

Research Article

Entropy vs. CRITIC Weighting for TOPSIS Ranking of Mobile Data Packages in Ambon City

Vederico Pitsalitz Sabandar¹, Sanriomi Sintaro^{2*}, Wisard Widsli Kalengkongan³,
Jumriadi⁴, Sitti Nur Isnian⁵

¹Mathematics Education Study Program, Faculty of Teacher Training and Education, Pattimura University, Ambon

²Information System Study Program, Faculty of Mathematics and Natural Science, Sam Ratulangi University, Manado

³Information System Study Program, Faculty of Mathematics and Natural Science, Sam Ratulangi University, Manado

⁴Department of Physics, Faculty of Mathematics and Natural Sciences, Sam Ratulangi University, Manado

⁵Department of Agricultural Extension, Faculty of Agriculture, Haluoleo University, Kendari

Received: 11 December 2025; Revision: 10 January 2026;

Accepted: 22 January 2026; Available Online: 26 January 2026

Abstract

This study proposes a decision-support approach for selecting prepaid mobile data packages in Ambon City that balances price, main quota, and validity period. Twelve packages from Telkomsel, XL, Indosat IM3, and Tri were evaluated using four criteria: price, main quota, validity, and price per main gigabyte. TOPSIS was used for ranking, and Entropy and CRITIC were compared as objective weighting methods to examine the effect of weighting choice. Entropy emphasized the main quota, producing a quota-focused evaluation. CRITIC gave greater weight to price and price efficiency, accounting for data variation and criterion correlations. Both methods selected Tri Happy 70GB as the best option. The overall rankings were highly consistent, with a Spearman rank correlation of 0.8741, although some alternatives changed positions within the top group. The analysis is limited to a single time snapshot based on published package attributes and excludes measured network performance in Ambon City. In practice, the framework is transparent, replicable, and can be extended with constraints such as maximum budget and minimum validity requirements. The study contributes a controlled comparison of Entropy and CRITIC effects while keeping TOPSIS constant.

Keywords: CRITIC weight; Decision support system; Entropy weight; Mobile data packages; Multi-criteria decision making; TOPSIS

How to cite: Sabandar V.P., Sintaro S., Kalengkongan W.W., Jumriadi, Isnian S.N. (2026). Entropy vs. CRITIC Weighting for TOPSIS Ranking of Mobile Data Packages in Ambon City. *Informatics and Software Engineering*, 3(2), 73–85. <https://doi.org/10.58777/ise.v3i2.575>

*Corresponding author: Sanriomi Sintaro (sanriomi@unsrat.ac.id)



This is an open-access article under the [CC-BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) international license.

1. Introduction

Mobile Internet has become a foundational enabler of daily activities and economic participation, supporting communication, learning, entertainment, digital payments, and online commerce. Recent global connectivity reports consistently show strong growth in Internet adoption, yet also highlight persistent gaps in affordability, usage, and quality of experience, especially outside high-income and highly urbanized areas. In its annual “Facts and Figures” series, the International Telecommunication Union (ITU) reports that mobile broadband coverage is now close to universal in population terms, but meaningful connectivity is still constrained by price, network quality, skills, and unequal deployment of newer technologies such as 5G (ITU, 2023, 2024, 2025).

In Indonesia, Internet access and mobile connectivity continue to expand rapidly. The Indonesian Internet Service Providers Association (APJII) reported that Internet users in Indonesia reached 221.56 million in 2024, with Internet penetration around 79.5%, indicating a continued upward trend over recent years (Haryanto, 2024). At the same time, Indonesia’s “archipelagic geography” creates distinctive infrastructure and service delivery challenges: coverage and service quality can differ considerably across islands and cities, and consumers often face trade-offs between price, quota, validity period, and expected network performance. Policy and market analyses also emphasize that inclusive digital transformation requires closing these gaps so that growth in the digital economy benefits more regions, not only major metropolitan centers (L. Chen et al., 2023; World Bank Group, 2021). A practical implication of this context is the increasing complexity of choosing an Internet package. Cellular providers frequently offer a range of prepaid data packages with varying features (e.g., total data quota, active period, bonus quota, and pricing structures). For consumers in a specific locality, such as Ambon City, the “best” package is not determined by a single factor. A low-priced package might have a short validity period; a large quota may come with restrictions; or an attractive promotion may not be optimal when multiple criteria are considered simultaneously. This makes package selection a multi-criteria decision problem, where decision-makers (users) benefit from structured evaluation rather than ad-hoc comparisons. National and regional digital reports also show that Internet and mobile use patterns evolve quickly, reinforcing the need for transparent and adaptable decision frameworks (Simon Kemp, 2023; Simon Kemp, 2024; Simon Kemp, 2025).

Decision Support Systems (DSS) and Multi-Criteria Decision Making (MCDM) methods are widely used to help rank alternatives based on several criteria. Among the best-known MCDM techniques, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) remains popular because it offers a clear logic: the preferred alternative should be closest to the “ideal” solution and farthest from the “anti-ideal” solution. Contemporary reviews and surveys continue to document TOPSIS usage across many domains due to its conceptual simplicity and practical interpretability (Taherdoost & Madanchian, 2024). However, a central issue in MCDM is the weighting of criteria. The final ranking can change significantly depending on how much importance (weight) is assigned to each criterion. In many real decisions, weights are determined subjectively (e.g., by expert judgment or user preference). While subjective weights can reflect human priorities, they can also introduce bias or inconsistency, especially when the objective is to compare alternatives in a more “fair” and data-driven way. Because of this, many studies recommend objective weighting approaches that compute weights from the data distribution itself. For example, the Entropy method assigns a higher weight to criteria with greater informational diversity across alternatives. At the same time, CRITIC (Criteria Importance Through Intercriteria Correlation) considers both contrast (variability) and the conflict/correlation structure among criteria, aiming to reduce redundancy across highly correlated criteria (Linh et al., 2025; Yudhistira et al., 2024). Recent literature also emphasizes that comparing weighting strategies is not merely a technical detail; it affects the stability and reliability of MCDM outcomes. Studies investigating the impact of different objective weighting methods show that rankings and scores can vary depending on whether the method emphasizes dispersion (e.g., Entropy) or also incorporates correlation/contrast mechanisms (e.g., CRITIC). Research focusing on score stability further motivates sensitivity-style comparisons when different weighting rules are applied to the same MCDM model.

Based on this motivation, this study designs a DSS framework for mobile Internet package selection in Ambon City by comparing TOPSIS results under two objective weighting schemes: Entropy and CRITIC. The alternatives are limited to packages from four major cellular providers commonly used in

Indonesia (Telkomsel, XL, Indosat, and Tri). At the same time, the dataset is constrained to offerings relevant to Ambon City to avoid overgeneralization across regions. The core research question is: How does the choice of objective weighting method (Entropy vs. CRITIC) influence the ranking of mobile Internet packages when TOPSIS is used as the decision model? This comparison is expected to provide a more transparent basis for recommendations and to demonstrate how "fairness" in evaluation can be improved by explicitly testing weighting assumptions rather than relying on a single weighting choice (Liu et al., 2022; Taherdoost & Madanchian, 2024).

2. Literature Review

Selecting a mobile Internet package is inherently a multi-criteria decision problem because users must balance multiple (often conflicting) attributes such as price, data quota, and validity period. In the broader telecommunications and Internet-service context, a systematic literature review on ISP selection criteria (covering studies from 2001–2022) reports that decisions commonly involve both quantitative and qualitative factors, and that the emphasis in the literature has increasingly shifted from purely cost-related criteria toward performance- and reliability-related considerations (Naji et al., 2023). This aligns with practical consumer experiences: a "cheap" plan may not be optimal if it provides insufficient usable quota or a short active period. In contrast, a large quota may not be attractive if it comes with a higher cost or constraints.

2.1 DSS/MCDM Applications in Telecommunications Package Selection

Decision Support Systems (DSS) and Multi-Criteria Decision Making (MCDM) methods are widely applied to structure such trade-offs, particularly when the decision-maker needs a transparent ranking of alternatives. In the Internet package domain, several applied studies (including in Indonesia) have implemented TOPSIS-based DSS to recommend service packages to customers. For example, a TOPSIS-based DSS has been proposed to help prospective customers choose among IndiHome packages, emphasizing how systematic evaluation can reduce confusion from the many package options (Candra & David, 2023). Other applied works in Indonesia also report using MCDM to support selection among internet providers or packages, typically relying on a small set of criteria such as price, quota, and perceived connection quality (Whistler, 2023).

Across these studies, TOPSIS is frequently chosen because it is intuitive and produces an easily interpretable preference score by comparing each alternative to an "ideal" and "anti-ideal" solution. Recent surveys continue to highlight TOPSIS as one of the most commonly used MCDM techniques across domains, with many extensions (e.g., fuzzy TOPSIS) proposed to handle uncertainty (Taherdoost & Madanchian, 2024). However, many DSS implementations for consumer-facing problems still rely heavily on subjective or ad hoc weighting (e.g., assigning weights based on assumed priorities or limited respondent input), which can make results difficult to reproduce or compare across studies.

2.2 Criteria Weighting: Subjective vs. Objective Approaches

A major determinant of MCDM outcomes is how the criteria weights are assigned. Broadly, weighting approaches can be classified into:

1. Subjective weighting, where weights reflect expert or user preferences (e.g., AHP-derived weights), and
2. Objective weighting, where weights are computed from the data structure itself (e.g., dispersion and correlation patterns).

Recent methodological reviews emphasize that criteria-weighting research has expanded beyond traditional approaches to include many "newer" weighting techniques, often designed to improve consistency, reduce redundancy, or enhance discrimination between alternatives (Ayan et al., 2023). Despite this diversity, two objective methods remain especially prominent and practical for data-driven DSS studies:

1. Entropy weighting, which increases weight for criteria that show higher informational diversity (greater dispersion across alternatives).
2. CRITIC weighting, which incorporates both contrast intensity (variability) and inter-criteria correlation (penalizing redundancy among correlated criteria).

A detailed discussion of objective weighting methods (including Entropy and CRITIC) also cautions that objective methods can be sensitive to data transformation/normalization choices and, therefore, should be applied transparently and, where possible, compared against alternatives to evaluate robustness (C.-H. Chen, 2021). In applied decision models, Entropy-weighted TOPSIS has been widely used to reduce subjective bias, and improved variants of entropy-weighted TOPSIS continue to appear in recent literature, indicating active interest in objective weighting as a practical mechanism for replicable decision support (Liu et al., 2022).

2.3 Why Compare Entropy and CRITIC?

Although both Entropy and CRITIC are objective methods, they can yield meaningfully different weight profiles because they “value” different aspects of the dataset:

1. Entropy tends to emphasize criteria with higher dispersion (more differentiating power).
2. CRITIC emphasizes criteria that are both discriminative and less redundant (lower correlation with others).

Empirically, comparative studies have shown that CRITIC can produce relatively “balanced” weights, whereas Entropy may yield more uneven weights when the dataset strongly differentiates alternatives on certain criteria; this can lead to different final rankings even under the same ranking method (Ariyanti & Fu’adi, 2025). This is particularly relevant for consumer package selection, where some criteria (e.g., price per GB or quota) may dominate variability. In contrast, others (e.g., the validity period) may vary less but remain important to users.

2.4 Ranking Robustness and Agreement Analysis

Because rankings can change with different weighting strategies, recent work has increasingly examined ranking stability and agreement between outcomes under different weighting methods. A 2025 study evaluating multiple weighting methods across several MCDM techniques reports that the choice of weighting method affects the stability/consistency of alternative scores and can be assessed through comparative analyses rather than assuming a single “correct” weighting approach (Linh et al., 2025). In practice, rank agreement measures such as Spearman’s rank correlation are frequently used to quantify whether two rankings are broadly consistent or substantially different, supporting a more transparent discussion of how methodological choices shape recommendations (Naji et al., 2023).

2.5 Research Gap and Positioning of This Study

From the reviewed literature, two gaps motivate this study:

1. Application gap (local consumer context): Many DSS/MCDM implementations for internet package selection are demonstrated in limited contexts or with provider-specific cases, and often do not explicitly address regional/local specificity. However, the literature on ISP selection criteria suggests that decision priorities and service realities can shift over time and context, especially regarding performance and quality dimensions (Candra & David, 2023).
2. Methodological gap (weighting-method effect): Numerous applied studies adopt TOPSIS (or other MCDM methods) but treat weights as fixed inputs rather than a core source of uncertainty. Meanwhile, methodological research explicitly warns that objective weighting outcomes can be sensitive to data characteristics and normalization, and comparative studies show that Entropy vs. CRITIC can lead to different weight distributions and decision outcomes (Ariyanti & Fu’adi, 2025; Krishnan et al., 2021).

To address these gaps, this paper focuses on Ambon City. It evaluates 12 mobile data packages (from Telkomsel, XL, Indosat/IM3, and Tri) using a fixed-ranking method (TOPSIS) and systematically compares two objective weighting schemes (Entropy vs. CRITIC). This design isolates the impact of weighting on ranking outcomes, supports replicability (weights are computed directly from the decision matrix), and enables an explicit comparison of rank agreement (e.g., via Spearman correlation and top-*k* overlap) as recommended by recent stability-oriented MCDM research.

3. Methods

3.1 Data scope and collection setting (Ambon City)

This study evaluates prepaid **mobile data packages** offered in **Ambon City, Indonesia**, where package availability and pricing can differ by location due to regional configurations and promotions. To keep the comparison fair and context-specific, all alternatives were collected for the Ambon City region from the official websites of four major providers 1) Telkomsel 2) XL 3) Indosat 4) Tri

Because provider catalogs and prices can change frequently, this dataset should be interpreted as a snapshot of offerings available at the time of collection. For transparency in the final manuscript, the data-collection date should be stated explicitly (e.g., “Data were collected on 28 November 2025”).

3.2 Alternatives (selected 12 packages)

To prevent the analysis from becoming overly broad while still capturing cross-provider variation, we select 12 alternatives, consisting of three packages per provider. Each alternative is encoded with a unique ID (e.g., A2, A5, ...) to simplify referencing throughout the analysis.

Below is the selected alternative set (12 packages):

Table 1. Selected Provider

| Code | Provider | Package name | Price (Rp) | Total quota (GB) | Main quota (GB) | Validity (days) |
|------|-----------|-----------------------|------------|------------------|-----------------|-----------------|
| A2 | Indosat | Freedom Internet | 25,000 | 4.00 | 4.00 | 30 |
| A5 | Indosat | Freedom Internet | 50,000 | 12.00 | 12.00 | 30 |
| A7 | Indosat | Freedom Internet | 85,000 | 28.00 | 28.00 | 30 |
| A25 | Telkomsel | Internet Bulanan 6GB | 50,000 | 6.00 | 6.00 | 30 |
| A28 | Telkomsel | Internet Bulanan 35GB | 120,000 | 35.00 | 35.00 | 30 |
| A30 | Telkomsel | Internet Bulanan 60GB | 185,000 | 60.00 | 60.00 | 30 |
| A37 | Tri | Happy 8GB | 32,000 | 8.00 | 8.00 | 30 |
| A42 | Tri | Happy 35GB | 80,000 | 35.00 | 35.00 | 30 |
| A44 | Tri | Happy 70GB | 125,000 | 70.00 | 70.00 | 30 |
| A19 | XL | Bebas Puas 12GB | 66,000 | 11.72 | 8.06 | 30 |
| A18 | XL | Bebas Puas 30GB | 99,000 | 29.30 | 20.51 | 30 |
| A17 | XL | Bebas Puas 90GB | 180,000 | 87.89 | 58.59 | 30 |

Note on quota structure: Some packages separate “main quota” from other quota types (e.g., app-based, local, or bonus quotas). To maintain comparability, this study distinguishes Total Quota and Main Quota as separate attributes at the data level, and prioritizes Main Quota for value assessment (see criteria below).

3.3. Research design and workflow

This study develops a decision support procedure for selecting prepaid mobile data packages in Ambon City, Indonesia. The methodological design isolates the effect of criteria weighting by keeping the ranking engine fixed. Specifically:

1. Fixed ranking method: Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)
2. Weighting methods compared: Entropy Weight vs CRITIC Weight (both objective weighting)

The workflow is:

1. Collect and structure the dataset into a decision matrix $X = [x_{ij}]$.
2. Define criteria types (benefit/cost) and compute any derived attributes (e.g., price per main GB).
3. Compute criteria weights using:
 - a. Entropy = $w^{(E)}$
 - b. CRITIC = $w^{(C)}$
4. Run TOPSIS twice (once per weight vector) to obtain two rankings.
5. Compare ranking outcomes (agreement and differences) using rank-based measures (reported in Results).

3.4 Alternatives, criteria, and decision matrix

Let m be the number of alternatives and n be the number of criteria.

1. Alternatives: $m = 12$ selected mobile data packages (3 per provider: Telkomsel, XL, Indosat/IM3, and Tri), collected for the Ambon City region from official provider websites.
2. Criteria: $n = 4$, all quantitative and consistently defined across providers:
 - a. C1 — Price (Rp) (*Cost*)
 - b. C2 — Main quota (GB) (*Benefit*)
 - c. C3 — Validity period (days) (*Benefit*)
 - d. C4 — Price per main GB (Rp/GB) (*Cost*)

The derived criterion C4 is computed as:

$$C4 = \frac{\text{Price (Rp)}}{\text{Main quota (GB)}} \tag{1}$$

The decision matrix is:

$$X = [x_{ij}], i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n \tag{2}$$

where x_{ij} represents the value of alternative i under criterion j .

3.5. Normalization for objective weighting

Entropy and CRITIC require criteria to be comparable across different units (Rp, GB, days). Therefore, the matrix is first converted into a normalized benefit-oriented matrix $R = [r_{ij}]$ with values in $(0,1]$, where higher is always better:

For benefit criteria:

$$r_{ij} = \frac{x_{ij}}{\max_i (x_{ij})} \tag{3}$$

For cost criteria:

$$r_{ij} = \frac{\min_i (x_{ij})}{x_{ij}} \tag{4}$$

This transformation enables objective weighting methods to consistently interpret variability and correlation.

3.6 Entropy Weight method

The Entropy method assigns higher weights to criteria with greater informational diversity (higher discrimination among alternatives).

Step 1 — Proportions

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}} \tag{5}$$

with $p_{ij} \geq 0$ and $\sum_i p_{ij} = 1$.

Step 2 — Entropy of each criterion

Let $k = \frac{1}{\ln(m)}$. Then:

$$e_j = -k \sum_{i=1}^m p_{ij} \ln(p_{ij}) \tag{6}$$

Step 3 — Degree of diversification

$$d_j = 1 - e_j \tag{7}$$

Step 4 — Entropy weights

$$w_j^{(E)} = \frac{d_j}{\sum_{j=1}^n d_j} \tag{8}$$

3.7 CRITIC Weight method

CRITIC (Criteria Importance Through Intercriteria Correlation) assigns higher weights to criteria that are both (i) more dispersed and (ii) less redundant with others.

Using the normalized matrix $R = [r_{ij}]$:

Step 1 — Standard deviation

$$\sigma_j = \text{std}(r_{1j}, r_{2j}, \dots, r_{mj}) \tag{9}$$

Step 2 — Correlation between criteria

Compute Pearson correlation ρ_{jk} for each pair (j, k) using the column vectors of R .

Step 3 — CRITIC information content

$$C_j = \sigma_j \sum_{k=1}^n (1 - \rho_{jk}) \tag{10}$$

Step 4 — CRITIC weights

$$w_j^{(C)} = \frac{C_j}{\sum_{j=1}^n C_j} \tag{11}$$

3.8 TOPSIS ranking procedure (fixed engine)

TOPSIS ranks alternatives based on their closeness to an ideal solution and their distance from an anti-ideal solution. TOPSIS is applied twice (Entropy weights and CRITIC weights).

Step 1 — Vector normalization

$$v_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \tag{12}$$

Step 2 — Weighted normalized matrix

For a weight vector w (either $w^{(E)}$ or $w^{(C)}$):

$$y_{ij} = w_j v_{ij} \tag{13}$$

Step 3 — Ideal and anti-ideal solutions

For each criterion j :

If j is benefit:

$$y_j^+ = \max_i (y_{ij}), y_j^- = \min_i (y_{ij}) \tag{14}$$

If j is cost:

$$y_j^+ = \min_i (y_{ij}), y_j^- = \max_i (y_{ij}) \tag{15}$$

Define:

$$A^+ = (y_1^+, \dots, y_n^+), A^- = (y_1^-, \dots, y_n^-) \tag{16}$$

Step 4 — Separation measures

$$S_i^+ = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^+)^2}, S_i^- = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^-)^2} \tag{17}$$

Step 5 — Closeness coefficient and ranking

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{19}$$

Higher CC_i indicates a better alternative. Alternatives are ranked in descending order of their CC_i scores.

3.9 Comparing the two rankings

To evaluate the impact of weighting choice (Entropy vs CRITIC), this study compares:

1. Rank agreement (Spearman’s rank correlation)

Let $R_i^{(E)}$ be the rank of alternative i under Entropy–TOPSIS and $R_i^{(C)}$ under CRITIC–TOPSIS. Define $d_i = R_i^{(E)} - R_i^{(C)}$. Spearman’s correlation is:

$$\rho = 1 - \frac{6 \sum_{i=1}^m d_i^2}{m(m^2 - 1)} \tag{20}$$

2. Top- k overlap (e.g., $k = 3$ and $k = 5$)

This reports how many alternatives appear in both top- k sets, providing an intuitive interpretation for decision-makers.

4. Results

4.1 Objective weights (Entropy vs. CRITIC)

Using the normalized decision matrix (Section 3), criteria weights were computed with the **Entropy** and **CRITIC** methods. The resulting weights are reported in Table 2.

Table 2. Criteria weights (objective weighting)

| Criterion | Type | Entropy weight $w^{(E)}$ | CRITIC weight $w^{(C)}$ |
|------------------------------|---------|--------------------------|-------------------------|
| C1 Price (Rp) | Cost | 0.319870 | 0.374091 |
| C2 Main quota (GB) | Benefit | 0.519600 | 0.340438 |
| C3 Validity (days) | Benefit | 0.000739 | 0.038559 |
| C4 Price per main GB (Rp/GB) | Cost | 0.159791 | 0.246912 |

4.2 One worked example (demonstration): TOPSIS calculation for A44 under Entropy weights

This subsection demonstrates the TOPSIS computation for one alternative. All other alternatives were computed using the same steps and are summarized in Table 3.

Alternative: A44 (Tri – Happy 70GB)

Raw values (C1–C4):

- C1Price (cost): $x_1 = 125,000$
- C2Main quota (benefit): $x_2 = 70$
- C3Validity (benefit): $x_3 = 28$
- C4Price per main GB (cost):

$$x_4 = \frac{125000}{70} = 1785.7143 \tag{21}$$

Entropy weights (from Table 1):

$$w^{(E)} = [0.319870, 0.519600, 0.000739, 0.159791] \tag{22}$$

Step 1 — Vector normalization

$$v_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \tag{23}$$

Denominators (computed across all 12 alternatives):

$$\sqrt{\sum x_{i1}^2} = 362051.1014 \tag{24}$$

$$\sqrt{\sum x_{i2}^2} = 126.1444 \tag{25}$$

$$\sqrt{\sum x_{i3}^2} = 102.2350 \tag{26}$$

$$\sqrt{\sum x_{i4}^2} = 16749.6075 \tag{27}$$

Thus, for A44:

$$v_1 = \frac{125000}{362051.1014} = 0.345255 \tag{28}$$

$$v_2 = \frac{70}{126.1444} = 0.554920 \tag{29}$$

$$v_3 = \frac{28}{102.2350} = 0.273879 \tag{30}$$

$$v_4 = \frac{1785.7143}{16749.6075} = 0.106612 \tag{31}$$

Step 2 — Weighted normalized values

$$y_{ij} = w_j \cdot v_{ij} \tag{32}$$

For A44:

$$y_1 = 0.319870(0.345255) = 0.110437$$

$$y_2 = 0.519600(0.554920) = 0.288336$$

$$y_3 = 0.000739(0.273879) = 0.000202$$

$$y_4 = 0.159791(0.106612) = 0.017036$$

Step 3 — Ideal and anti-ideal solutions

Cost criteria: $y_j^+ = \min (y_{ij}), y_j^- = \max (y_{ij})$

Benefit criteria: $y_j^+ = \max (y_{ij}), y_j^- = \min (y_{ij})$

Across all 12 alternatives (Entropy–TOPSIS):

$$A^+ = [0.022087, 0.288336, 0.000217, 0.017036]A^- \\ = [0.163446, 0.016476, 0.000202, 0.079500]$$

Step 4 — Distances and closeness coefficient

$$S_i^+ = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^+)^2}, S_i^- = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^-)^2} \tag{33}$$

For A44:

$$S^+ = 0.088349$$

$$S^- = 0.283936$$

$$CC_i = \frac{S^-}{S^+ + S^-} = \frac{0.283936}{0.088349 + 0.283936} = 0.762684 \tag{34}$$

Therefore, the **Entropy–TOPSIS score for A44** is:

$$CC^{(E)}(A44) = 0.7627 \tag{35}$$

4.3 TOPSIS scores and rankings (Entropy vs. CRITIC)

TOPSIS was executed twice: once using $w^{(E)}$ and once using $w^{(C)}$. The closeness coefficients and ranks are shown in Table 3.

Table 3. TOPSIS closeness coefficients and rankings (12 alternatives)

| Code | Provider | Package | $CC_i(\text{Entropy})$ | Rank (Entropy) | $CC_i(\text{CRITIC})$ | Rank (CRITIC) |
|------|-----------|-----------------------|------------------------|----------------|-----------------------|---------------|
| A44 | Tri | Happy 70GB | 0.7627 | 1 | 0.6722 | 1 |
| A30 | Telkomsel | Internet Bulanan 60GB | 0.6150 | 2 | 0.5018 | 5 |
| A17 | XL | Bebas Puas 90GB | 0.6133 | 3 | 0.5036 | 4 |
| A42 | Tri | Happy 35GB | 0.5247 | 4 | 0.5967 | 2 |
| A28 | Telkomsel | Internet Bulanan 35GB | 0.4684 | 5 | 0.4832 | 8 |
| A7 | Indosat | Freedom Internet | 0.4390 | 6 | 0.5260 | 3 |
| A37 | Tri | Happy 8GB | 0.3570 | 7 | 0.5003 | 6 |
| A5 | Indosat | Freedom Internet | 0.3503 | 8 | 0.4865 | 7 |
| A2 | Indosat | Freedom Internet | 0.3416 | 9 | 0.4696 | 9 |
| A18 | XL | Bebas Puas 30GB | 0.3319 | 10 | 0.4114 | 11 |
| A25 | Telkomsel | Internet Bulanan 6GB | 0.3055 | 11 | 0.4116 | 10 |
| A19 | XL | Bebas Puas 12GB | 0.2867 | 12 | 0.3858 | 12 |

4.4 Ranking agreement between Entropy–TOPSIS and CRITIC–TOPSIS

To quantify the similarity between the two rankings, Spearman’s rank correlation was computed using the rank differences across the 12 alternatives:

Spearman’s $\rho = 0.8741$

In addition, top- k overlap was evaluated:

Top-3 overlap: 1 package

Entropy Top-3 = {A44, A30, A17}

CRITIC Top-3 = {A44, A42, A7}

Top-5 overlap: 4 packages

Overlap = {A44, A42, A17, A30}

5. Discussion

The comparative analysis shows that the primary driver of ranking differences is the weighting philosophy. Under Entropy weighting, the model assigns the highest weight to the main quota, with a value of 0.5196. This occurs because the main quota varies strongly across the 12 packages. Consequently, the Entropy-based ranking is more quota-driven: packages with larger usable data volumes gain a clear advantage even when their absolute prices are higher. In contrast, CRITIC weighting distributes importance more evenly by combining dispersion with inter-criteria correlation.

This increases the influence of price, with a weight of 0.3741, and price per main GB, with a weight of 0.2469. As a result, the CRITIC-based ranking tends to reward packages that offer a better balance of affordability and efficiency rather than maximizing quota alone. The dataset structure also affects the validity period's role. Because most packages share similar validity, mostly 30 days with Tri at 28 days, Entropy assigns validity a minimal weight of 0.0007. CRITIC assigns validity a small but non-zero weight of 0.0386 because it captures contrast and correlation effects.

These weighting differences lead to ranking shifts that matter for decision-making. Both models consistently select the same package as the top recommendation, Tri Happy 70GB (A44). This indicates that the best option is robust, whether the evaluation emphasizes quota diversity, affordability, or non-redundant information. However, the next-best options differ. The Entropy-based results place higher-quota plans such as Telkomsel 60GB (A30) and XL 90GB (A17) in the top tier. The CRITIC-based results promote more cost-efficient options such as Tri 35GB (A42) and Indosat 28GB (A7). Although overall agreement between the two rankings remains strong, as reflected by a Spearman's rank correlation of 0.8741, differences beyond the first rank indicate that objective weighting methods can still yield different practical recommendations depending on how criterion importance is defined.

From a consumer perspective in Ambon City, the findings suggest two valid decision lenses. A quota-focused user, such as a heavy streaming user or frequent tethering user, is more aligned with Entropy-style outcomes because a large main quota is prioritized. A value-for-money user, such as a budget-conscious user who aims for better Rupiah per GB efficiency, is better served by CRITIC-style outcomes because price and cost-efficiency are given greater importance. This supports a practical decision support design principle: instead of presenting a single final ranking, the system can present both objective rankings, Entropy TOPSIS and CRITIC TOPSIS, and explain why they differ so that users can select according to their needs.

A further practical issue is the mismatch in validity between 28 and 30 days. In the current model, validity is treated as a standard benefit criterion. However, many users may treat a 30-day validity requirement as a hard constraint rather than a trade-off. If validity is non-negotiable, a realistic application should filter out packages that do not meet the minimum validity threshold before ranking the remaining alternatives. This highlights that multi-criteria ranking is most useful when combined with simple constraint rules, such as a budget ceiling and a minimum validity requirement, that reflect real purchasing behavior. Finally, because some providers separate the main quota from other quota types, using the main quota improves cross-provider comparability. Future extensions should incorporate location-specific network quality indicators in Ambon, such as coverage, speed, and latency, to reflect the real user experience beyond the listed package attributes.

6. Conclusion

This study developed a decision-support approach for selecting prepaid mobile data packages in Ambon City, using the TOPSIS method to rank and compare two objective weighting schemes: Entropy and CRITIC. The results confirm that the weighting choice materially affects the ranking because each method defines importance differently. Entropy places the most significant emphasis on the main quota because it varies the most across packages, leading to quota-driven recommendations. CRITIC distributes importance more evenly by considering dispersion alongside inter-criteria correlation, thereby increasing the influence of price and price efficiency. Despite these differences, both weighting schemes consistently identified Tri Happy 70GB (A44) as the best alternative, indicating that this package remains the strongest option under both a quota-focused and a value-focused evaluation.

Overall, the findings show that objective weighting does not guarantee a single universal ranking. Different objective weighting rules can reorder the top candidates beyond the first rank, even when the same TOPSIS procedure and the same dataset are used. For practical use, the proposed framework is most effective when combined with simple constraints that reflect real purchasing behavior, such as a maximum budget and a minimum validity requirement. This makes the recommendation process transparent, replicable, and more aligned with how users in Ambon City choose mobile data packages.

Recommendation

For Ambon City users, apply a two-stage decision rule: first filter packages by non-negotiable constraints (e.g., maximum budget and minimum validity period), then use the proposed TOPSIS framework to rank the remaining options under both Entropy and CRITIC weights. If both methods agree on the top option, users can be more confident in the recommendation; if they differ, users should decide whether they prioritize “maximum usable quota” (Entropy-like) or “best value/affordability” (CRITIC-like).

Limitations and avenues for future research

This study uses a snapshot of provider package data. It evaluates only quantitative attributes available from official listings, without incorporating measured network quality in Ambon (e.g., speed, latency, coverage), which may affect real user experience. Some packages also differ in validity period (e.g., 28 vs 30 days), which users may treat as a hard constraint rather than a trade-off. Future research should integrate location-specific quality of service (QoS) measurements, expand the alternative set and time window (to handle promotions), and test hybrid models that combine objective weights with user preference-based weighting.

Funding

This research received no external funding.

Acknowledgment

The authors thank the official websites of Telkomsel, XL, Indosat/IM3, and Tri for providing publicly accessible package information used to compile the Ambon City dataset.

Competing interests

The authors declare no competing interests.

ORCID ID:

Vederico Pitsalitz Sabandar : <https://orcid.org/0009-0007-1877-3836>

Sanriomi Sintaro: <https://orcid.org/0000-0002-7188-307X>

References

- Ariyanti, Y., & Fu'adi, D. (2025). A Comparative Analysis of the CRITIC and Entropy Methods for Objective Weighting of Priority Criteria. *Jurnal Masyarakat Informatika*, 16, 148–161. <https://doi.org/10.14710/jmasif.16.2.73143>
- Ayan, B., Abacıoğlu, S., & Basilio, M. P. (2023). A Comprehensive Review of the Novel Weighting Methods for Multi-Criteria Decision-Making. In *Information* (Vol. 14, Issue 5, p. 285). <https://doi.org/10.3390/info14050285>
- Candra, F., & David, D. (2023). Sistem Pemilihan Paket Indihome Dengan Metode Topsis. *Jikom: Jurnal Informatika Dan Komputer*, 12, 1–10. <https://doi.org/10.55794/jikom.v12i2.81>
- Chen, C. H. (2021). A Hybrid Multi-Criteria Decision-Making Approach Based on ANP-Entropy TOPSIS for Building Materials Supplier Selection. In *Entropy* (Vol. 23, Issue 12, p. 1597). <https://doi.org/10.3390/e23121597>
- Chen, L., Ramli, K., Hastiadi, F. F., & Suryanegara, M. (2023). *ACCELERATING DIGITAL TRANSFORMATION IN INDONESIA: Technology, Market, and Policy* (Artmosphere (ed.)). Economic Research Institute for ASEAN and East Asia (ERIA). <https://www.eria.org/uploads/Accelerating-Digital-Transformation-Indonesia-rev3.pdf>
- Haryanto, A. T. (2024). *APJII: Jumlah Pengguna Internet Indonesia Tembus 221 Juta Orang*. Detiknet. <https://inet.detik.com/cyberlife/d-7169749/apjii-jumlah-pengguna-internet-indonesia-tembus-221-juta-orang>
- ITU. (2023). *Measuring digital development: Facts and Figures 2023*. <https://www.itu.int/itu-d/reports/statistics/wp-content/uploads/sites/5/2023/11/Measuring-digital-development-Facts-and->

figures-2023-E.pdf

- ITU. (2024). *Measuring digital development: Facts and Figures 2024*. https://www.itu.int/itu-d/reports/statistics/wp-content/uploads/sites/5/2024/11/2402588_1e_Measuring-digital-development-Facts-and-Figures-2024_v4.pdf
- ITU. (2025). *Measuring digital development: Facts and Figures 2025*. http://itu.int/dms_pub/itu-d/opb/ind/d-ind-ict_mdd-2025-3-pdf-e.pdf
- Krishnan, A., Mat Kasim, M., Hamid, R., & Ghazali, M. F. (2021). A Modified CRITIC Method to Estimate the Objective Weights of Decision Criteria. *Symmetry*, 13. <https://doi.org/10.3390/sym13060973>
- Linh, N., Son, N., & Thao, D. (2025). Evaluating the Impact of Weighting Methods on the Stability of Scores for Alternatives in Multi-Criteria Decision-Making Problems. *Engineering, Technology & Applied Science Research*, 15, 19998–20004. <https://doi.org/10.48084/etasr.9518>
- Liu, L., Wan, X., Li, J., Wang, W., & Gao, Z. (2022). An Improved Entropy-Weighted Topsis Method for Decision-Level Fusion Evaluation System of Multi-Source Data. In *Sensors* (Vol. 22, Issue 17, p. 6391). <https://doi.org/10.3390/s22176391>
- Naji, M., Thiruchelvam, S., & Khudari, M. (2023). An investigation of Internet Service Provider selection criteria: A systematic literature review. *Iraqi Journal for Computer Science and Mathematics*, 4(4), 156–172. <https://doi.org/10.52866/ijcsm.2023.04.04.013>
- Simon Kemp. (2023). *Digital 2023: Indonesia — DataReportal — Global Digital Insights*. Retrieved 11 January 2026, from <https://datareportal.com/reports/digital-2023-indonesia>
- Simon Kemp. (2024). *Digital 2024: Indonesia — DataReportal — Global Digital Insights*. Retrieved 11 January 2026, from <https://datareportal.com/reports/digital-2024-indonesia>
- Simon Kemp. (2025). *Digital 2025: Indonesia — DataReportal — Global Digital Insights*. Retrieved 11 January 2026, from <https://datareportal.com/reports/digital-2025-indonesia>
- Taherdoost, H., & Madanchian, M. (2024). A Comprehensive Survey and Literature Review on TOPSIS. *International Journal of Service Science, Management, Engineering, and Technology*, 15(1). <https://doi.org/10.4018/IJSSMET.347947>
- Whistler, R. P. L. (2023). *Sistem Pendukung Keputusan Pemilihan Paket Internet Provider Terbaik Bagi Calon Pelanggan Di Kawasan Citraland Surabaya Dengan Menggunakan Metode Topsis*. Universitas Wijaya Putra.
- World Bank Group. (2021). *Digital Economy in Indonesia*. <https://www.worldbank.org/en/news/infographic/2021/10/28/digital-economy-in-indonesia>
- Yudhistira, A., Wang, J., & Rahmanto, Y. (2024). Decision Support System for Optimizing Supplier Selection Using TOPSIS and Entropy Weighting Methods. *Jurnal Pendidikan Dan Teknologi Indonesia*, 4, 175–185. <https://doi.org/10.52436/1.jpti.456>