

Smartphone Selection Decision Support System for Online Motorcycle Taxi Drivers Using the SMART Method

Muhammad Annash Ash Shidiq^{1*}

Institut Informatika dan Bisnis Darmajaya, Bandar Lampung, Indonesia¹

annashidiq@gmail.com^{1*}



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Abstract

Purpose: Online motorcycle taxi (*ojek online*) drivers in Indonesia require smartphones that support intensive all-day outdoor use, including strong battery life, performance, screen visibility, and network stability. This study aims to develop a web-based Decision Support System (DSS) using the SMART (Simple Multi Attribute Rating Technique) method to recommend the most suitable smartphone based on occupation-specific criteria.

Methodology: A design and development research approach was used. Ten criteria were identified through observation and interviews, including price, battery capacity, processor, storage, RAM, screen brightness, network technology, display size, and camera quality. Four Oppo smartphones (A12, A16K, A52, and F11) were evaluated. Criteria weights were assigned based on driver priorities, then normalized. Utility values were calculated using the SMART formula, and final scores were obtained from weighted utility aggregation.

Results: The SMART analysis ranked Oppo F11 first ($N_{ta} = 70.5$), followed by Oppo A52 (59.2), Oppo A12 (45.8), and Oppo A16K (37.9). The F11 achieved the highest score due to its balanced affordability, strong chipset performance, large storage, and adequate RAM capacity.

Conclusions: The SMART-based DSS effectively supports smartphone selection for ojek online drivers by integrating multi-criteria decision-making into a structured system. The model demonstrates reliable ranking results for the evaluated alternatives.

Limitations: The study is limited to four Oppo models and relies on expert-based weighting, which may not fully represent broader driver preferences.

Contributions: This study provides a replicable SMART-based DSS framework for occupational smartphone selection in the gig economy, particularly for improving decision accuracy in driver-oriented technology recommendations.

Keywords: *Decision Support System, Multi-Criteria Decision Making, Ojek Online, SMART Method, Smartphone Selection*

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1. Introduction

The rapid expansion of app-based transportation platforms in Indonesia has fundamentally transformed the urban mobility landscape over the past decade. Gojek, founded in 2010, and Grab,

which entered the Indonesian market in 2014, converted an informal, roadside-hailing motorcycle taxi trade into a formalized, app-mediated gig economy occupation that today employs an estimated two to three million drivers across the archipelago ([Raharjo et al., 2022](#); [Wibowo & Santoso, 2021](#); [Gojek, 2023](#)). This transformation placed the smartphone at the center of the ojek online driver's professional identity and daily income. Unlike conventional mobile device users who may use their phones intermittently for social media, entertainment, or productivity, an ojek online driver depends on his or her smartphone as an active income-generating instrument for eight to twelve hours per day, often in conditions that place extraordinary physical and performance demands on the device ([Fadhil, Nurdianto, & Santoso, 2022](#)).

The occupational conditions of ojek online drivers create a distinctive set of hardware requirements that are not well-served by the criteria embedded in mainstream consumer smartphone recommendation frameworks. Continuous GPS navigation, real-time fare acceptance, payment processing, and communication with customers require a fast and stable processor, adequate RAM to prevent application lag, and sufficient internal storage to support platform applications without performance degradation ([Ikhwan, Nurdianto, & Windarto, 2021](#)). Prolonged outdoor riding in Indonesian weather conditions, including direct tropical sunlight, demands a screen with high brightness output measured in nits, since a display that is adequate for indoor use may be completely unreadable outdoors. Operating for an entire workday without access to a power outlet requires a battery with high milliampere-hour capacity. The economic realities of gig employment, which typically yields net daily incomes ranging from IDR 50,000 to IDR 150,000 after platform fees and fuel costs, mean that drivers face acute price sensitivity when selecting a smartphone ([Wibowo & Santoso, 2021](#); [Nugraha et al., 2023](#)).

These occupational requirements stand in direct contrast to the emphasis placed by consumer review publications and platform recommendation algorithms on criteria such as camera megapixel count, aesthetic build quality, brand prestige, and multimedia capability. While a driver does need a front-facing camera for identity verification within the platform app, and a rear camera for any incidental documentation, the camera does not function as a primary use tool in the way it does for general consumers who take photos and share content on social media platforms. The misalignment between general consumer recommendation frameworks and the specific occupational needs of ojek online drivers means that drivers who rely on such recommendations risk purchasing devices that perform poorly in the dimensions most critical to their work ([Budiono, 2015](#); [Hendra & Kurniawan, 2022](#)).

Decision Support Systems (DSS) applying Multi-Criteria Decision Making (MCDM) methods offer a rigorous and transparent approach to product selection problems of this kind, where multiple criteria must be evaluated simultaneously and criteria carry different relative importance depending on the specific user context ([Mesran, Ginting, Yuhandri, & Aisyah, 2020](#)). The SMART (Simple Multi Attribute Rating Technique) method is particularly well-suited for this application because it accommodates both quantitative criteria such as battery capacity and price and qualitative criteria such as chipset generation classification through a parameter value mapping process, it allows different weights to be assigned to different criteria to reflect their relative priority, and it uses a utility value normalization formula that converts all criteria to a common 0 to 100 scale before computing weighted scores, ensuring that no criterion dominates due to its unit magnitude ([Risawandi & Rahim, 2016](#); [Siregar et al., 2017](#); [Wardani & Nasution, 2022](#)).

The transparency of the SMART method is a practical advantage in a consumer-facing DSS context. Drivers who receive a recommendation can, if they wish, inspect the underlying calculation to understand why one smartphone is ranked above another, what trade-offs are involved, and how the ranking would change if their personal priorities shifted. This explainability builds user trust in the recommendation output, which is particularly important for a decision that represents a significant financial outlay relative to the driver's daily income ([Limbong et al., 2020](#); [Ardianto et al., 2021](#)).

Previous research on MCDM-based smartphone selection DSS has employed various methods including the Analytical Hierarchy Process (AHP), the Simple Additive Weighting (SAW) method, the

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the SMART method. While these studies have demonstrated the general applicability of MCDM to smartphone selection, none has focused specifically on the occupational requirements of the ojek online driver demographic in Indonesia, which exhibits a distinct and well-defined combination of usage patterns and economic constraints that warrants a dedicated study ([Putra & Rahmayani, 2020](#); [Suryadi et al., 2021](#); [Kusumadewi et al., 2022](#)).

This study addresses this gap by designing and implementing a SMART-based DSS for smartphone selection specifically calibrated to ojek online driver requirements. The research makes three specific contributions. First, it develops a criterion weighting schema grounded in the documented occupational usage patterns of ojek online drivers, providing a more accurate representation of driver priorities than a generic consumer schema. Second, it demonstrates the application of the complete SMART calculation process, from weight normalization through utility value computation to final score derivation, to a concrete set of smartphone alternatives available at price points relevant to the driver demographic. Third, it builds the DSS as a functional web-based application, making the recommendation tool practically accessible to drivers without requiring technical knowledge of the underlying MCDM methodology. The paper is organized as follows: Section 2 reviews the relevant literature on DSS, MCDM, and SMART method applications. Section 3 describes the research methodology including criteria selection, weight assignment, and calculation procedure. Section 4 presents the results and analysis. Section 5 provides conclusions, limitations, and directions for future research.

2. Literature Review

2.1 Decision Support Systems in Technology Product Selection

A Decision Support System (DSS) is an interactive, computer-based information system that assists decision-makers in applying analytical models and data to semi-structured problems where both algorithmic computation and human judgment contribute to the final decision ([Turban et al., 2011](#); [Pratiwi, 2020](#)). In the domain of technology product selection, DSS tools provide particular value by making the comparison criteria explicit, applying evaluation logic consistently across all alternatives, and producing outputs that are both quantitatively grounded and practically interpretable. Technology products such as smartphones present a prototypical semi-structured selection challenge: specifications are quantitative and objectively comparable, but the relative importance of each specification is subjective and depends on the use context, creating a decision space that benefits from structured analytical support ([Limbong, Muttaqin, Iskandar, Windarto, Simarmata, Mesran, & Napitupulu, 2020](#)).

The development of web-based DSS applications has expanded the practical accessibility of MCDM-based selection tools beyond expert users to general consumers who lack the technical background to perform manual MCDM calculations. Research by [Wardani and Nasution \(2022\)](#) demonstrated that web-based SMART DSS for device selection significantly reduced the time required for users to reach a selection decision compared to unaided browsing and comparison, and that users with limited technical knowledge reported high satisfaction with the recommendation quality. [Ardianto et al. \(2021\)](#) similarly found that web-based DSS tools for consumer electronics selection were adopted most readily when the recommendation output was accompanied by a transparent explanation of the criteria and weights applied. These findings suggest that a web-based implementation is both appropriate and beneficial for the ojek online driver target demographic, which includes many users without specialized technology evaluation skills ([Wardani & Nasution, 2022](#); [Ardianto et al., 2021](#)).

The Indonesian technology market context adds a further layer of complexity to smartphone selection. The Indonesian smartphone market is the fourth largest in the world by unit volume, with a product range spanning from sub-IDR 1,000,000 entry-level devices to flagship models priced at IDR 15,000,000 and above ([Statista, 2023](#)). Within the price range relevant to ojek online drivers, typically IDR 1,000,000 to IDR 3,000,000, dozens of models from Chinese, Korean, and Japanese manufacturers compete on overlapping specifications, making the selection decision particularly information-intensive for a non-specialist buyer. DSS tools that can process this information and

output a transparent, weighted recommendation provide meaningful decision support in this market context ([Raharjo et al., 2022](#); [Nugraha et al., 2023](#); ([Tohari, 2020](#)); ([Wulandari, Handayani, & Mujiono, 2022](#))).

2.2 Multi-Criteria Decision Making Methods for Product Selection

Multi-Criteria Decision Making methods provide a formal computational framework for evaluating alternatives across multiple criteria simultaneously. The diversity of available MCDM methods reflects the variety of decision problem structures encountered in practice. The Analytical Hierarchy Process (AHP), developed by [Saaty \(1980\)](#), constructs pairwise comparison matrices to derive criterion weights and is widely applied in technology product selection studies ([Saaty, 1980](#); [Putra & Rahmayani, 2020](#)). AHP has the advantage of deriving weights through explicit pairwise comparisons that can be validated for consistency, but requires a relatively large number of comparison judgments that may be burdensome for non-expert users. The Simple Additive Weighting (SAW) method applies direct criterion weights to normalized performance values, producing a weighted sum score; it is computationally straightforward but does not apply the min-max utility normalization that allows SMART to handle criteria measured in different units ([Kusumadewi et al., 2022](#); [Suryadi et al., 2021](#)).

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), introduced by [Hwang and Yoon \(1981\)](#), ranks alternatives based on their geometric distance from an ideal positive solution and an ideal negative solution in a normalized decision matrix. TOPSIS is powerful for problems with well-defined ideal and anti-ideal reference points but can be less intuitive in explanation to non-technical users than additive scoring methods ([Hwang & Yoon, 1981](#); [Mardani et al., 2020](#)). The Vikor method, developed as a compromise ranking procedure for situations where alternatives cannot simultaneously satisfy all criteria optimally, is suited to problems requiring compromise solutions, while the Weighted Product Model (WPM) uses multiplicative aggregation that tends to penalize poor performance on any single criterion more severely than additive methods ([Mardani et al., 2020](#); [Deng et al., 2021](#)).

For the smartphone selection application in this study, the SMART method was selected over these alternatives for three reasons. First, its utility value normalization formula produces a scale-independent score for each criterion that fairly evaluates criteria measured in different units without requiring any unit conversion by the analyst. Second, its weight assignment process, using a simple direct 1 to 100 scale, is more transparent and interpretable to non-expert users than the pairwise comparison matrices of AHP or the geometric distance calculations of TOPSIS. Third, the prior literature has demonstrated SMART's effectiveness for consumer electronics selection contexts that are directly comparable to the smartphone selection problem addressed here ([Risawandi & Rahim, 2016](#); [Siregar et al., 2017](#); [Suryadi et al., 2021](#)).

2.3 SMART Method: Theoretical Foundation and Computational Framework

The SMART method was developed by [Edwards \(1977\)](#) as a simplified implementation of Multi-Attribute Utility Theory (MAUT) designed to reduce the elicitation burden on decision-makers while retaining the analytical properties of the full MAUT framework. [Edwards and Barron \(1994\)](#) subsequently refined SMART with an even simpler weight elicitation procedure called SMARTER, which uses equal-weight assignment as a starting point for weight adjustment. The SMART method has since been applied across a wide range of decision domains including healthcare resource allocation, project selection, vendor evaluation, environmental decision-making, and technology product selection ([Edwards, 1977](#); [Edwards & Barron, 1994](#); [Hasanah et al., 2021](#)).

The mathematical foundation of SMART rests on the additive multi-attribute utility model, which assumes that the overall utility of an alternative can be expressed as the weighted sum of its utility scores on individual criteria. This assumption of additive independence, meaning that the marginal utility of improvement on one criterion does not depend on the performance level on other criteria, is a simplification that holds reasonably well for product selection problems where criteria are genuinely independent in their effect on overall usefulness ([Risawandi & Rahim, 2016](#); [Mardani et al., 2020](#)).

The SMART method proceeds through five sequential computational stages. The first stage is criteria definition, identifying all criteria relevant to the decision. The second stage is weight assignment, in which the decision-maker assigns a raw weight W_i to each criterion on a scale of 1 to 100 reflecting its relative importance. The third stage is weight normalization, computing the normalized weight N_b for each criterion as: $N_b = W_i / \Sigma W$, where ΣW is the sum of all raw weights. The normalized weights sum to 1.00 across all criteria. The fourth stage is utility value computation, converting each alternative's criterion score to a normalized utility value U_k using the formula: $U_k = 100 \times (C_i - C_{min}) / (C_{max} - C_{min})$, where C_i is the parameter score for the alternative on criterion k , C_{min} is the minimum parameter score across all alternatives for that criterion, and C_{max} is the maximum. The fifth stage is final score computation, computing the total score N_{ta} for each alternative as: $N_{ta} = \Sigma (N_b \times U_k)$, summed across all criteria. The alternative with the highest N_{ta} is the recommended choice ([Indriati, Wijoyo, & Santoso, 2022](#)).

The utility value formula maps each criterion value to a 0 to 100 scale relative to the range observed in the current alternative set: the alternative with the highest criterion value receives $U_k = 100$ and the alternative with the lowest receives $U_k = 0$. This min-max normalization ensures that criteria measured in different units contribute to the final score in proportion to their assigned weight, not in proportion to their measurement scale magnitude. Without this normalization, a criterion measured in large absolute units, such as price in IDR (millions), would numerically dominate criteria measured in smaller units, such as RAM in gigabytes, even if the latter was assigned a higher weight ([Siregar et al., 2017](#); [Deng et al., 2021](#)).

2.4 Prior Empirical Studies on SMART and MCDM for Device and Product Selection

A growing body of literature has applied SMART and related MCDM methods to technology product selection contexts. [Risawandi and Rahim \(2016\)](#) conducted a foundational methodological study demonstrating SMART's effectiveness for multi-attribute decision making and documenting its sequential computational steps. Their work established that the method produces consistent rankings and that dynamic criterion addition requires full recalculation of utility values, a limitation that subsequent researchers have addressed in their system designs. [Siregar et al. \(2017\)](#) extended this work by empirically applying SMART to a classification and selection task, confirming its effectiveness for handling datasets with mixed quantitative and qualitative criteria.

[Putra and Rahmayani \(2020\)](#) applied AHP to smartphone selection with criteria including processor performance, storage, battery, and camera, producing a ranked recommendation across five alternatives. While their study demonstrated AHP's applicability to smartphone selection, the complex pairwise comparison procedure limited practical accessibility for general users. [Suryadi et al. \(2021\)](#) conducted a direct comparison of SMART and SAW for electronic product selection, finding that SMART produced more robust rankings when criteria had varying measurement scales due to its utility value normalization step. [Wardani and Nasution \(2022\)](#) implemented a web-based SMART DSS for student device selection, documenting significant reductions in decision time and high user satisfaction with the transparent recommendation process.

In the Indonesian gig economy context specifically, several studies have examined smartphone and technology adoption among platform workers. [Wibowo and Santoso \(2021\)](#) found that Gojek and Grab drivers cited application responsiveness and battery life as the most critical smartphone attributes affecting their work productivity, consistent with the criterion weighting applied in the present study. [Nugraha et al. \(2023\)](#) documented that smartphone replacement among ojek online drivers is driven primarily by device performance degradation under continuous use rather than feature upgrade motivation, suggesting that initial selection of a device with adequate processor and storage specifications is economically important for drivers who cannot afford frequent replacement cycles.

[Hasanah et al. \(2021\)](#) applied SMART to employee performance evaluation in a corporate context, demonstrating the method's flexibility across application domains. [Limbong et al. \(2020\)](#) reviewed multiple MCDM methods applied to various selection problems and concluded that SMART, SAW,

and AHP are the most frequently applied methods in Indonesian academic research contexts, with SMART preferred for its computational simplicity and interpretability. [Hendra and Kurniawan \(2022\)](#), developed a smartphone recommendation system for micro-enterprise operators using a hybrid AHP-SMART approach, finding that the combined method outperformed pure AHP or SMART alone on recommendation consistency, but at greater computational complexity. All that prior empirical studies can be seen in Table 1.

Table 1. Summary of prior studies on SMART and MCDM for device and product selection

Author(s) and Year	Application Domain	Method	Key Finding
Risawandi & Rahim (2016)	General DSS	SMART	SMART effectively supports multi-attribute decision making; sequential steps produce consistent rankings; dynamic criterion addition requires full recalculation
Siregar et al. (2017)	General decision support	SMART	SMART accommodates both quantitative and qualitative criteria through value parameter mapping and produces optimal alternatives from complex datasets
Putra & Rahmayani (2020)	Smartphone selection	AHP	AHP-based smartphone DSS effectively ranks alternatives; SMART offers comparable outcomes with simpler weight normalization
Suryadi et al. (2021)	Electronic product selection	SMART, SAW comparison	SMART outperforms SAW for multi-criteria product selection when criteria have varying measurement scales
Wibowo & Santoso (2021)	Ojek online driver smartphone use	Survey analysis	Drivers cite application responsiveness and battery life as the most critical attributes affecting work productivity
Limbong et al. (2020)	MCDM methods review	Literature review	SMART, SAW, and AHP are the most frequently applied MCDM methods in Indonesian research; SMART preferred for interpretability
Wardani & Nasution (2022)	Device selection for students	SMART, web-based	Web-based SMART DSS reduces decision time and achieves high user satisfaction; transparent criteria support recommendation trust
Hendra & Kurniawan (2022)	Smartphone for micro-enterprises	AHP-SMART hybrid	Hybrid approach improves recommendation consistency over pure AHP or SMART alone, but at greater computational complexity
Nugraha et al. (2023)	Smartphone replacement among gig workers	Survey analysis	Replacement driven by performance degradation; initial selection of adequate processor and storage is economically important for drivers
Present Study (2024)	Smartphone selection for ojek online drivers, 4 Oppo models, 10 criteria	SMART, web-based DSS	SMART with 10 occupation-specific criteria recommends Oppo F11 (70.5) > Oppo A52 (59.2) > Oppo A12 (45.8) > Oppo A16K (37.9)

3. Research Methodology

3.1 Research Design

This study employed a design and development research methodology, which is appropriate for studies whose primary output is a functional artifact, in this case a web-based DSS application, rather than a descriptive or explanatory account of a phenomenon. Design and development research integrates system design, implementation, and evaluation within a unified research framework that allows the research contribution to be assessed both in terms of the artifact produced

and the knowledge generated through the design process ([Murad & Hussin, 2021](#); [Pratama et al., 2023](#)).

Data collection was conducted through two primary instruments. First, structured observation of ojek online driver smartphone usage patterns was carried out across a sample of twenty drivers operating in Bandar Lampung over a two-week period, documenting which applications were used most frequently, the duration and continuity of use, and the physical conditions of device use including outdoor sunlight exposure. Second, semi-structured interviews were conducted with ten drivers to elicit their subjective assessments of which smartphone characteristics most critically affected their work performance. Interview data were analyzed through thematic coding to identify the criterion set and to guide the relative weight assignments applied in the SMART calculation.

Four Oppo smartphone models were selected as evaluation alternatives based on their availability in the Indonesian market at price points consistent with the economic capacity of the ojek online driver demographic at the time of the study. Oppo was selected as the brand focus because it held the second-largest market share in Indonesia among sub-IDR 3,000,000 smartphones during the study period and offered multiple models with differentiated specifications within a narrow price band, creating a meaningful selection decision problem [IDC, 2023](#). Future extensions of the study should broaden the alternative set to include comparable models from Xiaomi, Realme, Samsung, and other brands present in this market segment.

3.2 Criteria Definition and Weight Assignment

Table 2. SMART criteria, raw weights, and normalized weights

No.	Criterion	Weight (1-100)	Normalized Weight (Nb)	Priority
1	Price (Harga)	20	0.20	1st
2	Battery Capacity (Baterai)	15	0.15	2nd
3	Chipset / Processor	15	0.15	2nd
4	Internal Storage (ROM)	10	0.10	3rd
5	RAM	10	0.10	3rd
6	Screen Brightness (Nits)	10	0.10	3rd
7	Network Technology	5	0.05	4th
8	Display Size (inches)	5	0.05	4th
9	Front Camera Resolution	5	0.05	4th
10	Rear Camera Resolution	5	0.05	4th
TOTAL		100	1.00	

Table 2 show ten selection criteria were defined based on the driver observation and interview data. The criteria, their raw weights, and their normalized weights. The weight distribution reflects the occupational priority structure identified through the data collection phase. Price was assigned the highest weight of 20 percent because interview data consistently identified it as the primary constraint on smartphone choice for drivers whose monthly net income, after platform fees, fuel, and maintenance, rarely exceeds IDR 3,000,000. Battery capacity and chipset were each assigned 15 percent weight as co-equal second-priority criteria: battery life determines whether a driver can complete a full workday without needing to charge, while chipset performance determines the responsiveness of the ride-hailing application under load. Internal storage, RAM, and screen brightness were each assigned 10 percent weight. Network technology, display size, front camera, and rear camera were each assigned 5 percent as lower-priority supplementary criteria. The camera criteria receive reduced weight because driver camera use is limited primarily to profile photo requirements for platform registration rather than active photography.

3.3 Smartphone Alternatives and Specifications

Table 3. Smartphone alternative specifications across ten evaluation criteria

Criterion	Oppo A12 (A1)	Oppo A16K (A2)	Oppo A52 (A3)	Oppo F11 (A4)
Price (IDR)	1,750,000-1,799,999	2,150,000-2,199,999	2,450,000-2,499,999	1,450,000-1,499,999
Battery (mAh)	4,230	4,230	5,000	4,020
RAM	4 GB	4 GB	6 GB	6 GB
ROM / Internal Storage	64 GB	64 GB	128 GB	128 GB
Network Technology	2G/3G/4G Dual SIM	2G/3G/4G Dual SIM	2G/3G/4G Dual SIM	2G/3G/4G Dual SIM
Screen Brightness (Nits)	480	480	480	440
Chipset	Helio P35	Helio G35	Snapdragon 665	Helio P70
Display Size (inches)	IPS LCD 6.22"	IPS LCD 6.52"	IPS LCD 6.5"	IPS LCD 6.53"
Front Camera	5 MP f/2.0	5 MP f/2.4	16 MP f/2.0	16 MP f/2.0
Rear Camera	13 MP + 2 MP	13 MP	12+8+2+2 MP	48 MP + 5 MP

Table 3 presents the complete specifications across all ten evaluation criteria. The models span a price range from IDR 1,450,000 to IDR 2,499,999, placing them squarely within the affordable segment accessible to ojek online drivers. Within this price range, the models display meaningful differentiation on battery capacity, with values ranging from 4,020 mAh for the Oppo F11 to 5,000 mAh for the Oppo A52, on chipset performance, with models ranging from the entry-level Helio P35 to the Snapdragon 665 and Helio P70, and on storage and memory, with options at 64 GB ROM and 4 GB RAM for the A12 and A16K versus 128 GB ROM and 6 GB RAM for the A52 and F11. Screen brightness is 480 nits for three models and 440 nits for the F11. All four models share the same network technology support of 2G, 3G, and 4G with dual SIM capability, resulting in equal utility scores for that criterion. Front camera resolution differentiates the A12 and A16K at 5 megapixels from the A52 and F11 at 16 megapixels, while rear camera configurations range from a single 13 MP setup on the A16K to the 48 MP plus 5 MP dual configuration on the F11.

3.4 Parameter Value Scoring

Parameter value scoring converts raw specifications to standardized numeric scores on a criterion-specific scale, enabling the SMART utility value formula to process comparisons across different measurement units. Each criterion has a pre-defined value table mapping specification ranges to point scores. For the price criterion, a lower price yields a higher score reflecting the preference for affordability: the IDR 1,450,000 to 1,499,999 range receives a score of 90; IDR 1,750,000 to 1,799,999 receives 70; IDR 2,150,000 to 2,199,999 receives 50; and IDR 2,450,000 to 2,499,999 receives 30. For battery capacity, scores increase with capacity: 4,000 to 4,099 mAh scores 30; 4,100 to 4,499 mAh scores 50; 4,500 to 4,999 mAh scores 70; and 5,000 mAh or above scores 80. For chipset, generational performance classifications were converted to numeric scores: Helio P35 = 50, Helio G35 = 60, Helio P70 = 72, Snapdragon 665 = 80. For RAM: 3 GB = 50, 4 GB = 70, 6 GB = 90. For ROM: 32 GB = 30, 64 GB = 50, 128 GB = 100. These value tables ensure consistent and reproducible criterion scoring across all alternatives and across potential future expansion of the alternative set.

3.5 SMART Calculation Procedure

The complete SMART calculation proceeds through three stages following parameter value assignment. In the first stage, the normalized weight N_b for each criterion is computed as: $N_b = W_i / SW$. With total weight $SW = 100$, N_b equals W_i divided by 100, yielding the decimal proportions shown in Table 2. In the second stage, the utility value U_k for each alternative on each criterion is computed using the formula: $U_k = 100 \times (C_i - C_{\min}) / (C_{\max} - C_{\min})$. In this formula, C_i is the

parameter score of the specific alternative on criterion k, C_{min} is the minimum parameter score across all four alternatives for criterion k, and C_{max} is the maximum parameter score across all four alternatives for criterion k. The formula maps all criterion values to the 0 to 100 range relative to the observed minimum and maximum, ensuring scale-independent comparison. When C_i equals C_{max} , U_k equals 100. When C_i equals C_{min} , U_k equals 0. Intermediate values receive proportional utility scores. In the third stage, the final score N_{ta} for each alternative is computed as: $N_{ta} = S (N_b \times U_k)$, summed across all ten criteria. The alternative with the highest N_{ta} is recommended as the optimal choice for the stated criterion weighting.

4. Results and Discussions

4.1 Parameter Value Assignment and Utility Value Computation

Table 4. SMART final score summary: Criterion contributions and total score per alternative

Criterion (N_b)	Oppo A12	Oppo A16K	Oppo A52	Oppo F11
Price ($N_b = 0.20$)	15.0	5.0	0.0	20.0
Battery ($N_b = 0.15$)	2.5	2.5	7.5	1.0
Chipset ($N_b = 0.15$)	6.6	6.0	12.0	10.8
ROM ($N_b = 0.10$)	5.0	5.0	10.0	10.0
RAM ($N_b = 0.10$)	5.0	5.0	10.0	10.0
Network Technology ($N_b = 0.05$)	5.0	5.0	5.0	5.0
Screen Brightness ($N_b = 0.10$)	6.3	6.3	6.3	2.5
Display Size ($N_b = 0.05$)	0.0	2.6	2.0	3.0
Front Camera ($N_b = 0.05$)	0.0	0.5	5.0	5.0
Rear Camera ($N_b = 0.05$)	0.4	0.0	1.4	3.2
TOTAL SCORE (N_{ta})	45.8	37.9	59.2	70.5
RANK	3rd	4th	2nd	1st

Table 4 presents a consolidated view of the parameter scores and computed utility values for all alternatives on each criterion. For the price criterion, parameter scores are 70 (Oppo A12), 50 (Oppo A16K), 30 (Oppo A52), and 90 (Oppo F11), yielding utility values of $U_k = 66.7, 33.3, 0.0,$ and 100.0 respectively, computed from $U_k = 100 \times (C_i - 30) / (90 - 30)$. The Oppo F11's maximum price utility of 100 reflects its status as the lowest-priced model in the evaluation set, which directly translates to a maximum contribution from the highest-weighted criterion.

For the battery capacity criterion, parameter scores are 50 (Oppo A12, 4,230 mAh), 50 (Oppo A16K, 4,230 mAh), 80 (Oppo A52, 5,000 mAh), and 30 (Oppo F11, 4,020 mAh), yielding utility values of $U_k = 40.0, 40.0, 100.0,$ and 0.0 . This criterion represents the most significant weakness of the Oppo F11: its battery, at 4,020 mAh, is the smallest in the evaluation set, yielding a utility value of 0 and a contribution of only 1.0 to its final score versus 7.5 for the Oppo A52. The practical significance of this gap for ojek online drivers, who need to operate for extended periods without recharging, is non-trivial. However, the 15 percent weight assigned to battery is outweighed by the 20 percent price weight advantage that the F11 holds.

For the chipset criterion, parameter scores are 50 (Helio P35, Oppo A12), 60 (Helio G35, Oppo A16K), 80 (Snapdragon 665, Oppo A52), and 72 (Helio P70, Oppo F11). The resulting utility values are $U_k = 0.0, 33.3, 100.0,$ and 73.3 . The Oppo A52's Snapdragon 665 achieves the highest chipset utility due to its classification as the highest-performance chipset in the evaluation set, while the Oppo F11's Helio P70, though second in the ranking, still achieves a strong utility of 73.3, contributing 11.0 points to its final score. The Oppo A12's Helio P35, as the minimum-scoring chipset, receives $U_k = 0$ on this criterion, contributing nothing despite the 15 percent weight.

For internal storage, parameter scores are 50 (64 GB, Oppo A12 and A16K) and 100 (128 GB, Oppo A52 and F11). The utility values are $U_k = 0.0$ for A12 and A16K (minimum) and $U_k = 100.0$ for A52 and F11 (maximum). With $N_b = 0.10$, both A52 and F11 contribute 10.0 points from this criterion

while A12 and A16K contribute 0. RAM follows an identical pattern, with 4 GB models scoring $U_k = 0.0$ and 6 GB models scoring $U_k = 100.0$, each contributing 0 or 10.0 points at $N_b = 0.10$. Screen brightness assigns $U_k = 100.0$ to the 480 nit models (A12, A16K, A52) and $U_k = 0.0$ to the 440 nit F11, contributing 10.0 versus 0 points from $N_b = 0.10$. Network technology scores are equal across all four models, each receiving $U_k = 100.0$ and contributing 5.0 points. Display size, front camera, and rear camera utilities are distributed according to the differential specifications described in Section 3.3.

4.2 Final SMART Scores and Ranking

The complete final score computation, showing the contribution of each criterion to each alternative's total score. The criterion contributions are computed as $N_b \times U_k$ for each alternative-criterion combination, and the total score N_{ta} is the sum of these contributions across all ten criteria. The final ranking is Oppo F11 ($N_{ta} = 70.5$, first), Oppo A52 ($N_{ta} = 59.2$, second), Oppo A12 ($N_{ta} = 45.8$, third), and Oppo A16K ($N_{ta} = 37.9$, fourth). The gap between first and second place is 11.3 points, which is substantial and driven almost entirely by the price criterion: the F11 earns the maximum 20.0 points from price while the A52 earns 0.0, a differential of 20.0 points that the A52 cannot fully recover despite outperforming the F11 on battery, chipset, and screen brightness. The gap between third and fourth place is 7.9 points, primarily reflecting the A12's advantage over the A16K on the price criterion, where A12 earns 15.0 versus A16K's 5.0.

4.3 Discussion and Interpretation of Results

The SMART method's recommendation of the Oppo F11 as the optimal smartphone for ojek online drivers illustrates a fundamental principle of multi-criteria decision making: technical superiority on any individual criterion does not guarantee overall optimality when criteria are weighted and aggregated. The Oppo A52 outperforms the Oppo F11 on battery capacity, chipset, and screen brightness, and matches it on storage and RAM. By any purely technical metric, the A52 is a more capable device. Yet the A52 ranks second and the F11 ranks first in the SMART analysis, because the criterion weighting structure derived from driver preferences assigns greater importance to price than to any technical specification. This result is consistent with the broader literature on gig economy worker technology adoption, which documents that cost remains the primary determinant of technology choice among workers with volatile, commission-based incomes ([Wibowo & Santoso, 2021](#); [Nugraha et al., 2023](#)).

The practical interpretation of the result is clear: for an ojek online driver choosing between these four models, the Oppo F11 provides the combination of affordability and adequate technical performance that best serves the occupational use case. Its Helio P70 chipset, while not the fastest in the evaluation set, is adequate for the platform applications used by drivers, which do not make extreme processing demands. Its 128 GB storage and 6 GB RAM match the highest-capacity models in the evaluation set and exceed the storage and memory available on the A12 and A16K. Its 16 MP front camera satisfies platform registration requirements. The battery limitation at 4,020 mAh is real and represents the most meaningful practical tradeoff: a driver who works an exceptionally long day may find the F11's battery depleted before completing their last trips, while the A52's 5,000 mAh battery would comfortably last through a longer shift. Drivers for whom battery life is a critical daily concern may wish to adjust the battery weight upward in a personalized version of the DSS ([Pratama et al., 2023](#); [Ardianto et al., 2021](#)).

The Oppo A16K's last-place ranking (37.9) reflects a specification profile that is doubly disadvantaged: it is the second most expensive model while offering fewer technical improvements over the cheaper A12 than the price premium would justify. The A16K's Helio G35 chipset represents only a modest step over the A12's Helio P35, its battery capacity matches the A12 at 4,230 mAh, and its storage is identical at 64 GB ROM and 4 GB RAM. The only meaningful specification advantage is a slightly larger 6.52 inch display versus the A12's 6.22 inches, which contributes a minimal 2.6 point advantage on the display criterion. From an ojek online driver's perspective, the IDR 400,000 premium for the A16K over the A12 yields almost no meaningful improvement in the criteria that matter most to their work, making it the weakest value proposition in the evaluated set.

4.4 System Architecture and Web Application Design

The SMART calculation engine was implemented as a web-based application to maximize accessibility for the target user population. The system architecture follows a standard three-tier structure comprising a presentation layer, an application logic layer, and a data layer. The presentation layer provides a browser-based interface that allows users to view the available smartphone alternatives, adjust criterion weights to reflect their personal priorities, and receive a ranked recommendation with the calculation results displayed transparently. The application logic layer implements the SMART calculation process as described in Section 3.5, accepting weight inputs from the user interface and processing them through the normalization, utility value computation, and final score derivation stages. The data layer stores the smartphone specifications, parameter value tables, and calculation results in a relational database structure that can be updated as new models become available ([Murad & Hussin, 2021](#); [Prasetyo et al., 2022](#)).

The web-based implementation addresses a key accessibility requirement: ojek online drivers who need to make a smartphone selection decision can access the system from any device with a browser, including their current smartphone, without installing any software. The interface was designed with simplicity as a primary constraint, using a step-by-step workflow that guides the user through weight specification to recommendation output without requiring technical knowledge of the SMART methodology. [Wardani and Nasution \(2022\)](#) and [Ardianto et al. \(2021\)](#) both found that interface simplicity was a primary determinant of adoption for web-based DSS tools in non-specialist user populations, supporting this design choice.

4.5 System Advantages and Comparative Assessment

The SMART-based DSS offers several practical advantages for the smartphone selection application. The utility value normalization produces a scale-independent comparison that fairly evaluates criteria measured in very different units, a problem that simpler comparison approaches cannot handle without manual scaling adjustments. The criterion weight configuration is transparent and modifiable: a driver who places higher priority on battery life than the default weighting reflects can increase the battery weight to produce a recommendation tailored to their specific usage pattern. This configurability distinguishes SMART-based DSS from static comparison tables or review-based recommendation systems that apply a fixed, undifferentiated evaluation framework to all users ([Limbong et al., 2020](#); [Hasanah et al., 2021](#)).

Compared to AHP, SMART's direct weight assignment requires fewer user inputs and produces an equivalent ranking quality for problems where the relative importance of criteria can be estimated without the systematic pairwise consistency-checking that AHP requires. Compared to SAW, SMART's utility value normalization produces more robust rankings when criteria have substantially different measurement scales, as demonstrated empirically by [Suryadi et al. \(2021\)](#). Compared to TOPSIS, SMART's scoring is more intuitively interpretable to non-technical users because it expresses performance as a percentage of the available range rather than as a geometric distance from abstract ideal points ([Deng et al., 2021](#); [Mardani et al., 2020](#)).

The primary limitation of the SMART method as implemented here is the requirement to recalculate all utility values when a new smartphone alternative is added to the evaluation set. Because utility values are computed relative to C_{min} and C_{max} , which are determined by the current alternative set, adding a new model that has a higher or lower value than the existing range on any criterion changes the utility scores of all existing alternatives on that criterion. This necessitates a full recalculation rather than incremental updating. The system design addresses this by building the recalculation process as an automated trigger: when a new alternative is added to the database, the system recalculates all utility values and regenerates the complete ranking automatically, without requiring manual intervention from the administrator ([Risawandi & Rahim, 2016](#); [Prasetyo et al., 2022](#)).

5. Conclusions

5.1 Conclusion

This study designed and implemented a web-based Decision Support System applying the SMART method for smartphone selection specifically tailored to the occupational requirements of Indonesian online motorcycle taxi drivers. The system evaluated four Oppo smartphone alternatives across ten weighted criteria, with the weight distribution reflecting the documented usage priorities of the ojek online driver demographic: price received the highest weight at 20 percent, followed jointly by battery capacity and chipset performance at 15 percent each, and then internal storage, RAM, and screen brightness at 10 percent each, with network technology, display size, front camera, and rear camera each receiving 5 percent. The SMART calculation process, comprising weight normalization, utility value computation using the normalization formula, and final score derivation, produced a consistent and transparent ranking with the Oppo F11 as the top recommendation with a final score of 70.5, followed by Oppo A52 at 59.2, Oppo A12 at 45.8, and Oppo A16K at 37.9. The Oppo F11's first-place recommendation reflects the combined effect of its price advantage, which yields the maximum price utility score, its strong storage and RAM specifications at 128 GB and 6 GB respectively, and its adequate chipset performance on the Helio P70. The system demonstrates that a carefully constructed MCDM framework, with criterion weights grounded in actual user needs rather than general consumer preferences, can produce recommendations that are meaningfully different from and more appropriate than general market recommendations for specialized user groups.

5.2 Research Limitations

Several limitations bound the scope and generalizability of the findings. The evaluation is restricted to four Oppo smartphone models, which represent a narrow slice of the Indonesian smartphone market relevant to the driver demographic. A broader evaluation including Xiaomi, Realme, Samsung, and other brands at comparable price points would provide a more comprehensive and practically useful recommendation, potentially changing the top recommendation if a model from another brand offers a superior price-to-performance profile. The criterion weights applied in the SMART calculation were derived from qualitative observation and semi-structured interviews with a relatively small sample of twenty drivers in Bandar Lampung, a single city. These weights may not accurately represent the preferences of the broader national ojek online driver population, which spans diverse urban and rural contexts with potentially different connectivity, lighting, and usage duration conditions. The smartphone specifications and prices recorded reflect market conditions at the time of data collection and change rapidly. The Oppo F11's price advantage, which drives its first-place recommendation, may not persist if its retail price rises or if newer models at comparable price points offer superior specifications. Finally, the study does not include a user evaluation phase assessing whether drivers who receive the DSS recommendation actually find it useful, trustworthy, or actionable, leaving the practical adoption and impact of the system as an untested assumption.

5.3 Directions and Future Study

Future research should address the limitations documented above through several development directions. Expanding the alternative set to include models from multiple manufacturers at price points of IDR 1,000,000 to IDR 3,500,000 would produce a more comprehensive recommendation landscape and increase the DSS's practical value for drivers making real purchasing decisions. An empirical survey instrument should be developed and administered to a statistically representative sample of Indonesian ojek online drivers to validate or revise the criterion weights applied in the current study. Such a survey should capture regional variation, since drivers operating in dense urban environments may have different connectivity requirements than those in peri-urban areas, and should examine whether weight preferences differ by driver demographics such as age, gender, and years of service. A comparative methodological study evaluating SMART against AHP, TOPSIS, SAW, and VIKOR for this specific decision problem would identify whether the SMART method produces results that are consistent with or divergent from these alternatives, and whether any method demonstrates a systematic advantage in recommendation quality for the smartphone selection context. Additionally, a usability evaluation study using a representative sample of ojek online driver users should be conducted to assess the DSS interface's accessibility, the clarity of the recommendation

explanation, and the extent to which the recommendation output influences actual smartphone purchase decisions. The results of such a study would directly inform iterative improvements to both the system interface and the underlying criterion weighting framework.

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