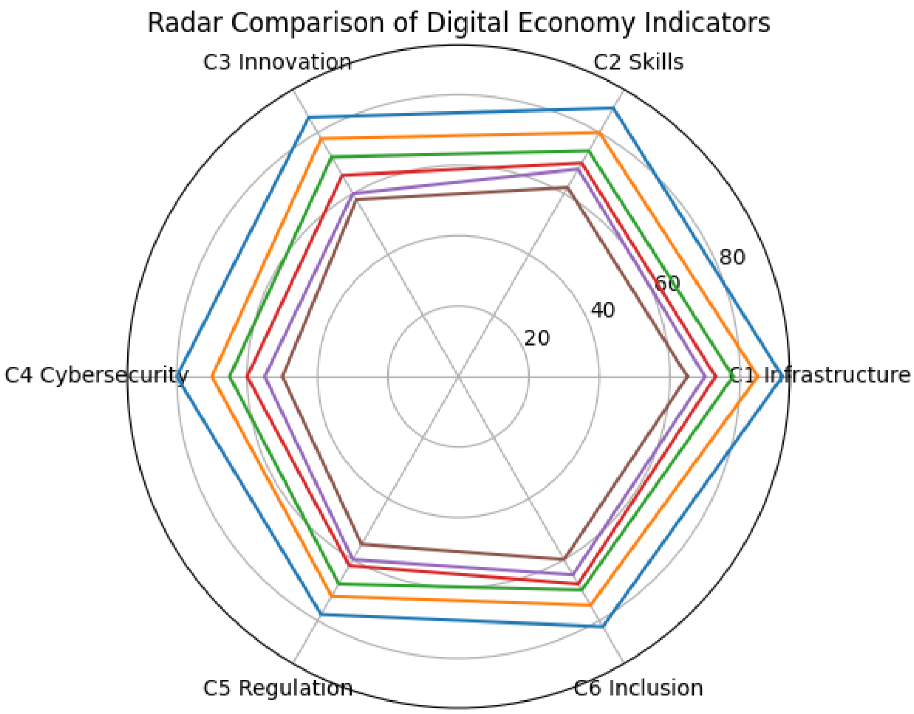

Figure 2. Comparison of Digital Economy

4. Conclusion

The research employs an integrated Multi-Criteria Decision Support System, combining the Analytic Hierarchy Process with the Technique for Order Preference by Similarity to Ideal Solution to measure the performance of the digital economy with reference to six different regions. The integration of the methodology facilitates the determination of weights for the criteria through the geometric mean method, as well as consistency ratio checking.

The results obtained from the Analytic Hierarchy Process (AHP) show a high degree of logical consistency, with CR = 0.00149. This further reinforces the reliability and consistency of the expert opinions. The weights calculated for each criterion show that the most important criterion for a digital resilience framework is cybersecurity and digital trust, with a weight of 0.3214, followed by digital infrastructure, digital skills, and digital inclusion with weights equal to 0.1686 each. The weights for innovation capacity and regulatory readiness are lower. This shows that digital resilience works as a systemic enabler within the current digital transformation ecosystem.

The TOPSIS result ranked Jakarta first (CC=1.000), followed by West Java (0.6816), and then East Java (0.4928). The regions with balanced conditions in terms of infrastructure, skills, and cybersecurity tended to perform better compared to those with uneven conditions in digital development. The separation metrics show large gaps between the top performers and developing ones, especially in high-weight areas such as cybersecurity and institutional readiness.

The sensitivity analysis revealed that this order remains solid with Spearman's rho consistently above 0.90, even with changes in the weights. To summarize, this model is stable and does not overreact to minor adjustments in the parameters.

There are various ways that this framework could be extended in future research. Firstly, by using non-compensatory methods like ELECTRE or PROMETHEE, it might be possible to gain some relative insights into outranking behavior, where certain criteria are used as veto conditions. This might be of particular interest in digital governance, where certain cybersecurity vulnerabilities might not be compensable.

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Secondly, the hybrid approach of using the combination of the Analytic Hierarchy Process (AHP) with objective entropy weighting may address the issue of subjectivity while maintaining an optimal balance between the opinions of experts and statistical variance. Thirdly, the employment of dynamic modeling with the help of panel data may help in tracking the evolution of the digital economy's performance over time. This would enable the evaluation of policy impact paths. Fourthly, the integration of machine learning/predictive analytics with the architecture of the decision support system (DSS) may help in facilitating scenario forecasting and real-time digital monitoring. Lastly, the extension of the hierarchy of criteria to include sustainability measures, green ICT adoption, and digital ethics may help in aligning the assessment of the digital economy with the new paradigms of Industry 5.0 and Industry 6.0..

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