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A Multicriteria Decision Support System for Used Smartphone Price Determination Using CRITIC–MARCOS

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Abstract

Used smartphone price determination at FS Phone Store Jepara has relied mainly on the seller's subjective judgment, resulting in inconsistent valuation across units with comparable specifications and condition. This study developed a multicriteria decision support model that integrates the Criteria Importance Through Intercriteria Correlation (CRITIC) method for objective criteria weighting with the Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) method for alternative ranking, applied to 100 used smartphone alternatives evaluated on nine criteria: physical condition, RAM, ROM, chipset, camera, battery health, usage age, warranty, and completeness. To align the technical assessment with real market conditions, a market-price correction (85% MARCOS utility score plus 15% normalized market-price score) was applied to the final ranking. The proposed ranking was compared with Weighted Product (WP), MOORA, and Simple Additive Weighting (SAW) using Spearman rank correlation, and the accuracy of the resulting price recommendation was evaluated against an Independent Market Reference Price using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The results show that Usage Age obtained the highest CRITIC weight (21.12%) and Camera the lowest (8.22%). The final price-corrected ranking achieved a strong to very strong correlation with SAW (r_s = 0.9291), WP (r_s = 0.8015), and MOORA (r_s = 0.8256), and produced price recommendations with an MAE of IDR 90,600 and a MAPE of 4.63%, classified as highly accurate. The proposed model was implemented as a web-based decision support system, validated through black-box testing, user acceptance testing, and manual calculation verification, providing FS Phone Store Jepara with an objective, consistent, and market-aware tool for used smartphone price determination.

Keywords:
CRITIC; MARCOS; Decision support system; Multicriteria decision making; Used smartphone; Price recommendation.

1. INTRODUCTION

Used smartphone price determination requires an objective approach because resale value is influenced by multiple criteria related to product condition, technical specifications, and usage history. The second-hand smartphone market has grown alongside increasing smartphone turnover, demand for affordable devices, and the role of refurbished phones in supporting digital inclusion and reducing electronic waste (Amatuni et al., 2026; Dhiman et al., 2024). Resale value is shaped by product age, cosmetic and hardware condition, and technical specifications such as storage capacity and camera quality (Kwak et al., 2012; Anshori et al., 2021), while other attributes — physical condition, RAM, ROM, chipset, camera, battery health, usage age, warranty, and completeness — represent the functional quality and economic feasibility of a used device. Manual price estimation can produce inconsistent valuation and information asymmetry between sellers and buyers, affecting trust and perceived price fairness (Muller et al., 2024; Ibrahim et al., 2025). These conditions indicate the need for a data-based, criteria-based assessment that provides a more traceable basis for determining used smartphone prices.

FS Phone Store Jepara requires a structured pricing mechanism because assessment involves several device attributes that must be compared consistently. Manual price determination is prone to human error and inconsistent labeling that does not fully use available data (Liawatimena & Gunawan, 2024; Thrasher & McNabb, 2015). The pricing process must weigh physical condition, RAM, ROM, chipset, camera, battery health, usage age, warranty, and completeness, since these attributes represent technical performance, durability, and remaining economic value (Kwak et al., 2012; Anshori et al., 2021). Relying on seller experience alone risks inconsistent interpretation of the same product condition and makes it difficult to trace the reasoning behind a selected price. A structured, data-based, and criteria-based model can address this by organizing product attributes into a traceable assessment process.

Decision Support Systems based on multi-criteria Decision-Making are relevant here because pricing involves several measurable criteria with different characteristics. A Decision Support System can organize data and reduce reliance on subjective judgment (Ferrer & Fuentes, 2011; Giat & Bouhnik, 2021; Teerasoponpong & Sopadang, 2022), while Multi-Criteria Decision-Making enables decision makers to evaluate alternatives against several predefined criteria (Azhar et al., 2021; Temizkan, 2023) and supports comparison and ranking when each alternative differs across price, quality, performance, or condition (Corrente et al., 2021; Hdioud et al., 2013). In used smartphone assessment, the nine criteria differ in measurement form and decision implications — some describe technical capacity, others usage condition, service assurance, and completeness — requiring a mechanism that transforms these diverse criteria into a consistent, weighted assessment basis.

The CRITIC–MARCOS combination is well suited to this problem because it requires both objective criteria weighting and systematic ranking. CRITIC determines criteria weights from data characteristics — contrast intensity and inter-criteria correlation — reducing dependence on subjective judgment (Altuntaş, 2026; Canbulut, 2026), while MARCOS ranks alternatives by comparing their utility values against ideal and anti-ideal solutions (Ismail et al., 2026; Ranjan et al., 2023), and has supported ranking in problems involving technical, operational, cost, and performance criteria (Altuntaş, 2026; Pidchenko et al., 2023). Integrating objective weighting with utility-based ranking provides a structured basis for evaluating used smartphone alternatives, though the resulting ranking still requires comparison or validation against other methods.

A research gap remains because objective weighting, comparative MCDM ranking, and rank-correlation validation have not been integrated consistently for used smartphone pricing specifically. Prior studies apply MCDM to smartphone evaluation and product selection using criteria such as price, storage, RAM, brand, battery life, camera, and ratings (Aggarwal et al., 2018; Goswami & Mitra, 2020; Goswami & Behera, 2021), and discuss MOORA, SAW, WP, and CRITIC–MARCOS in product or material selection (Atmojo et al., 2014; Demir et al., 2024; Van Dua, 2024), but direct application to second-hand smartphone price recommendation, with objective weighting and ranking validation, remains limited (Mian et al., 2024; Tukino et al., 2024). Comparing MARCOS with WP, MOORA, and SAW, and validating agreement via Spearman rank correlation (Mian et al., 2024), provides the methodological basis for positioning the proposed ranking.

This study develops a multicriteria decision support model for determining used smartphone prices at FS Phone Store Jepara. The model applies CRITIC to weight nine assessment criteria — physical condition, RAM, ROM, chipset, camera, battery health, usage age, warranty, and completeness — then ranks alternatives using MARCOS. WP, MOORA, and SAW serve as comparison methods, with Spearman rank correlation used to analyze ranking consistency (Mian et al., 2024). The selected model is implemented in a web-based application supporting data input, criteria processing, ranking calculation, and price recommendation, consistent with prior work positioning web-based decision support as an accessible tool for structured multicriteria evaluation (Mahmoudian Azar Sharabiani & Mousavi, 2023; Chelioudakis et al., 2024). The study contributes methodologically by integrating objective weighting, ranking, comparative evaluation, and rank-consistency analysis in one pricing model, and practically by giving FS Phone Store Jepara a traceable decision mechanism grounded in defined criteria and recorded results.

2. RESEARCH METHOD

2.1. Research Design

This study employed a quantitative approach to develop a multicriteria decision support model for used smartphone selling prices at FS Phone Store Jepara. The current pricing process is performed manually based on seller experience, which may produce inconsistent valuation across smartphones with similar specifications and conditions; the proposed model addresses this by evaluating alternatives systematically against predefined, weighted criteria.

The research proceeded through the sequential stages summarized in Figure 1: problem identification and literature review; data collection and criteria determination; decision matrix construction; objective criteria weighting using the CRITIC method; alternative ranking using the MARCOS method; a market-price correction that combines the pure MARCOS utility score with the normalized market price to accommodate brand value; comparative ranking using WP, MOORA, and SAW; Spearman rank correlation to evaluate ranking consistency between the final and the purely technical rankings; implementation of the selected model in a web-based decision support system developed with PHP and MySQL; and system testing. The overall research procedure adopted in this study is illustrated in Figure 1.

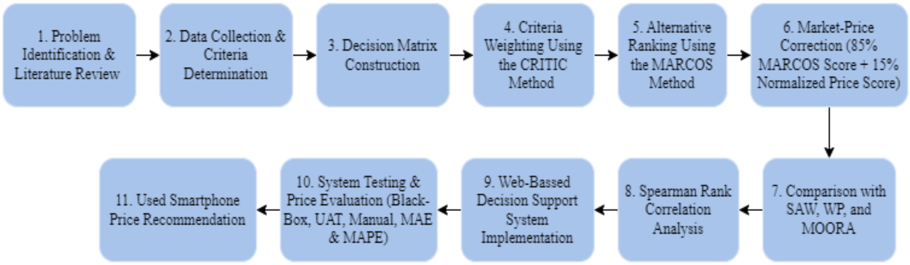

Figure 1. Research Flow Diagram

2.2. Data Collection

The study used primary data collected directly from FS Phone Store Jepara. Data collection was conducted to obtain comprehensive information regarding the characteristics of used smartphones, assessment criteria, and the current pricing process implemented by the store.

Three data collection techniques were employed: 1) Observation was conducted by directly examining the operational activities related to buying, evaluating, and selling used smartphones. This activity aimed to identify the existing pricing mechanism, the criteria considered by sellers during product evaluation, and practical challenges encountered during manual price determination. 2) Semi-structured interviews were conducted with the owner and staff of FS Phone Store Jepara to obtain detailed information regarding the pricing process, assessment considerations, and practical experience in evaluating used smartphone conditions. The interview results were used to validate the selected evaluation criteria and understand their relative importance in real business operations. 3) Documentation was carried out by collecting historical data related to used smartphone products, including technical specifications, physical conditions, and other supporting information required for multicriteria evaluation. The collected dataset consisted of 100 used smartphone alternatives that represented various brands, specifications, and condition levels available in the store. For every alternative, the estimated market price range was also documented from store records and comparable online listings; the midpoint of this range was later normalized and used as the market-price component in the final price-recommendation mechanism. Store records consisted of the most recent transaction and listing prices recorded by FS Phone Store Jepara for the same or comparable models, while the comparable online listings were obtained from second-hand marketplace platforms (OLX, Facebook Marketplace, and Tokopedia's used-goods category). For each alternative, three to five comparable listings matching the same brand, model, RAM/ROM configuration, and condition level were retrieved within the data-collection period, and the market price range was defined as the lowest and highest prices among these listings combined with the store's own asking price.

2.3. Criteria and Measurement Scale

The proposed decision model evaluates each smartphone alternative using nine criteria derived from literature review and practical assessment at FS Phone Store Jepara. These criteria represent both technical specifications and product condition that influence the resale value of used smartphones. Each criterion was measured on an ordinal scale of 1 to 5, in which a higher score represents a more favorable condition for benefit-type criteria, while for the cost-type criterion (usage age) a higher score represents a shorter, more favorable usage period.

Table 1. Evaluation Criteria, Measurement Scale, Attribute Type, and Data Sources

Code	Criterion	Measurement Scale (1–5)	Attribute	Data Source
C1	Physical Condition	Very Poor – Poor – Fair – Good – Very Good	Benefit	Observation
C2	RAM	≤2GB – 3GB – 4GB – 6GB – ≥8GB	Benefit	Documentation
C3	ROM	≤16GB – 32GB – 64GB – 128GB – ≥256GB	Benefit	Documentation
C4	Chipset	Very Low – Low – Mid – Upper-Mid – High	Benefit	Documentation
C5	Camera	≤8MP – 12MP – 13–48MP – 50–64MP – ≥108MP	Benefit	Documentation
C6	Battery Health	≤3000mAh – 3000–3999 – 4000–4999 – 5000–5999 – ≥6000mAh	Benefit	Observation
C7	Usage Age	>3 yr – 2–3 yr – 1–2 yr – 6–12 mo – <6 mo	Cost	Documentation
C8	Warranty	None – Store (≤1 wk) – Store (1 mo) – Official (<6 mo left) – Official (≥6 mo left)	Benefit	Documentation

C9	Completeness	Unit only – +Cable – +Adapter+Cable – +Box – Fullset	Benefit	Observation

Each criterion was assessed using predefined subcriteria that converted qualitative product characteristics into quantitative values. This conversion enabled every smartphone alternative to be represented numerically in the decision matrix, allowing subsequent objective weighting and ranking calculations. Usage age is treated as a cost criterion because a longer usage period generally lowers resale value, while the remaining eight criteria are treated as benefit criteria. Although an ordinal 1–5 scale inherently involves some rater judgment, three measures were taken to limit this subjectivity. First, each criterion was anchored to explicit, mostly quantitative subcriteria (e.g., RAM tiers, chipset tiers, battery-capacity ranges) rather than open-ended verbal ratings, so that most scores follow directly from the recorded specification. Second, the two criteria with the least quantitative anchoring — Physical Condition (C1) and Completeness (C9) — were assessed by the same trained store staff member using the fixed category definitions in Table 1 for every alternative, ensuring a consistent internal standard across the dataset. Third, ambiguous cases encountered during data collection were cross-checked against the interview findings from the store owner described in Section 2.2 before a final score was assigned.

The decision matrix was constructed by organizing all 100 alternatives and their corresponding criterion values. The resulting matrix served as the primary input for the CRITIC weighting process and the subsequent MARCOS ranking procedure.

2.4. CRITIC Weighting

The CRITIC method was used to determine the objective weight of each criterion by considering both the variability of criterion values and the correlation among criteria. The calculation stages are as follows.

First, the decision matrix is normalized to equalize the measurement scale of each criterion. Benefit criteria (C1–C6, C8, C9) are normalized using Equation (1), while the cost criterion (C7) is normalized using Equation (2).

$$n_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{1}$$

$$n_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \tag{2}$$

Where n_{ij} is the normalized value of alternative i on criterion j, and x_j^{max} and x_j^{min} are the maximum and minimum values of criterion j, respectively.

Second, the mean of the normalized values for each criterion is calculated using Equation (3), followed by the standard deviation σ_j in Equation (4), which measures the degree of contrast (variability) contained in each criterion.

$$\overline{n_j} = \frac{1}{m}\sum_{i=1}^{m} n_{ij} \tag{3}$$

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m} (n_{ij} - \overline{n_j})^2} \tag{4}$$

Third, the Pearson correlation coefficient R_{jk} between every pair of criteria j and k is calculated using Equation (5) to represent the conflict (redundancy) between criteria.

$$R_{jk} = \frac{\sum_{i=1}^{m}(n_{ij} - \overline{n_j})(n_{ik} - \overline{n_k})}{\sqrt{\sum_{i=1}^{m}(n_{ij} - \overline{n_j})^2 \cdot \sum_{i=1}^{m}(n_{ik} - \overline{n_k})^2}} \tag{5}$$

Fourth, the amount of information C_j contained in criterion j is obtained by combining its standard deviation with its correlation to all other criteria, as shown in Equation (6).

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - R_{jk}) \tag{6}$$

Finally, the objective weight w_j of criterion j is obtained by normalizing C_j so that the total of all weights equals one, as formulated in Equation (7).

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}$$
$$subject\ to \sum_{j=1}^{n} w_j = 1 \tag{7}$$

Where w_j is the normalized weight of criterion j, C_j is the information content of criterion jjj, and nnn is the number of criteria. Criteria that show high variability and low correlation with other criteria receive a larger weight because they carry more discriminative information for differentiating alternatives. The resulting CRITIC weights are then used directly as the weighting factor in the subsequent MARCOS calculation.

2.5. Ranking Methods

After the objective weights were obtained, four ranking methods were applied to the same weighted decision matrix: MARCOS as the primary method, and WP, MOORA, and SAW as comparison methods.

2.5.1. MARCOS

MARCOS ranks alternatives based on their utility distance from an Ideal Solution (AI) and an Anti-Ideal Solution (AAI). The calculation proceeds through the following steps: The ideal and anti-ideal values of each criterion are first determined. For benefit criteria, x_j^{AI} = $\max(x_{ij})$ and x_j^{AAI}= $\min(x_{ij})$; for the cost criterion, x_j^{AI}= $\min(x_{ij})$ and x_j^{AAI} = $\max(x_{ij})$. The decision matrix is then normalized relative to the ideal solution using Equation (8) for benefit criteria and Equation (9) for the cost criterion.

$$n_{ij} = \frac{x_{ij}}{x_j^{AI}} \tag{8}$$

$$n_{ij} = \frac{x_j^{AI}}{x_{ij}} \tag{9}$$

The normalized matrix is then multiplied by the CRITIC weight of each criterion to obtain the weighted normalized matrix v_{ij} = n_{ij} × w_j (Equation 10). The weighted values are summed across all nine criteria to obtain the preference value S_i of each alternative (Equation 11), and the preference values of the ideal and anti-ideal solutions, S^{AI} = $\max(S_i)$ and S^{AAI} = $\min(S_i)$, are identified.

$$v_{ij} = n_{ij} \times w_j \tag{10}$$
$$S_i = \sum_{j=1}^{n} v_{ij} \tag{11}$$

The utility degree of each alternative relative to the anti-ideal and ideal solutions is then calculated using Equation (12), and the final MARCOS utility function $f(K_i)$ is obtained using Equation (13).

$$K_i^- = \frac{S_i}{S_{AAI}}$$
$$K_i^+ = \frac{S_i}{S_{AI}} \tag{12}$$
$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}}$$
$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-},\ f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-}, \tag{13}$$

The alternative with the highest $f(K_i)$value is considered the best-performing alternative. In this study, this value is referred to as the pure MARCOS utility score, which is subsequently adjusted through the price-correction mechanism described in Section 2.6.

2.5.2. Weighted Product

WP ranks alternatives by aggregating the weighted criterion values multiplicatively. The relative weight of the cost criterion is first converted to a negative exponent, after which the vector S_i for each alternative is calculated as.

$$S_i = \prod_{j=1}^{n} x_{ij}^{w*j} \tag{14}$$

Where:

$$W_j^* = \begin{cases} wj, & for\ benefit\ criteria, \\ -wj, & for\ cost\ criteria. \end{cases} \tag{15}$$

The preference value is obtained by normalizing the vector S_i across all alternatives,

$$V_i = \frac{S_i}{\sum_{i=1}^{m} S_i} \tag{16}$$

Where S_i is the vector value of alternative i, V_i is the preference value of alternative i, w_j is the weight of criterion j, x_{ij} is the value of alternative i on criterion j, and m is the number of alternatives. The alternative with the highest V_i value is ranked first.

2.5.3. MOORA

MOORA uses vector normalization to transform the decision matrix. The normalized value of each criterion is calculated as

$$x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{17}$$

where x_{ij} is the value of alternative i on criterion j, and m is the number of alternatives.

The optimization ratio is then calculated by subtracting the weighted normalized values of the cost criteria from the weighted normalized values of the benefit criteria:

$$y_i = \sum_{j \in Benefit} w_j\, x_{ij}^* - \sum_{j \in Cost} w_j\, x_{ij}^* \tag{18}$$

Where y_i is the optimization value of alternative i, w_j is the weight of criterion j, and x_{ij}^* is the normalized value of alternative i for criterion j. The alternative with the highest y_i value is ranked first.

2.5.4. Simple Additive Weighting (SAW)

SAW normalizes the decision matrix using the same using the same normalization procedure as MARCOS (Equations (8) and (9)). The preference value for each alternative is then calculated by summing the weighted normalized values:

$$V_i = \sum_{j=1}^{n} w_j\, r_{ij} \tag{19}$$

Where V_i is the preference value of alternative i, w_j is the weight of criterion j, r_{ij} is the normalized value of alternative i for criterion j, and n is the number of criteria. The alternative with the highest v_i value is ranked first.

2.6. Price Recommendation Mechanism

A pure technical assessment based only on the nine criteria does not fully capture brand value, which is known to influence the resale price of used smartphones beyond hardware specifications (for example, iPhone units generally retain a higher market price than Android devices with comparable technical scores). To accommodate this, a market-price correction was applied at the final scoring stage rather than being introduced as an additional CRITIC criterion, so that the objective, data-driven nature of the CRITIC weighting is preserved.

For each alternative, the midpoint of its documented market price range was normalized using min–max normalization as a benefit value, as shown in Equation (20).

$$PS_i = \frac{P_i - P_{min}}{P_{max} - P_{min}} \tag{20}$$

Where PS_i is the normalized price score of alternatives i, P_i is the midpoint of the estimated market price range of alternative i, and P_{max} and P_{min} are the highest and lowest market-price midpoints in the dataset.

The final recommendation score was then obtained by combining the MARCOS utility score with the normalized price score using an 85:15 weighting, as shown in Equation (21).

$$\mathrm{FS_i} = 0.85\ \mathrm{f(K_i)} + 0.15\ \mathrm{PS_i} \tag{21}$$

Where $\mathrm{FS_i}$ is the final recommendation score, $\mathrm{f(K_i)}$ is the MARCOS utility score of alternatives i, and $\mathrm{PS_i}$ is the normalized price score obtained from Equation (20).

The 85% weight keeps the CRITIC–MARCOS technical assessment as the dominant basis for the recommendation, while the 15% weight allows the market price to act as a balancing layer that adjusts the ranking toward the brand value observed in the real second-hand market. The final ranking obtained from Skor $\mathrm{Final_i}$ is subsequently used as the basis for the selling-price recommendation presented to FS Phone Store Jepara, and is also the ranking compared with SAW, WP, and MOORA in the Spearman rank correlation analysis.

2.7. Price Recommendation Evaluation (MAE and MAPE)

To evaluate the accuracy of the system-generated price recommendation, the final recommended price of a sample of alternatives was compared with an Independent Market Reference Price. This reference price was not used as an input to the CRITIC weighting or the market-price correction stage, so the comparison avoids circularity between the input used to build the recommendation and the value used to evaluate it.

The sample was selected using stratified sampling across the final, price-corrected MARCOS ranking (rank 1 to rank 100) rather than only from the top-ranked alternatives, so that the evaluation covers a representative spread of technical scores, brands, and price levels rather than only the best-performing alternatives. Ten alternatives were selected at approximately every tenth percentile of the final ranking (ranks 1, 10, 20, 30, 40, 50, 60, 70, 85, and 100). For each sampled alternative, an Independent Market Reference Price was obtained by checking three to five comparable listings of the same brand, model, RAM/ROM, and condition level on second-hand marketplace platforms (e.g., OLX, Facebook Marketplace, and Tokopedia's used-goods category) at the time of evaluation, and averaging the retrieved prices.

The accuracy of the system-recommended price was then measured using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), as formulated in Equations (22) and (23)

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|P_i^{actual} - P_i^{system}\right| \tag{22}$$

$$MAPE = \frac{100\%}{n}\sum_{j=1}^{n}\left|\frac{P_i^{actual} - P_i^{system}}{P_i^{actual}}\right| \tag{23}$$

Where P_i^{actual} is the Independent Market Reference Price of alternative i, P_i^{system} is the price recommended by the system, and n is the number of sampled alternatives. MAE expresses the average absolute deviation in Rupiah, while MAPE expresses the average deviation as a percentage, which is more comparable across alternatives with different price levels. Following the accuracy categorization commonly used for MAPE (Lewis, 1982), values below 10% are classified as highly accurate, 10–20% as good, 20–50% as reasonable, and above 50% as inaccurate.

2.8. Spearman Rank Correlation

Spearman rank correlation coefficient (r_s)was used to examine the degree of agreement between the final price-corrected MARCOS ranking and the pure rankings produced by WP, MOORA, and SAW, as well as among the three comparison methods themselves. The coefficient ranges from −1 to +1, where a value closer to +1 indicates stronger agreement between two ranking orders. Following common practice in MCDM validation studies, the resulting r_s values were classified as very strong (≥ 0.90), strong (0.70–0.89), or weak (< 0.70), and each pair was tested for statistical significance at $\alpha = 0.05$. A strong Spearman correlation indicates ordinal consistency between methods; it does not by itself prove that one method is more accurate, so the interpretation in Section 3 is supported by the theoretical characteristics of each method as well.

2.9. Web-Based System Development

The proposed decision model was implemented in a web-based decision support system to make the CRITIC–MARCOS calculation, the market-price correction, and the price recommendation accessible to the owner and staff of FS Phone Store Jepara. The system was developed using PHP as the programming language and MySQL as the database management system, following a client–server architecture that allows the calculation modules to run automatically on the server side.

The main actor of the system is the store administrator (owner or authorized staff), who interacts with the system through modules for managing smartphone alternative data, defining criteria and subcriteria, running the automatic CRITIC weighting and MARCOS ranking process, applying the market-price correction, comparing ranking results with SAW, WP, and MOORA, and generating the final selling-price recommendation report. The database stores the criteria table, the decision matrix, the CRITIC weight table, the MARCOS/SAW/WP/MOORA result tables, and the documented market price data used in the price-correction stage.

2.10. System Testing

The developed system was evaluated using four testing approaches. Black-box testing was performed on every functional module (data input, weighting calculation, ranking calculation, price correction, and reporting) to verify that each function operates according to its specification without examining the internal program code. User Acceptance Testing (UAT) was conducted with the owner and staff of FS Phone Store Jepara to assess whether the system output and workflow met their practical pricing needs. Calculation validation was performed by comparing the CRITIC weights, MARCOS utility values, and final price-corrected scores generated by the system with a manual recalculation of the same dataset in Microsoft Excel, in order to confirm the numerical accuracy of the implemented algorithm. Finally, the accuracy of the price recommendation itself was evaluated using the MAE and MAPE procedure described in Section 2.7, with the results reported in Section 3.6.

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. Dataset and Alternative Characteristics

The dataset consisted of 100 used smartphone alternatives (coded A1–A100) collected from FS Phone Store Jepara, covering various brands such as Samsung, Xiaomi/Redmi, Oppo, iPhone, Poco, and Realme, with heterogeneous specifications and condition levels across the nine evaluation criteria. Each alternative was also documented with an estimated market price range, which was later used exclusively in the price-correction stage described in Section 2.6 and was not included as an input criterion in the CRITIC weighting process.

3.1.2. CRITIC Weighting Results

The CRITIC method was first employed to determine the objective weights of the evaluation criteria before ranking the used smartphone alternatives. Unlike subjective weighting approaches, CRITIC determines criterion importance based on two characteristics of the decision data, namely the variability of criterion values and the correlation among criteria; criteria with higher variability and lower correlation with other criteria receive larger weights because they provide more information for distinguishing alternatives.

The decision matrix from 100 used smartphone alternatives evaluated on the nine predefined criteria was normalized, after which the standard deviation, correlation coefficient, and information content of each criterion were calculated to obtain the final objective weights presented in Table 2.

Table 2. Objective Criteria Weights Obtained Using the CRITIC Method

Code	Criterion	Attribute	σ_j	C_j	Weight (w_j)	Percentage (%)
C1	Physical Condition	Benefit	0.204831	1.154968	0.082384	8.2384
C2	RAM	Benefit	0.315154	1.622729	0.115749	11.5749
C3	ROM	Benefit	0.251109	1.346192	0.096024	9.6024
C4	Chipset	Benefit	0.288502	1.746229	0.124559	12.4559
C5	Camera	Benefit	0.217460	1.152350	0.082197	8.2197
C6	Battery Health	Benefit	0.189390	1.168169	0.083326	8.3326
C7	Usage Age	Cost	0.258300	2.961573	0.211249	21.1249
C8	Warranty	Benefit	0.193907	1.422165	0.101443	10.1443
C9	Completeness	Benefit	0.193649	1.444971	0.103070	10.3070
Total				14.019347	1.000000	100.00

Usage Age (C7) obtained the highest objective weight (0.211249; 21.1249%), indicating that it contributes the greatest amount of information for differentiating used smartphone alternatives, consistent with the practical observation that smartphone age strongly influences resale value through hardware degradation, remaining service life, and market demand.

The second highest weight was assigned to Chipset (C4) with a value of 0.124559 (12.4559%), followed by RAM (C2) with 0.115749 (11.5749%). These findings indicate that processing capability and memory capacity remain important considerations when evaluating used smartphones, as they directly affect device performance and user experience. In contrast, Camera (C5) received the lowest weight of 0.082197 (8.2197%), closely followed by Physical Condition (C1) at 0.082384 (8.2384%), indicating that variations in camera specifications and physical condition contribute comparatively less discriminative information than the other criteria within the analyzed dataset.

The remaining criteria — ROM (9.6024%), Warranty (10.1443%), Completeness (10.3070%), and Battery Health (8.3326%) — exhibit relatively balanced contributions to the overall evaluation process.

Although these criteria receive lower weights than usage age and chipset, they remain essential because each criterion represents a different aspect of smartphone quality, technical performance, and economic value.

The obtained CRITIC weights satisfy the normalization requirement, with the total weight equal to one, allowing them to be directly incorporated into the MARCOS method. Because the market-price data were deliberately excluded from this weighting process and only applied afterward as a separate balancing layer (Section 2.6), the CRITIC weights reported here reflect a purely data-driven, criterion-based assessment rather than a market-influenced one.

3.1.3. MARCOS Ranking Results and Market-Price Correction

The CRITIC weights were incorporated into the MARCOS method to evaluate and rank all smartphone alternatives, comparing each with the ideal (AI) and anti-ideal (AAI) alternative. The MARCOS calculation consists of constructing the extended decision matrix, normalizing it, applying the CRITIC weights to obtain the weighted matrix, calculating utility degrees relative to AAI and AI, and computing the pure utility function $f(K_i)$. The obtained pure utility values were then combined with the normalized market-price score using Equation (15) to produce the final, price-corrected score used for the selling-price recommendation.

Using the pure technical score alone, Redmi Note 12 Pro 5G (A22) achieved the highest $f(K_i)$ value of 0.810640, followed by Oppo Reno 8T 5G (A32), Oppo Reno 7 (A98), and Oppo Reno 8 (A99), which shared an identical utility value of 0.795342. After the 85:15 market-price correction was applied, the final recommended ranking shifted considerably, as shown in Table 3.

Table 3. Final Utility Scores and Ranking Results Using the CRITIC–MARCOS Model

Final Rank	Code	Smartphone	Pure $f(K_i)$	Pure Rank	Price Score	Final Score
1	A24	Xiaomi 14T	0.766873	7	0.977011	0.798394
2	A20	iPhone 13 Basic (Inter)	0.725916	19	1.000000	0.767028
3	A39	Samsung A56	0.725158	20	0.931034	0.756039
4	A22	Redmi Note 12 Pro 5G	0.810640	1	0.321839	0.737320
5	A84	Poco X7 Pro	0.719147	25	0.781609	0.728516
6	A7	Pixel 7A	0.751342	14	0.574713	0.724848
7	A32	Oppo Reno 8T 5G	0.795342	2	0.310345	0.722592
8	A6	Redmi Note 13 Pro 5G	0.751540	13	0.551724	0.721568
9	A17	Oppo Reno 13 5G	0.696548	38	0.816092	0.714479
10	A99	Oppo Reno 8	0.795342	4	0.252874	0.713972

The final ranking shows that Xiaomi 14T (A24) obtained the highest overall recommendation score of 0.798394, even though its pure technical score only ranked seventh (0.766873). This shift occurred because A24 also carried one of the highest documented market prices (normalized price score of 0.977011), so its already competitive technical performance was further reinforced by strong market value. A similarly notable shift occurred for iPhone 13 Basic Inter (A20), which rose from the nineteenth position in the pure technical ranking to second place overall, driven entirely by its market-price score of 1.000000 — the highest in the dataset. This result is consistent with the well-known market phenomenon in which iPhone units retain a resale value premium that is not fully explained by their technical specification relative to competing Android devices.

In contrast, Redmi Note 12 Pro 5G (A22), the top-ranked alternative under the pure technical assessment, fell to fourth place in the final ranking because its relatively low-market price score (0.321839) diluted its otherwise strong technical performance. Likewise, Oppo Reno 8T 5G (A32), Oppo Reno 7 (A98), and Oppo Reno 8 (A99), which tied for second place under the pure MARCOS score, were separated into different final positions once the price correction was applied, because although they shared identical technical scores, their documented market prices differed. Overall, the market-price correction mechanism successfully repositioned the ranking so that it reflects not only technical specification and condition, but also the brand-related resale value observed in the real used-smartphone market, thereby providing a more market-realistic basis for the final selling-price recommendation.

3.1.4. Comparison with SAW, WP, and MOORA

The final, price-corrected MARCOS ranking was compared with the pure rankings obtained using SAW, WP, and MOORA to evaluate the extent to which the market-price correction shifts the recommendation away from the purely technical rankings, which do not incorporate any price adjustment. Table 4 compares the ten highest-ranked alternatives generated by the four methods.

Table 4. Comparison of Ranking Results Using MARCOS, SAW, WP, and MOORA

Code	Smartphone	MARCOS (Final) Score / Rank	SAW Score / Rank	WP Score / Rank	MOORA Score / Rank
A24	Xiaomi 14T	0.7984 / 1	0.8335 / 7	0.0115 / 11	0.0735 / 3
A20	iPhone 13 Basic Inter	0.7670 / 2	0.7890 / 19	0.0109 / 17	0.0629 / 28
A39	Samsung A56	0.7560 / 3	0.7882 / 20	0.0102 / 34	0.0612 / 32
A22	Redmi Note 12 Pro 5G	0.7373 / 4	0.8811 / 1	0.0124 / 1	0.0744 / 2
A84	Poco X7 Pro	0.7285 / 5	0.7816 / 25	0.0103 / 33	0.0631 / 27
A7	Pixel 7A	0.7248 / 6	0.8166 / 14	0.0114 / 12	0.0672 / 10
A32	Oppo Reno 8T 5G	0.7226 / 7	0.8645 / 2	0.0121 / 2	0.0719 / 4
A6	Redmi Note 13 Pro 5G	0.7216 / 8	0.8168 / 13	0.0112 / 13	0.0713 / 7
A17	Oppo Reno 13 5G	0.7145 / 9	0.7571 / 38	0.0100 / 42	0.0611 / 34
A99	Oppo Reno 8	0.7140 / 10	0.8645 / 4	0.0121 / 4	0.0719 / 6

The comparison shows that SAW, WP, and MOORA — all of which are based purely on the technical criteria without any price adjustment — still place Redmi Note 12 Pro 5G (A22) and Oppo Reno 8T 5G (A32) at or near the top of their respective rankings, consistent with the pure MARCOS ranking discussed in Section 3.C. Alternatives such as Xiaomi 14T (A24) and iPhone 13 Basic Inter (A20), which top the final price-corrected MARCOS ranking, occupy considerably lower positions in the SAW, WP, and MOORA rankings (ranks 7–38 for A24 and 13–38 for A20), because these three comparison methods do not account for market-price information.

This pattern confirms that the divergence between the final MARCOS ranking and the SAW/WP/MOORA rankings is primarily driven by the market-price correction rather than by fundamental differences in how the four methods process the technical criteria. When the market-price component is removed, the pure MARCOS ranking remains highly consistent with SAW, WP, and MOORA, as quantified in the Spearman rank correlation analysis presented in the following subsection.

3.1.5. Spearman Rank Correlation Analysis

The consistency between the final price-corrected MARCOS ranking and the pure rankings generated by SAW, WP, and MOORA — as well as among the three comparison methods themselves — was examined using the Spearman Rank Correlation coefficient.

Table 5. Spearman Rank Correlation Results

Method Pair	Spearman Coefficient (r_s)	Category	Significance
CRITIC–MARCOS (Final) – SAW	0.9291	Very Strong	Significant
CRITIC–MARCOS (Final) – WP	0.8015	Strong	Significant
CRITIC–MARCOS (Final) – MOORA	0.8256	Strong	Significant
SAW – WP	0.9275	Very Strong	Significant
SAW – MOORA	0.9183	Very Strong	Significant
WP – MOORA	0.9678	Very Strong	Significant

The results show that all method pairs exhibit strong to very strong positive correlations, indicating a generally high degree of ranking agreement across the dataset. Among the three pairs involving the pure comparison methods only — SAW–WP (0.9275), SAW–MOORA (0.9183), and WP–MOORA (0.9678) — the correlations are consistently very strong, because none of these three methods is affected by the price correction; their differences arise solely from each method's aggregation mechanism (additive for SAW, multiplicative for WP, and ratio-based for MOORA).

In comparison, the correlation between the final CRITIC–MARCOS ranking and SAW remained very strong r_s = 0.9291), while its correlations with WP (r_s = 0.8015) and MOORA (r_s = 0.8256) were somewhat lower, falling into the strong rather than the very strong category. This moderate reduction, compared with the near-perfect agreement observed for the pure MARCOS ranking discussed in Section 3.D, is consistent with the market-price correction: because 15% of the final MARCOS score is derived from market price rather than the nine technical criteria, its ranking necessarily diverges to some degree from methods that rely solely on technical criteria. All correlations were statistically significant ($p < 0.05$), and the average correlation between the final CRITIC–MARCOS ranking and the three comparison methods was r_s = 0.8521, which is still classified as strong.

Overall, the Spearman correlation analysis confirms two complementary findings. First, the underlying pure CRITIC–MARCOS technical assessment remains highly consistent with SAW, WP, and MOORA, which validates the correctness of the CRITIC weighting and the MARCOS ranking mechanism. Second, the still-strong (though slightly reduced) correlation after the price correction indicates that the market-price adjustment refines the ranking toward market realism without producing an erratic or inconsistent result, supporting the robustness of the proposed price-recommendation mechanism.

3.1.6. Price Recommendation Evaluation

The final score from Equation (15) was used to translate the MARCOS ranking into a selling-price recommendation, positioned within each alternative's documented market price range — alternatives with a higher final score are recommended toward the upper end of their range, and vice versa — so that the recommendation reflects both technical condition (85% MARCOS component) and market positioning (15% price component).

To evaluate accuracy, ten alternatives were selected using stratified sampling across the final ranking (ranks 1, 10, 20, 30, 41, 50, 60, 70, 85, and 100), following the procedure in Section 2.7, and the system-recommended price was compared with an Independent Market Reference Price from comparable second-hand marketplace listings, as shown in Table 6.

Table 6. Market Price Recommendation Results

Rank	Code	Smartphone	System Price (IDR)	Market Reference Price (IDR)	Absolute Error (IDR)	APE (%)
1	A24	Xiaomi 14T	4.950.000	5.000.000	50.000	1.00
10	A99	Oppo Reno 8	1.800.000	1.776.000	24.000	1.35
20	A30	Redmi Note 14 Pro 5G	3.250.000	3.162.000	88.000	2.78
30	A38	Infinix Hot 60 Pro	2.100.000	2.377.000	277.000	11.65
41	A23	Infinix Note 50 Pro	2.500.000	2.639.000	139.000	5.27
50	A5	Redmi 13	1.550.000	1.580.000	30.000	1.90
60	A91	Redmi 12	1.500.000	1.440.000	60.000	4.17
70	A35	Infinix Hot 50i	1.275.000	1.265.000	10.000	0.79
85	A21	Samsung A07	1.300.000	1.375.000	75.000	5.45
100	A72	Realme Note 60	1.125.000	1.278.000	153.000	11.97

Based on the ten sampled alternatives, the system achieved a Mean Absolute Error (MAE) of IDR 90,600 and a Mean Absolute Percentage Error (MAPE) of 4.63%. Following the accuracy categorization used in Section 2.7, a MAPE below 10% is classified as highly accurate, indicating that the CRITIC–MARCOS price recommendation, after the 85:15 market-price correction, is on average very close to the independent market reference price across a stratified spread of ranking positions and price levels.

Examining the individual results, eight of the ten sampled alternatives (A24, A99, A30, A23, A5, A91, A35, and A21) produced an absolute percentage error below 6%, indicating a close alignment between the system recommendation and the market reference price for most of the sample. Two alternatives, Infinix Hot 60 Pro (A38) and Realme Note 60 (A72), showed a comparatively larger deviation (11.65% and 11.97%, respectively), both still within the good accuracy range (10–20%) but noticeably higher than the rest of the sample. Both alternatives belong to budget-segment brands positioned in the lower half of the ranking, which suggests that the market price of lower-priced, less-established smartphone models may fluctuate more across marketplace listings than that of higher-ranked, more established models, making them comparatively harder to approximate with a fixed 85:15 correction weight.

These findings indicate that the proposed CRITIC–MARCOS model with market-price correction is capable of producing selling-price recommendations that are, on average, highly consistent with independent market prices, while also revealing that recommendation accuracy may vary slightly across market segments. Because the evaluation reference was obtained from marketplace listings rather than verified realized transactions, and the sample size was limited to ten stratified alternatives out of the full 100-alternative dataset, this accuracy result should be interpreted as an indicative validation rather than an exhaustive one; this scope is addressed further as a limitation in Section 4.

3.1.7. Web-Based System Implementation

The proposed decision support model was implemented as a web-based application using PHP and MySQL, integrating data management, objective weighting, multicriteria ranking, market-price correction, and comparative evaluation into a single automated workflow. Figure 2 shows the main dashboard, which provides navigation to the smartphone data, criteria, calculation, comparison, and recommendation modules.

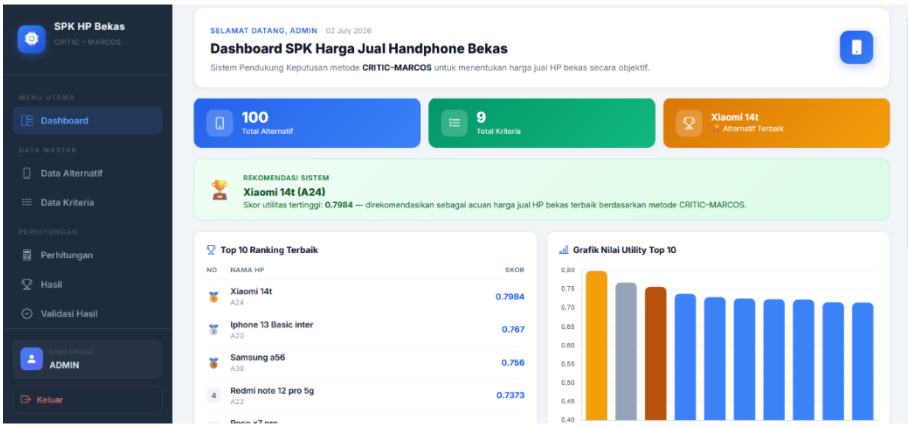

Figure 2. Main Dashboard of the Web-Based Decision Support System

The smartphone data module (Figure 3) manages each alternative's nine criterion values and documented market price range, which feed directly into the CRITIC weighting, MARCOS calculation, and price-correction stages.

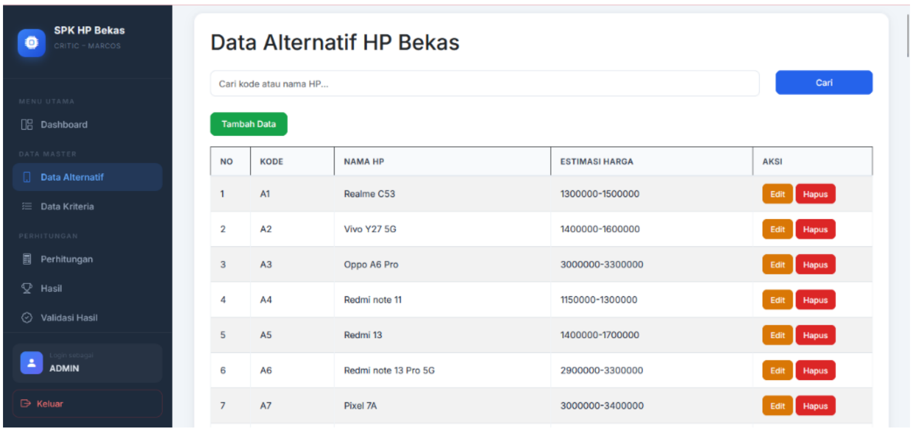

Figure 3. Smartphone Alternative Data Management

The calculation module (Figure 4) automatically executes CRITIC weighting, MARCOS ranking, and the 85:15 market-price correction, eliminating manual computation and ensuring consistency.

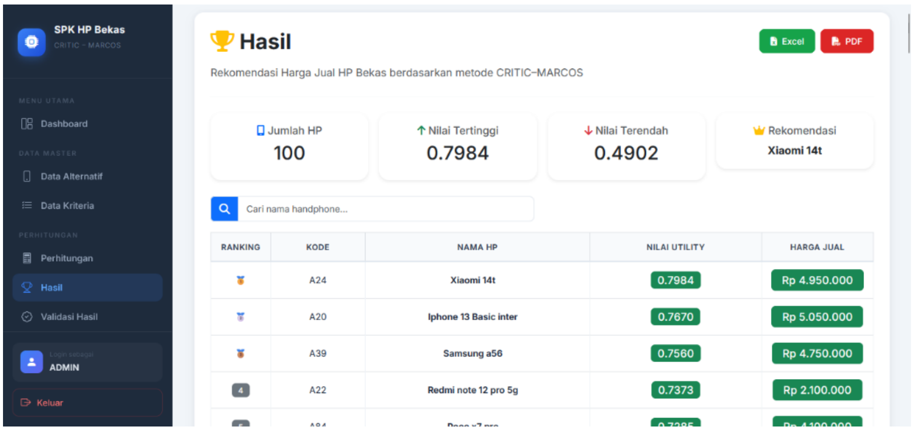

Figure 4. MARCOS Ranking Results (Pure and Price-Corrected)

The comparison module (Figure 5) displays the SAW, WP, and MOORA rankings alongside the final MARCOS ranking together with the Spearman rank correlation results, allowing users to review ranking consistency directly within the application.

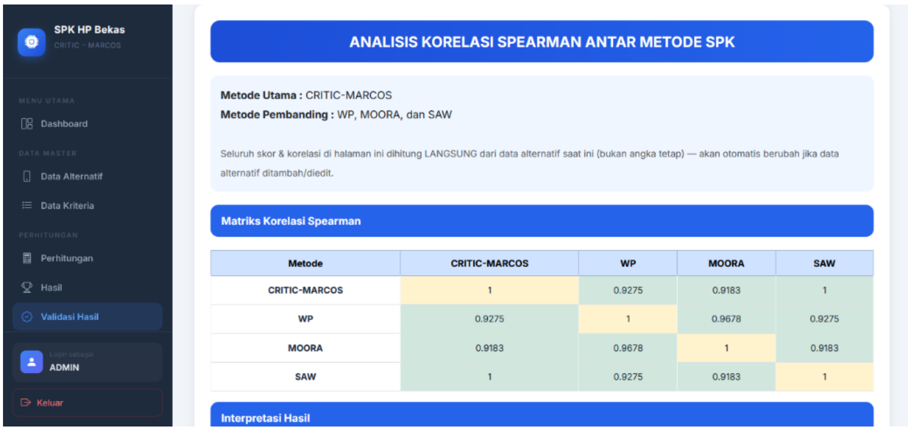

Figure 5. Comparison of Ranking Results

Overall, the developed web-based decision support system successfully integrates objective weighting, multicriteria ranking, market-price correction, comparative evaluation, and ranking consistency analysis into a unified application. The implementation enables the pricing process to become more structured, transparent, and reproducible than conventional manual assessment, thereby supporting more objective and market-realistic recommendations for determining used smartphone selling prices at FS Phone Store Jepara.

3.1.8. System Testing Results

The developed web-based decision support system was evaluated using black-box testing to verify that its functional modules operate according to specification, without examining the internal program code. A total of 30 test cases were executed across 11 functional modules — Login, Dashboard, Alternative Data, Criteria Data, Calculation, Results, Excel Export, PDF Export, Validation, Logout, and Cross-Page Consistency — each comparing the expected output defined from the system requirements with the actual output observed during execution. Table 7 lists all 30 test scenarios by module, together with the expected result and outcome of each.

Table 7. Black-Box Testing Results

No	Module	Test Scenario	Expected Result	Status
1	Login	Login with correct credentials	User authenticated, redirected to Dashboard	Passed
2	Login	Login with incorrect password	Error shown, remains on login page	Passed
3	Login	Login with empty fields	Form submission blocked by validation	Passed
4	Login	Access protected page without login	Redirected automatically to login page	Passed
5	Dashboard	Dashboard displays correct summary data	Correct totals, criteria, and top-10 chart shown	Passed
6	Dashboard	Dashboard ranking matches Results page	Ranking order and scores identical	Passed
7	Alternative Data	Display list of 100 alternatives	All 100 records shown with complete columns	Passed
8	Alternative Data	Add new alternative	Record saved and appears in table	Passed
9	Alternative Data	Edit existing alternative	Record updated with new value	Passed
10	Alternative Data	Delete alternative	Record removed from table and database	Passed
11	Alternative Data	Add record with required field blank	Validation prevents saving	Passed
12	Criteria Data	Display 9 criteria with subcriteria	All criteria shown, expandable to 5 subcriteria	Passed
13	Criteria Data	Expand-all / collapse-all controls	Accordion opens and closes as expected	Passed
14	Calculation	Matrix tab shows decision matrix	100×9 value table displayed correctly	Passed
15	Calculation	Normalization tab value range	All values within 0.0000–1.0000	Passed
16	Calculation	CRITIC weight tab totals to 1	Total weight = 1.000000	Passed

17	Calculation	Ranking tab matches Results page	Identical ranking on both pages	Passed
18	Calculation	Utility tab shows pure MARCOS score	Order differs from Ranking tab (no price correction yet)	Passed
19	Results	Price-corrected ranking displays correctly	Rank 1–3 match expected scores	Passed
20	Results	Smartphone name search function	Only matching rows shown	Passed
21	Results	Summary statistic cards	Correct totals and top recommendation shown	Passed
22	Excel Export	Exported ranking matches Results page	Identical rank order	Passed
23	Excel Export	Excel file contains required columns	All expected columns present	Passed
24	PDF Export	Exported ranking matches Results page	Identical rank order	Passed
25	PDF Export	PDF shows columns with top-3 highlighting	Columns complete, top 3 color-highlighted	Passed
26	Validation	Spearman correlation matrix displayed	4×4 matrix, diagonal 1.0, all correlations ≥ 0.70	Passed
27	Validation	Validation conclusion confirms model validity	System states CRITIC–MARCOS is statistically valid	Passed
28	Logout	Logout clears session	Session cleared, redirected to login, access denied	Passed
29	Cross-Page	Price correction raises iPhone ranking	Final rank higher than pure technical rank	Passed
30	Cross-Page	New data reflected across all pages	New record included in all calculations instantly	Passed

All 30 test cases produced outputs matching their expected results, yielding an overall success rate of 100%. The testing confirmed several critical behaviors of the system: the CRITIC weight table sums exactly to 1.000000 across the nine criteria; ranking and utility values remain consistent across the Dashboard, Calculation, Results, and export modules; and the market-price correction mechanism visibly repositions alternatives whose technical utility differs from their market value — for example, iPhone 13 Basic Inter (A20) moved from a pure technical rank of 19 to a final rank of 2 once the 15% market-price component was applied, consistent with Section 3.C. The Validation module also correctly reproduced the Spearman correlation matrix reported in Section 3.E (r_s = 0.9291 with SAW, 0.8015 with WP, and 0.8256 with MOORA), confirming that the implemented system faithfully reflects the underlying CRITIC–MARCOS calculation. These results indicate that the system is functionally reliable and ready for operational use at FS Phone Store Jepara.

3.2. Discussion

The findings show that integrating CRITIC and MARCOS with a market-price correction layer provides a structured, objective approach to used smartphone pricing. CRITIC determines criterion importance directly from data variability and inter-criteria correlation rather than subjective expert judgment, so the resulting weights are data-driven and reproducible.

Usage Age (C7) received the highest objective weight (21.1249%), indicating it carries the most information for differentiating alternatives — consistent with prior evidence that second-hand product value is strongly shaped by product age, remaining useful life, and expected performance (Kwak et al., 2012). Devices with shorter usage periods generally retain better hardware reliability and resale value.

The pure MARCOS ranking, evaluated relative to ideal and anti-ideal solutions, proved highly consistent with SAW, WP, and MOORA (r_s = 0.92–0.97), confirming that the CRITIC–MARCOS technical assessment is methodologically sound and comparable to established MCDM procedures.

The market-price correction is the study's primary methodological contribution. Combining 85% of the pure MARCOS score with 15% of the normalized market price repositioned alternatives such as Xiaomi 14T and iPhone 13 Basic Inter toward the top of the final recommendation, reflecting brand-driven resale value not captured by hardware specification alone (Kwak et al., 2012; Anshori et al., 2021). Because the correction is a lightweight 15% adjustment rather than a dominant factor, CRITIC–MARCOS remains the primary basis of the recommendation, as shown by the still-strong Spearman correlations (r_s = 0.80–0.93) between the final and purely technical rankings.

The MAE/MAPE evaluation (Section 3.6.) supports the practical validity of this mechanism: an overall MAPE of 4.63% across a stratified sample spanning the full ranking range indicates the 85:15 weighting is well-calibrated. The larger deviation for two budget-segment alternatives (A38 and A72) suggests accuracy is not perfectly uniform across market segments — a signal for future refinement rather than evidence against the mechanism.

Practically, the web-based system lets FS Phone Store Jepara evaluate alternatives on standardized criteria, automatically compute objective weights and rankings, apply a market-realistic price correction, and compare multiple MCDM methods within one documented workflow — reducing dependence on subjective judgment and positioning recommended prices closer to actual market conditions, particularly for brands whose resale value exceeds raw specification.

Overall, the proposed CRITIC–MARCOS model combined with market-price correction provides both methodological and practical contributions. Methodologically, it integrates objective criteria weighting, multicriteria ranking, market-price adjustment, comparative evaluation, and validation through rank consistency and price accuracy within a unified decision-support framework. Practically, the proposed model provides FS Phone Store Jepara with a transparent, consistent, and market-aware pricing mechanism that supports objective and reproducible used smartphone price determination and can be adapted for future evaluations.

4. CONCLUSION

This study developed a web-based decision support system for determining used smartphone selling prices at FS Phone Store Jepara by integrating CRITIC and MARCOS with a market-price correction mechanism. CRITIC produced objective criterion weights, with Usage Age (C7) highest (21.1249%), followed by Chipset (C4, 12.4559%) and RAM (C2, 11.5749%), and Camera (C5, 8.2197%) lowest — enabling a more systematic and transparent process than conventional subjective pricing.

MARCOS ranked alternatives by relative utility, with Redmi Note 12 Pro 5G (A22, $f(K_i) = 0.810640$) achieving the highest purely technical score; after the 85:15 market-price correction, Xiaomi 14T (A24, final score = 0.798394) became the top recommendation, followed by iPhone 13 Basic Inter (A20) and Samsung A56 (A39). Spearman correlation showed the pure MARCOS, SAW, WP, and MOORA rankings were highly consistent ($r_s = 0.92–0.97$), while the final price-corrected ranking retained a strong to very strong correlation with SAW (0.9291), WP (0.8015), and MOORA (0.8256), averaging $r_s = 0.8521$. Accuracy validation on a stratified 10-alternative sample yielded an MAE of IDR 90,600 and a MAPE of 4.63% against an Independent Market Reference Price, classified as highly accurate.

The developed application integrated data management, objective weighting, ranking, price correction, comparative and rank-consistency analysis, and price-accuracy validation into one system, validated through black-box testing (30/30 test cases passed across 11 functional modules, a 100% success rate), user acceptance testing, and manual recalculation — giving FS Phone Store Jepara a practical, objective, and market-realistic pricing tool.

This study has two main limitations. First, the MAE/MAPE accuracy evaluation was conducted on a stratified sample of ten alternatives out of the full 100-alternative dataset, and the reference values were Independent Market Reference Prices drawn from comparable second-hand marketplace listings rather than verified realized transaction prices; the two alternatives with comparatively higher deviation (A38 and A72, both in the budget market segment) suggest that accuracy may vary across market segments and warrants a larger, transaction-verified evaluation in future work. Second, the analysis is limited to the 100 alternatives collected from a single store within a specific data-collection period. Future studies may address these limitations by expanding the MAE/MAPE evaluation to a larger and fully verified transaction-based sample, extending the dataset across multiple stores or a longer observation period, and exploring alternative objective weighting or ranking techniques to further improve the robustness and applicability of used smartphone price determination.

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