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Smartphone Selection through AHP, Value Engineering, and Adapted QSPM Evaluation

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ABSTRACT

Smartphone selection depends on criterion importance, perceived product attractiveness, monetary value, and ranking stability. This follow-up case study evaluates VIVO Y29 4G, POCO M6 PRO, and REDMI NOTE 14 4G using new paper questionnaires from 11 purposively selected assessors in Gresik, Indonesia, from 3 to 15 August 2026. We aggregated individual pairwise judgments geometrically for Analytic Hierarchy Process weighting, while averaging and rounding attractiveness ratings for an adapted quantitative strategic planning matrix. A post hoc value-engineering benchmark separated functional performance from monetary cost by using renormalized performance-camera weights and documented Indonesian suggested retail prices for standardized 8/256 GB variants. Camera received the highest AHP weight (0.574228), followed by performance (0.314461) and price (0.111312), with a group consistency ratio of 0.001290. Rounded QSPM scores ranked VIVO first (3.462916), REDMI second (3.111312), and POCO third (2.740233); normalized value indices were 0.642260, 0.610822, and 0.463032, respectively, preserving the same order. Retaining unrounded means reduced the VIVO–REDMI QSPM margin from 0.351604 to 0.257318, while all 12 one-at-a-time weight perturbations and all group-exclusion checks retained the ranking. The contribution is an explicit AHP-weighted operational adaptation of QSPM for product alternatives, not a new ranking algorithm; preference weighting, perceived attractiveness, function-to-cost value, and robustness are kept analytically separate, while the normalized value index (VI) remains a post hoc convergence benchmark rather than a reconstruction of survey-period market conditions.

1. INTRODUCTION

Smartphone selection involves trade-offs among affordability, performance, and features that support everyday use. Adoption research links these decisions to technological expectations and perceived value, while studies of younger consumers identify product features, brand image, and price as relevant considerations [1], [2]. Their relative importance varies with context: research among Jordanian students, for example, highlights ease of use, support services, and price [3]. A local decision model therefore requires priorities elicited from the people whose judgments it is intended to represent.

Previous studies have examined smartphone selection using qualitative adoption factors, AHP–TOPSIS combinations, and Kano-based feature classification [4], [5], [6]. A more recent recommendation system combines content-based filtering and TOPSIS with candidate screening and sensitivity scenarios [7]. These applications establish a basis for weighting and robustness analysis. Another question concerns processing group ratings: how strongly does an

aggregation rule affect the recommended device's apparent advantage? This study examines that question using individual judgments from a documented panel.

The study follows Fais et al.'s value-engineering and AHP analysis, which evaluated the VIVO Y29 4G, POCO M6 PRO, and REDMI NOTE 14 4G against price, performance, and camera criteria [8]. We retained the same devices and criteria and collected new judgments in August 2026. This continuity lets us discuss the new results alongside the earlier findings. However, changes in elicitation and alternative scoring mean we cannot attribute rank differences solely to changing consumer preferences. The earlier value-engineering framing also provides a basis for separating functional performance from monetary cost in the present follow-up rather than treating a price-attractiveness rating as cost.

AHP derives criterion weights from reciprocal pairwise comparisons [9], [10]. Its interpretation depends on how the decision is structured and how judgments are processed [11], [12]. In group applications, aggregating individual judgments differs from aggregating the resulting priorities [13], [14]. Consistency also differs from agreement: a coherent aggregate matrix can coexist with variation among assessors [15], [16]. These distinctions matter especially for a panel combining users, retail practitioners, and researchers.

The quantitative strategic planning matrix (QSPM) compares organizational strategies through weighted attractiveness assessments [17], [18]. Its application to a retail computer store illustrates business strategy evaluation [19], while fuzzy extensions and tourism applications broaden the analytical setting [20], [21]. The present study transfers the weighted-attractiveness logic to product alternatives. We describe this procedure as an AHP-weighted adaptation of QSPM and specify its additive scoring structure so the methodology matches the analysis. Conceptually, the transfer retains QSPM's weighted-attractiveness principle: criterion importance acts as the factor weight and each product receives an alternative-specific attractiveness score. In this study, AHP supplies the criterion weights, while the adapted QSPM applies a compensatory additive aggregation across product criteria. The procedure therefore operationally transfers the QSPM scoring logic to product alternatives, not a conventional strategic-planning QSPM or a new MCDA algorithm.

Value engineering (VE) treats value as a relationship between required function or performance and the resources used to obtain it, rather than as cost reduction alone [22], [23]. Here, VE is used as a post hoc analytical benchmark rather than a replacement for AHP or the adapted QSPM. Performance and camera form the functional numerator, while a documented monetary benchmark forms the cost denominator. This separation avoids counting the price criterion as both a perceived preference and a monetary cost.

A central issue in this adaptation is how to treat integer ratings. Averaging and then rounding them may preserve the ranking while changing the distance between alternatives. Research on ordinal data shows why numerical treatment requires care, even where some statistical procedures tolerate departures from interval measurement [24], [25], [26]. Similarly, MCDA and composite-index research treats weighting and aggregation as substantive modeling choices [27], [28], [29]. Examining the score margin alongside the rank makes the consequences of those choices visible.

Four questions guide the analysis: which criterion priorities emerge from the new judgments; how rounding affects alternative scores and their margins; whether a function-to-cost VE benchmark converges with the attractiveness ranking; and which weight changes displace the leading device. Sensitivity research supports examining both parameter changes and the assumptions that define them [30], [31]. Work on simultaneous parameter changes and the limits of one-at-a-time analysis further motivates examining the full feasible weight domain [32], [33]. The study therefore provides a reproducible account of how aggregation, documented cost, criterion weights, and panel composition shape the recommendation in this case.

2. RESEARCH METHOD

This study followed a series of interconnected stages: data collection, AHP-based criterion weighting, adapted QSPM scoring, post hoc Value Engineering benchmark, and sensitivity analysis. The overall research procedure is presented in Figure 1.

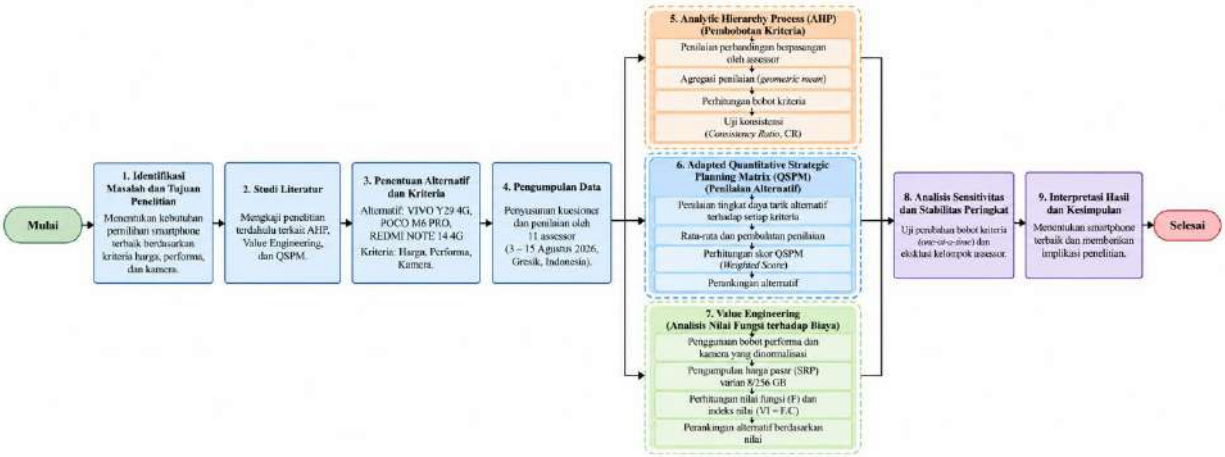


Figure 1. *Research flow of the study.*

2.1 Case setting and new data collection

This applied decision-analysis study was conducted in Gresik, Indonesia, with 11 purposively selected assessors: three smartphone users, two sales staff, two phone-shop owners, and four researchers who also authored the manuscript. Each user owned one of the three devices, while the sales staff and owners sold all three brands. The researchers contributed an academic perspective. Recruitment sought complementary experience with the decision context; the panel was not designed to represent the wider consumer population. Individual experience durations and detailed expert eligibility criteria were unavailable in the study record. Because four of the 11 assessors (36.4%) were manuscript authors, their judgments may not be independent of the study framing. The panel is therefore treated as a case-specific decision panel rather than a sample for estimating population preferences. The later group-exclusion analysis is an influence diagnostic and cannot retrospectively remove selection, shared-information, or self-assessment bias.

Participants completed paper questionnaires with direct explanation on three dates in 2026: users on 3 August, sales staff and shop owners on 5 August, and researchers on 15 August. All 11 provided both AHP comparisons and attractiveness ratings for every alternative. The research team reported respondent consent to participate and to the use of their responses; the available materials did not include an institutional ethics approval number. The team collected data by group rather than through Delphi rounds or a consensus meeting. Table 1 records the assessor codes, roles, and dates.

Table 1. Panel composition and collection dates

Codes	*Role*	*n*	*Date (2026)*
R1–R2	Sales staff	2	5 August
R3–R5	Users	3	3 August
R6–R7	Shop owners	2	5 August
R8–R11	Researcher-authors	4	15 August

The three devices were selected purposively to maintain continuity with the preceding study and reflect the experience of the participating users and retailers. Selection was not based on a verified sales ranking. The code mapping was A = VIVO Y29 4G, B = POCO M6 PRO, and C = REDMI NOTE 14 4G. Because the original code key was unavailable, the analysis used respondent-confirmation recaps dated 25 September 2026 and supplied by the research team. These retrospective records establish the operational mapping used here, subject to recall uncertainty; signatures and supporting archives were not independently authenticated.

2.2 Criterion meaning and product information

The criteria were price, performance, and camera. Higher ratings indicated greater perceived attractiveness on each criterion. Price was therefore evaluated as an attractiveness judgment rather than entered as a monetary cost for inverse normalization. Performance and camera ratings likewise captured assessors' perceptions. The available record preserved the 1–4 range and scoring direction, but not the original verbal anchors. It also did not resolve whether price meant affordability, value for money, or both. Arithmetic aggregation consequently assumes equal spacing between rating categories.

We consulted official product pages on 25 September 2026 to contextualize the devices. VIVO lists Y29 variants with 6/128, 8/128, and 8/256 GB, a Snapdragon 685 processor, and 50 + 2 MP rear cameras. The Indonesian POCO M6 PRO page lists 8/256 GB, Helio G99-Ultra, and a 64 MP main camera with optical image stabilization. REDMI NOTE 14 lists 8/128 and 8/256 GB, Helio G99-Ultra, and a 108 MP main camera. For the post hoc VE benchmark, we standardized the comparison to the 8/256 GB configuration. We used documented Indonesian suggested retail prices: Rp2.899 million for VIVO Y29 4G, Rp2.999 million for POCO M6 PRO, and Rp2.599 million for REDMI NOTE 14 4G. These prices come from public sources after data collection and are not verified transaction prices from the August 2026 questionnaire sessions; assessors did not retrospectively convert specifications and prices into attractiveness ratings.

2.3 Group AHP weighting and consistency

For assessor r, let a_r denote performance/price, b_r camera/price, and c_r camera/performance. We formed a reciprocal 3 × 3 matrix in the order price, performance, camera. We aggregated individual judgments using an equally weighted geometric mean, an aggregation-of-individual-judgments procedure [13]. No geometric mean was rounded before weight extraction. Criterion weights were obtained from the normalized principal right eigenvector [10], [34]. This gives equal influence to each person; because group sizes differ, it does not give equal influence to each occupational group.

$$M_r = \begin{bmatrix} 1 & \frac{1}{a_r} & \frac{1}{b_r} \\ a_r & 1 & \frac{1}{c_r} \\ b_r & c_r & 1 \end{bmatrix} \quad (1)$$

$$\bar{m}_{ij} = \left(\prod_{r=1}^{11} m_{ij}^{(r)} \right)^{1/11} \quad ; \quad \bar{M}w = \lambda_{\max} w; \quad \sum_j w_j = 1 \tag{2}$$

We evaluated consistency for each individual matrix and the aggregate matrix using $\mathrm{CI} = (\lambda_{\max} - 3)/2$ and $\mathrm{CR} = \mathrm{CI}/0.58$. We used the conventional $\mathrm{CR} < 0.10$ threshold as a consistency screen [12], [16]. Appendix A reports the original comparison triplets and individual CRs; Table 2 presents the recomputed aggregate matrix, eigenvalue, CI, and CR. These measures assess the coherence of pairwise judgments and do not establish response authenticity or external validity.

Table 2. Aggregate reciprocal matrix and criterion weights

Criterion	*Price*	*Performance*	*Camera*	*Weight*
Price	1.000000	0.340549	0.201490	0.111312
Performance	2.936438	1.000000	0.526849	0.314461
Camera	4.963026	1.898077	1.000000	0.574228

$\lambda_{\max} = 3.001496$; $\mathrm{CI} = 0.000748$; $\mathrm{CR} = 0.001290$.

2.4 Adapted QSPM scoring and the rounding comparison

Let x_{rij} be assessor r's attractiveness rating for alternative i under criterion j. We averaged ratings across the 11 people and then rounded to the nearest integer using $q_{ij} = \mathrm{floor}(\mu_{ij} + 0.5)$, following the aggregation procedure reported by the research team. The main score was $S_i = \sum_j w_j \, q_{ij}$. The term criterion contribution denotes $w_j q_{ij}$, and the sum across criteria is the total attractiveness score for the alternative. We retained all three criteria for all three products. Since weights sum to one and ratings range from 1 to 4, final scores also range from 1 to 4; they do not need to sum to one across alternatives.

$$\mu_{ij} = \frac{\sum_{r=1}^{11} x_{rij}}{11}; \quad q_{ij} = \mathrm{floor}(\mu_{ij} + 0.5) \tag{3}$$

$$S_i = \sum_{j=1}^{3} w_j \, q_{ij}; \quad U_i = \sum_{j=1}^{3} w_j \, \mu_{ij} \tag{4}$$

The adaptation uses three product criteria instead of organizational factors and three devices instead of strategies. Their weights sum globally to one, and no SWOT or SOAR analysis precedes the scoring. QSPM literature provides the weighted-attractiveness rationale [17], [18], [19]; the resulting arithmetic is a compensatory weighted-sum model [27]. This formulation makes the adaptation scope explicit. The comparison below evaluates two ways of processing the same ratings, without claiming superiority over other MCDA methods. Equation (4) is the formal bridge between the two frameworks: AHP-derived criterion priorities serve as weights and assessor-derived product ratings serve as attractiveness scores. We use the term adapted QSPM only for this weighted-attractiveness structure; the study does not claim to reproduce the full strategic-planning QSPM process.

The parallel score $U_i = \sum_j w_j \, \mu_{ij}$ retained unrounded means. Holding judgments, weights, alternatives, and criterion directions fixed isolates the rounding effect. Both procedures retain the equal-spacing assumption required to treat the rating codes arithmetically [24], [26]. Results are reported to six decimal places to support reproduction. These digits describe computational precision, and no inferential tests or population confidence intervals are assigned to the deterministic scores. Because rounding can change score distances without changing rank order, the rounded procedure is retained to reproduce the reported scoring rule, whereas the unrounded calculation is used as the interpretive reference for the size of the margin between alternatives.

Table 3. Attractiveness aggregation (price/performance/camera)

Alternative	*Totals*	*Means*	*Rounded AS*
A · VIVO	22 / 33 / 43	2.0000 / 3.0000 / 3.9091	2 / 3 / 4
B · POCO	34 / 43 / 22	3.0909 / 3.9091 / 2.0000	3 / 4 / 2
C · REDMI	43 / 33 / 34	3.9091 / 3.0000 / 3.0909	4 / 3 / 3

2.5 Sensitivity and assessor composition

One-at-a-time (OAT) analysis applied relative changes $\delta = -0.20, \quad -0.10, \quad +0.10, \quad \text{and} \quad +0.20$ to each criterion weight, giving 12 scenarios. For focal criterion j, $w'_j = w_j(1+\delta)$; each other weight k was set to $w'_k = w_k \frac{1-w'_j}{1-w_j}$. The rule preserves the ratio of the other weights and keeps the total weight at one. We evaluated both rounded and unrounded scoring matrices. The perturbations are deterministic preference scenarios, not confidence limits or estimated probabilities of consumer behavior [31], [32].

We solved critical weights analytically from pairwise score equalities, retaining the same proportional adjustment rule. A threshold was accepted only if the tying alternatives were at least as highly scored as the third alternative. At the boundary, first place is shared; the challenger leads only beyond it in the tested direction. In addition, we examined the complete feasible domain $h \geq 0, k \geq 0, h + k \leq 1$, with performance weight $p = 1 - h - k$. This provides exact decision regions for the rounded linear model rather than extrapolating global robustness from OAT paths [30], [33].

To assess the influence of panel composition, we excluded each occupational group in turn and recalculated both AHP weights and attractiveness means. Excluding the four researcher-authors specifically examined the overlap between authorship and assessment. We also calculated individual scores under the full-panel weights to determine whether the aggregate ranking reflected unanimous preference. These analyses make the effects of group aggregation explicit [14], [15]; they remain internal influence checks.

2.6 Post hoc value-engineering benchmark

The post hoc VE benchmark was constructed after questionnaire collection to separate monetary cost from the panel's price-attractiveness rating. We excluded price from the functional numerator because the documented suggested retail price served as the cost denominator. We therefore renormalized the performance and camera AHP weights to 0.353848 and 0.646152, respectively. Using the unrounded panel means reduced the influence of the integer-rounding rule already examined in the adapted QSPM. This construction follows the VE principle that value reflects function relative to cost and uses vector normalization to place function, cost, and value on comparable scales [23]. It was not part of the August 2026 respondent decision process and does not represent observed transaction conditions.

$$\widehat{w}_P = \frac{w_P}{w_P + w_K} = 0.353848; \quad \widehat{w}_K = \frac{w_K}{w_P + w_K} = 0.646152 \tag{5}$$

$$F_i = \widehat{w}_P \mu_{iP} + \widehat{w}_K \mu_{iK}; \quad \mathrm{FI}_i = \frac{F_i}{\sqrt{\sum_i F_i^2}}; \quad \mathrm{CI}_i = \frac{C_i}{\sqrt{\sum_i C_i^2}}; \quad V_i = \frac{\mathrm{FI}_i}{\mathrm{CI}_i}; \quad \mathrm{VI}_i = \frac{V_i}{\sqrt{\sum_i V_i^2}} \tag{6}$$

Here C denotes the standardized 8/256 GB suggested retail price expressed in million rupiah; the scale choice does not affect CI after normalization. The normalized value index VI is used only as a post hoc convergence check against the adapted QSPM ranking. Because respondents did not archive the actual variants and transaction prices they considered, the VE layer does not reconstruct the economics of the August 2026 decision sessions. The resulting VI is therefore an analytical benchmark conditional on the selected standardized variants and documented SRPs, rather than an estimate of realized market value at the time of survey.

3. RESULTS

3.1 The new priority structure

The geometric means of performance/price, camera/price, and camera/performance were 2.936438, 4.963026, and 1.898077. Their source products were 139,968; 45,000,000; and 1,152, respectively. The eigenvector yielded weights of 0.111312 for price, 0.314461 for performance, and 0.574228 for camera. With $\lambda_{\max} = 3.001496$ and $\mathrm{CI} = 0.000748$, the group CR was 0.001290. Individual CRs ranged from zero to 0.033199, all below 0.10. Thus, neither aggregate nor individual consistency required excluding a matrix under the stated screen.

Camera received 57.42% of the total criterion weight, exceeding performance by 25.98 percentage points. This concentration makes camera attractiveness particularly influential in the subsequent ranking. The low CR indicates coherent pairwise judgments, while the meaning and quality of the alternative ratings require separate consideration. CR measures the internal consistency of the pairwise-comparison matrix, not the validity, balance, or representativeness of the resulting weights. The 57.42% camera weight is therefore a substantive preference of this panel and the dominant driver of the baseline ranking; it should not be interpreted as an objective statement that camera is inherently the most important smartphone attribute.

3.2 Baseline ranking and the source of the lead

Rounded attractiveness profiles were A = (2, 3, 4), B = (3, 4, 2), and C = (4, 3, 3). VIVO ranked first at 3.462916, REDMI second at 3.111312, and POCO third at 2.740233. Table 4 and Figure 2 decompose these totals. VIVO received 2.296910 from the camera, compared with 1.722683 for REDMI and 1.148455 for POCO. REDMI had the largest price contribution

(0.445247), while POCO had the largest performance contribution (1.257842). The highest-ranked product therefore did not lead on all criteria.

Table 4. Weighted contributions and alternative totals

Alternative	*Price*	*Performance*	*Camera*	*S*	*U*	*Rank*
A · VIVO	0.222624	0.943382	2.296910	3.462916	3.410713	1
B · POCO	0.333936	1.257842	1.148455	2.740233	2.721765	3
C · REDMI	0.445247	0.943382	1.722683	3.111312	3.153395	2

S: rounded AS; U: unrounded means. All calculations retain full precision.

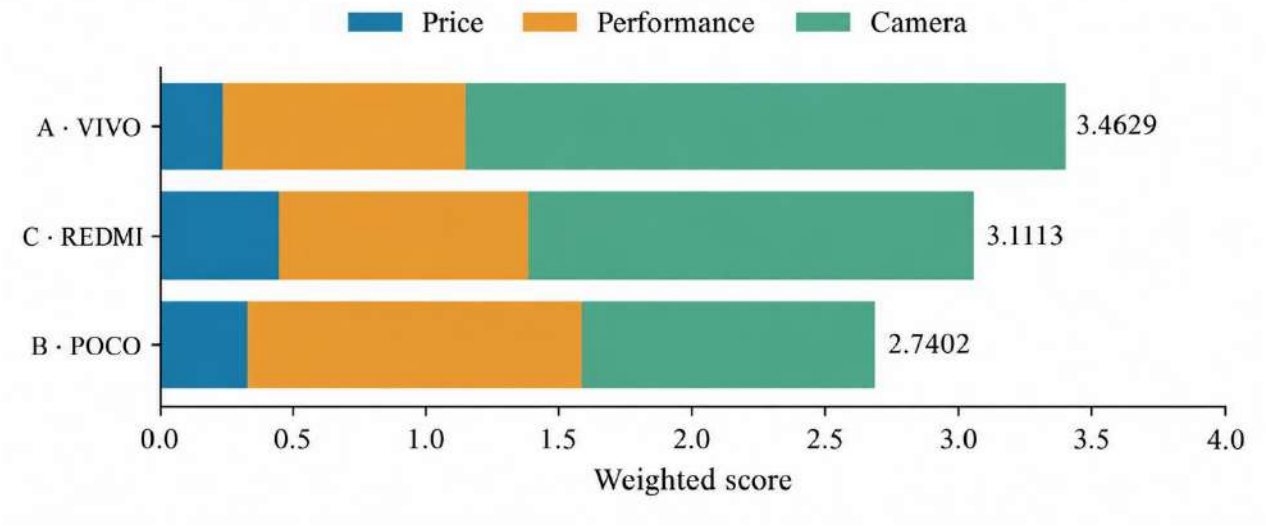


Figure 2. *Criterion contributions to rounded-rating totals.*

Equal rounded performance ratings simplify the VIVO–REDMI comparison to $S_A - S_C = w_{\text{camera}} - 2w_{\text{price}} = 0.351604$. VIVO's one-category camera advantage outweighs its two-category price disadvantage. The corresponding margin over POCO is $S_A - S_B = 3w_{\text{camera}} - 1 = 0.722683$. These relationships identify the trade-offs behind the ranking. Agreement was substantial but incomplete: under the common full-panel weights, nine individual rating profiles favored VIVO and two favored REDMI.

3.3 Rounding preserves order but enlarges the margin

Using unrounded means produced 3.410713 for VIVO, 3.153395 for REDMI, and 2.721765 for POCO. The order was unchanged, but the VIVO–REDMI margin declined to 0.257318. Rounding increased this margin by 0.094286, or 36.64% relative to the unrounded margin. VIVO benefited from rounding its mean camera rating from 3.909091 to 4, while REDMI lost part of its camera contribution when 3.090909 was rounded down to 3. REDMI's price mean increased on rounding, but the smaller price weight could not offset the camera effect.

The ranking is therefore stable to the choice of rounding rule, but the lead size is not. Reporting both calculations separates the panel's preferred alternative from the apparent strength of its advantage. The unrounded result provides a necessary reference for interpreting the larger margin produced by the main procedure. Accordingly, the 36.64% enlargement of the VIVO-REDMI margin is treated as a consequence of the processing rule, not as stronger evidence of substantive superiority of VIVO over REDMI.

3.4 Local perturbations and exact thresholds

All 12 OAT scenarios retained VIVO > REDMI > POCO for both scoring procedures (Appendix C). At a 20% relative reduction in camera weight, the rounded scores were 3.318046, 3.141337, and 2.939899 for VIVO, REDMI, and POCO, respectively. Unrounded scores under the same weights were 3.276284, 3.170250, and 2.916450. The leading margin narrowed in both calculations. A stable rank within this range therefore coexists with a substantial change in how clearly the alternatives are separated.

Table 5. First tie boundaries along proportional weight paths

Rule	*Criterion*	*Initial*	*Tie weight*	*Δ %*	*Challenger*
Rounded	Price	0.111312	0.244186	119.37	C · REDMI
Rounded	Performance	0.314461	0.602051	91.46	B · POCO
Rounded	Camera	0.574228	0.343345	-40.21	C · REDMI

Rule	*Criterion*	*Initial*	*Tie weight*	*Δ %*	*Challenger*
Mean	Price	0.111312	0.216867	94.83	C · REDMI
Mean	Performance	0.314461	0.610011	93.99	B · POCO
Mean	Camera	0.574228	0.378888	-34.02	C · REDMI

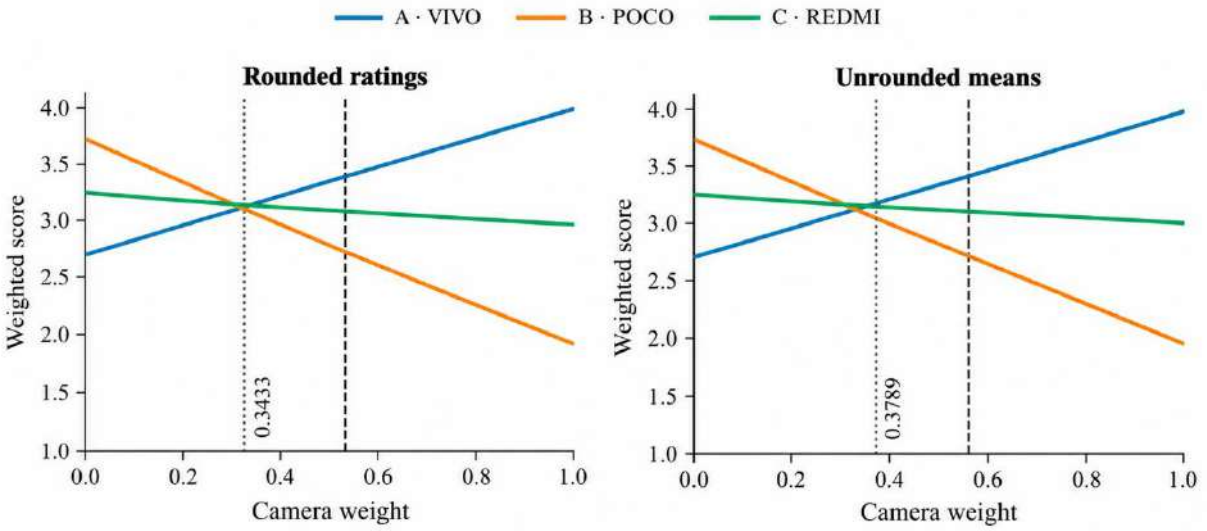


Figure 3. Camera-weight sensitivity. Dashed line: baseline; dotted line: first VIVO–REDMI tie. The remaining weight is allocated proportionally to price and performance.

REDMI becomes the first challenger as camera weight decreases along the proportional adjustment path. It ties VIVO at 0.343345 with rounded ratings and 0.378888 with unrounded means, corresponding to reductions of 40.21% and 34.02% from the observed camera weight. Rounding therefore extends the range over which VIVO remains first on this path. Increasing price weight produces a VIVO–REDMI tie at 0.244186 or 0.216867, respectively, whereas increasing performance weight produces a VIVO–POCO tie at 0.602051 or 0.610011. Table 5 links each boundary to the relevant challenger.

The full rounded-score weight domain explains why a second-place alternative can be the first challenger. With h, p, and k denoting price, performance, and camera weights, $S_A = 3 - h + k$, $S_B = 4 - h - 2k$, and $S_C = 3 + h$. VIVO is a maximizer when $k \geq \frac{1}{3}$ and $k \geq 2h$; POCO when $k \leq \frac{1}{3}$ and $h + k \leq \frac{1}{2}$; REDMI when $k \leq 2h$ and $h + k \geq \frac{1}{2}$. Equalities define shared boundaries. Figure 4 displays these exact regions. Their areas are geometric properties of the specified model and are not interpreted as probabilities of consumer preference.

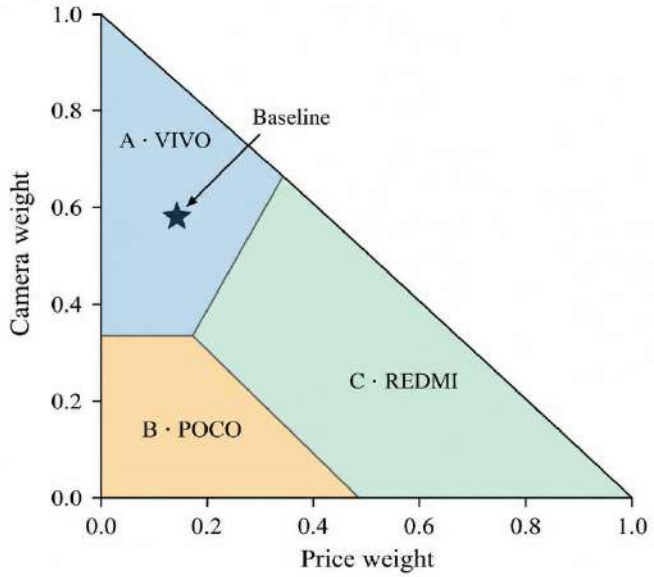


Figure 4. *Exact maximizing regions for rounded ratings. Performance weight equals 1 – price weight – camera weight. Shared boundaries indicate ties; the star marks baseline weights.*

3.5 Post hoc function-to-cost value engineering comparison

The post hoc VE benchmark used the same panel-derived performance and camera means but replaced perceived price attractiveness with documented monetary SRP. With renormalized functional weights of 0.353848 for performance and 0.646152 for camera, the resulting function scores were 3.587411 for VIVO, 2.675528 for POCO, and 3.058741 for REDMI. These prices were introduced after data collection and were not inputs to the assessors' August 2026 ratings.

Table 6. Post hoc value-engineering benchmark using standardized 8/256 GB SRPs

Alternative	*F*	*SRP (Rp m)*	*FI*	*CI*	*V = FI/CI*	*VI*
A · VIVO	3.587411	2.899	0.661800	0.589879	1.121925	0.642260
B · POCO	2.675528	2.999	0.493577	0.610226	0.808843	0.463032
C · REDMI	3.058741	2.599	0.564272	0.528836	1.067008	0.610822

F: functional score; FI: normalized function index; CI: normalized cost index; V: function-to-cost value; VI: normalized value index. SRP values are documented launch/list benchmarks, not August 2026 transaction prices. The comparison is analytical and should not be interpreted as observed market performance.

The VE ordering was VIVO > REDMI > POCO, matching the adapted QSPM result. VIVO combined the highest functional score with a value index of 0.642260. REDMI's lower function score was partly offset by the lowest documented SRP, yielding VI = 0.610822 and narrowing the distance to VIVO to 0.031438. POCO had the strongest performance mean, but the weakest camera mean and the highest SRP of the three standardized variants, yielding VI = 0.463032. The agreement of the two rankings is interpreted as cross-model convergence under distinct constructions of value, not as external validation of the panel ratings. Thus, the VI supports only a post hoc convergence comparison under a standardized cost scenario; it does not validate the QSPM ranking against actual August 2026 purchases or prices.

3.6 Influence of panel composition

Excluding any one occupational group retained the same aggregate order with rounded and unrounded ratings (Table 7). After excluding all four researcher-authors, weights were price 0.110913, performance 0.313287, and camera 0.575800. Rounded scores remained 3.464887 for VIVO, 3.110913 for REDMI, and 2.737487 for POCO. With unrounded means, the VIVO–REDMI margin was 0.205305. The lead therefore does not depend on including the researcher group in this diagnostic, but its magnitude is smaller when their ratings are excluded, and rounding is avoided.

Table 7. Group-exclusion diagnostics

Excluded	*n*	*Camera w*	*S_A*	*S_C*	*S_B*	*U_A − U_C*
Sales staff	9	0.583466	3.472504	3.110962	2.722107	0.244213
Users	8	0.563310	3.447923	3.115386	2.757995	0.262124
Shop owners	9	0.573358	3.464958	3.108401	2.744883	0.304895
Researcher-authors	7	0.575800	3.464887	3.110913	2.737487	0.205305

The four researcher-authors supplied identical attractiveness profiles, and several other assessors also gave matching ratings (Appendix B). Excluding groups shows how these observed responses affect the result, but cannot determine whether agreement reflects independent assessment, shared information, or the explanations provided during questionnaire completion. The absence of a documented common product-information protocol leaves these possibilities unresolved. Accordingly, retention of the ranking after excluding researcher-authors should not be interpreted as evidence that author-related bias is absent; it shows only that the observed ordering is not numerically dependent on that group under the specified model.

4. DISCUSSION

4.1 Preference fit and the follow-up contribution

VIVO's lead arises from the combination of a high camera weight and favorable camera ratings. The result therefore expresses preference fit within the panel. Official specifications describe differences in sensors and stabilization, but megapixel counts cannot establish the perceived or tested camera performance underlying these judgments. REDMI's higher price rating and POCO's higher performance rating show the competing advantages the aggregate result conceals. Studies of purchase intention similarly identify multiple determinants whose importance depends on context [2], [3], [4]. The post hoc VE benchmark sharpens this interpretation: after price attractiveness is removed from the function score and replaced by documented SRP, VIVO still leads, while REDMI closes the gap because its standardized cost is lower. This dependence is visible in the sensitivity thresholds: REDMI ties VIVO when the camera weight falls to 0.343345 under rounded ratings or 0.378888 under unrounded means. The baseline recommendation is therefore conditional on the panel's strong camera priority rather than being implied by the low CR alone.

The preceding study ranked REDMI at 0.354, POCO at 0.348, and VIVO at 0.298 [8]. The reversal in the present study occurs alongside new elicitation, a different alternative-rating procedure, and a different aggregation scale. Consequently, the earlier normalized global scores and the current 1–4 weighted scores cannot be directly compared in

magnitude. The follow-up explains how the new decision is formed and how sensitive it is to processing choices; it does not establish a change in device quality or a longitudinal effect on consumer preference.

Existing smartphone studies use AHP–TOPSIS, Kano, and fuzzy formulations to represent attributes, requirements, and uncertainty [5], [6]; recommendation systems also incorporate screening and sensitivity analysis [7]. Against this background, the present contribution focuses on the effect of aggregation. Rounding preserves the order while enlarging the first–second margin by 36.64% and shifting the camera-weight boundary from 0.378888 to 0.343345. A reproducible recommendation therefore requires both the rating-processing rule and the final criterion weights.

4.2 Interpretation of the QSPM adaptation

The adapted matrix makes each criterion's contribution traceable. However, its transfer to product selection changes the decision structure: conventional QSPM and its fuzzy and tourism applications evaluate organizational strategies against strategic factors [20], [21]. Here, products and their perceived attributes occupy those roles. The VE layer is intentionally parallel rather than embedded inside QSPM: AHP supplies the functional priorities, QSPM represents perceived attractiveness, and VE represents function relative to documented monetary cost. Keeping the layers separate prevents the same price construct from being counted twice and makes agreement or divergence between preference and economic value observable. The adaptation remains valuable for transparent scoring and interpretable trade-offs, while its validity as a product-selection instrument requires further empirical evaluation. Accordingly, the conceptual contribution is methodological transparency rather than algorithmic novelty: the study defines the boundary of the QSPM transfer, isolates the effects of aggregation and rounding, and compares perceived attractiveness with a separate post hoc function-to-cost benchmark.

Rounding adds a transformation to an already numerical treatment of ordinal responses; ordinal measurement does not itself require that transformation. Norman’s discussion of robust parametric procedures addresses tolerance for certain statistical assumptions [25], while Liddell and Kruschke show the potential consequences of treating ordinal observations as metric [24]. Sullivan and Artino likewise emphasize careful interpretation of rating data [26]. In this study, retaining the category-level inputs and both score versions exposes the numerical consequences. Clearer documentation of the original anchors would still be needed to assess how consistently participants understood the categories. The agreement in rank between the two calculations supports order stability, but the 36.64% margin inflation means that the rounded score should not be used to claim stronger separation or greater certainty between VIVO and REDMI.

4.3 Practical meaning and limitations

For retailers and consumers with priorities similar to the panel's, the results support a conditional shortlist. Lower camera priority can favor REDMI, while sufficiently high performance priority can favor POCO. Each device maximizes the rounded score in part of the feasible weight domain, so the practical decision depends on the trade-offs a buyer accepts. The model can structure that discussion, provided that its ratings remain relevant to the buyer’s information and the device variant under consideration.

The evidence is limited by a small purposive panel (n = 11), of whom four (36.4%) were manuscript authors. The available record also lacks the actual RAM/storage variants, survey-period transaction prices, original verbal rating anchors, and a common information or hands-on testing protocol. Although every participant rated all three devices, owning one does not ensure equal familiarity with the others. Retrospective code confirmation introduces possible recall error. The team reported respondent consent, but independent verification and an institutional approval identifier were unavailable. The VE calculation therefore uses standardized 8/256 GB variants and documented Indonesian suggested retail prices retrieved after data collection. Interpret it as a post hoc function-to-cost benchmark, not evidence that respondents faced those exact prices or variants in August 2026. The group-exclusion results are therefore interpreted as robustness diagnostics within this observed panel, not as a correction for non-independence or a substitute for validation in a larger independent sample.

The model also assumes additive, compensatory contributions from three criteria and equally spaced rating categories. Weight changes and group exclusions test sensitivity within that structure; they do not validate the underlying measurement assumptions. The authors collected no purchase outcomes, market shares, or independent quality measurements for external validation. Future work should preserve the original instrument and code key, document variants and dated prices, and incorporate assessment independent of the authors. These steps would address the present evidence gaps more directly than adding another ranking algorithm to the same inputs [28], [29].

5. CONCLUSION

The new Gresik panel assigned the greatest importance to camera (0.574228), followed by performance (0.314461) and price (0.111312), with group CR = 0.001290. The adapted QSPM ranked VIVO Y29 4G first, REDMI NOTE 14 4G second, and POCO M6 PRO third. A post hoc VE benchmark based on standardized 8/256 GB suggested retail prices produced the same order, with normalized value indices of 0.642260, 0.610822, and 0.463032, respectively. The QSPM order also persisted across 12 local weight scenarios, both rating-processing rules, and all group-exclusion checks. However, rounding increased the VIVO–REDMI QSPM margin by 36.64% and shifted the camera-weight tie boundary from

0.378888 to 0.343345. The main finding is therefore not a single rank alone, but convergence across perceived attractiveness and function-to-cost value, along with sensitivity to the size of the apparent advantage. Interpretation remains conditional on this panel, the three criteria, and the post hoc nature of the monetary benchmark. The low CR indicates internal coherence only; because camera carries 57.42% of the baseline weight, the recommendation remains conditional on this panel-specific preference structure.

Data and assessor role disclosure

Appendices A–C provide the individual numerical inputs and all local sensitivity results. Four assessors were manuscript authors; we included their ratings in the main analysis and excluded them together in an influence check. The research team provided respondent recaps to confirm product codes. We used product specifications and documented suggested retail prices retrieved after data collection only for contextualization and a subsequent Value Engineering benchmark. Respondent tables contain codes without personally identifying details. The author-exclusion analysis is reported as an influence check only and should not be interpreted as eliminating potential assessor-related bias.

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Appendix A. Individual AHP inputs

Table A1. Original pairwise judgments and consistency

Assessor	*Role*	*P/H*	*K/H*	*K/P*	*CR*
R1	Sales staff	3	5	2	0.003185
R2	Sales staff	3	5	1	0.025055
R3	Users	3	5	3	0.033199
R4	Users	3	5	2	0.003185
R5	Users	4	6	2	0.007933
R6	Shop owners	2	4	2	0.000000
R7	Shop owners	3	5	2	0.003185
R8	Researcher-authors	3	5	3	0.033199
R9	Researcher-authors	3	5	1	0.025055
R10	Researcher-authors	4	6	2	0.007933
R11	Researcher-authors	2	4	2	0.000000

H = price; P = performance; K = camera. Comparisons describe criterion importance, not product scores.

Appendix B. Individual attractiveness ratings

Table B1. Paper-questionnaire numerical recap

Assessor	*A: H / P / K*	*B: H / P / K*	*C: H / P / K*
R1	2 / 3 / 4	3 / 4 / 2	4 / 3 / 3
R2	2 / 3 / 4	3 / 4 / 2	4 / 3 / 3
R3	3 / 4 / 4	3 / 4 / 2	4 / 3 / 3
R4	1 / 3 / 4	3 / 4 / 1	3 / 3 / 4
R5	2 / 2 / 4	4 / 3 / 2	4 / 3 / 3
R6	2 / 3 / 3	3 / 4 / 2	4 / 4 / 3
R7	2 / 3 / 4	3 / 4 / 3	4 / 2 / 3
R8	2 / 3 / 4	3 / 4 / 2	4 / 3 / 3
R9	2 / 3 / 4	3 / 4 / 2	4 / 3 / 3
R10	2 / 3 / 4	3 / 4 / 2	4 / 3 / 3
R11	2 / 3 / 4	3 / 4 / 2	4 / 3 / 3

A = VIVO Y29 4G; B = POCO M6 PRO; C = REDMI NOTE 14 4G. Codes follow the respondent-confirmation recap of 25 September 2026.

Appendix C. Complete local weight sensitivity

Table C1. Perturbed weights and rounded-rating scores

Criterion	*Δ %*	*w_H*	*w_P*	*w_K*	*S_A*	*S_C*	*S_B*
Price	-20	0.08905	0.32234	0.58861	3.49956	3.08905	2.73373
Price	-10	0.10018	0.31840	0.58142	3.48124	3.10018	2.73698
Price	10	0.12244	0.31052	0.56704	3.44459	3.12244	2.74349
Price	20	0.13357	0.30658	0.55984	3.42627	3.13357	2.74674
Performance	-20	0.12152	0.25157	0.62691	3.50538	3.12152	2.62466
Performance	-10	0.11642	0.28301	0.60057	3.48415	3.11642	2.68245
Performance	10	0.10621	0.34591	0.54789	3.44168	3.10621	2.79802
Performance	20	0.10110	0.37735	0.52155	3.42045	3.10110	2.85581
Camera	-20	0.14134	0.39928	0.45938	3.31805	3.14134	2.93990
Camera	-10	0.12632	0.35687	0.51680	3.39048	3.12632	2.84007
Camera	10	0.09630	0.27205	0.63165	3.53535	3.09630	2.64040
Camera	20	0.08129	0.22964	0.68907	3.60779	3.08129	2.54057

Table C2. Scores using unrounded means for the same scenarios

Criterion	*Δ %*	*U_A*	*U_C*	*U_B*	*Order*
Price	-20	3.44605	3.13446	2.71252	A > C > B
Price	-10	3.42838	3.14393	2.71714	A > C > B
Price	10	3.39304	3.16286	2.72639	A > C > B
Price	20	3.37537	3.17233	2.73101	A > C > B
Performance	-20	3.44839	3.16747	2.61284	A > C > B
Performance	-10	3.42955	3.16043	2.66730	A > C > B
Performance	10	3.39187	3.14636	2.77623	A > C > B
Performance	20	3.37303	3.13932	2.83069	A > C > B
Camera	-20	3.27628	3.17025	2.91645	A > C > B
Camera	-10	3.34350	3.16182	2.81911	A > C > B
Camera	10	3.47793	3.14497	2.62442	A > C > B
Camera	20	3.54514	3.13654	2.52708	A > C > B

Each change is relative to the selected baseline weight. The other two weights are rescaled proportionally so the total remains one.