Journal of Applied Informatics and Computing (JAIC)
Vol.10, No.4, August 2026, pp. 4124~4132
e-ISSN: 2548-6861

Comparative Analysis of the SMART and ARAS Methods in a Decision Support System for Motorcycle Loan Applicant Eligibility

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Article Info

Article history:

Received 2026-06-26
Revised 2026-08-10
Accepted 2026-08-13

Keyword:

Decision Support System,
SMART,
ARAS,
Motorcycle Financing,
Credit Eligibility,
Multi-Criteria Decision Making (MCDM).

ABSTRACT

Motorcycle financing is one of the most popular consumer financing products in Indonesia. However, the credit eligibility assessment process at PT Mega Central Finance (MCF) Lhokseumawe Branch is still performed manually, making it susceptible to inconsistent evaluations and increasing the risk of non-performing loans. This study aims to implement and compare two Multi-Criteria Decision-Making (MCDM) methods, namely the Simple Multi-Attribute Rating Technique (SMART) and the Additive Ratio Assessment (ARAS), for evaluating motorcycle financing eligibility based on seven criteria, including age, monthly income, occupation, marital status, number of dependents, outstanding debt balance, and down payment (DP). The study utilized primary data from 223 loan applicants collected during the 2024 to 2025 period through interviews and document reviews using a total sampling technique. Criterion weights were determined using expert judgment from credit analysts. The results show that the SMART method classified 96 applicants as eligible and 127 applicants as not eligible, whereas the ARAS method classified 181 applicants as eligible and 42 applicants as not eligible, using a minimum eligibility threshold of 0.60. The difference in the results is primarily attributed to the distinct normalization mechanisms of the two methods. SMART is more sensitive to extreme values in highly weighted criteria, resulting in a more selective evaluation process, whereas ARAS produces a more balanced distribution of preference scores by normalizing criterion values relative to the optimal solution, leading to a more flexible assessment. The findings indicate that the two methods complement each other. SMART is recommended for organizations adopting a conservative credit approval policy, while ARAS is more suitable for organizations seeking to expand the number of eligible applicants while maintaining a balanced consideration of all evaluation criteria.

I. INTRODUCTION

A Decision Support System (DSS) is a computer-based system designed to assist decision-making processes in semi-structured and unstructured situations by integrating data, analytical models, and interactive user interfaces [1]. In practice, DSS has been widely applied to facilitate objective evaluations of multiple alternatives based on predefined criteria, including destination selection and eligibility assessment in the financial services sector [2].

One of the most popular forms of consumer financing in Indonesia is motorcycle financing, which enables customers to purchase motorcycles through a down payment (DP) followed by monthly installments over a specified repayment period. PT Mega Central Finance (MCF) is one of Indonesia's national financing companies that, through its branch office in Lhokseumawe City, Aceh, provides motorcycle financing services to the local community. Before approving a financing application, the company is required to assess the creditworthiness of loan applicants to ensure their financial capability and commitment to meeting repayment obligations while minimizing the risk of non-performing loans.

Currently, the motorcycle financing eligibility assessment process at PT MCF Lhokseumawe Branch is still performed manually. This process is relatively time-consuming and prone to inconsistencies in evaluation, potentially resulting in the approval of ineligible applicants or the rejection of qualified ones. As the number of financing applications continues to increase, these limitations raise the likelihood of loan defaults and may lead to financial losses for the company. Therefore, a decision support system capable of evaluating applicant eligibility in a more objective, consistent, and efficient manner is required.

Various Multi-Criteria Decision-Making (MCDM) methods have been developed to address such challenges. Among them, the Simple Multi-Attribute Rating Technique (SMART) and the Additive Ratio Assessment (ARAS) methods are widely recognized for their computational simplicity and ease of interpretation. Brata et al. compared the TOPSIS and ARAS methods in selecting Customer Relationship Management partners for a charitable organization and found that differences in the normalization procedures produced different priority rankings [3]. In the context of motorcycle financing, Ruekhadee and Chomtohsuwan identified the factors contributing to motorcycle loan defaults without proposing a quantitative decision support model [4], whereas Azzahra et al. applied the ARAS method independently to determine motorcycle financing eligibility without comparing it to other decision-making methods [5]. Similarly, Putranto and Maulina employed SMART independently to identify outstanding teachers in the education sector [6], while Lestari et al. implemented ARAS as a standalone method for student specialization selection [7]. Furthermore, the comparative study by Pinem et al. evaluated ELECTRE, SMART, and ARAS for post-disaster rehabilitation prioritization and reported that ARAS achieved the highest accuracy for the investigated case [8]. Meanwhile, Taherdoost and Mohebi noted that SMART still suffers from subjectivity in determining criterion weights [9]. In the credit assessment domain, Yang and Ou demonstrated that the integration of AHP and TOPSIS improved the accuracy of green credit rating evaluations compared with single-method approaches [10], whereas Goswami and Behera confirmed the robustness of the ARAS method when combined with entropy weighting for engineering material selection [11]. Despite these studies, comparative research specifically evaluating the performance of SMART and ARAS for motorcycle financing eligibility assessment in the multifinance industry remains limited. This gap highlights the need for further investigation. Specifically, SMART and ARAS were deliberately selected for direct comparison in this study, rather than other MCDM methods, because they represent two contrasting normalization philosophies that are particularly consequential in a credit-eligibility context: SMART performs range-based (min–max) normalization and produces a compensatory additive score that closely mirrors the scorecard logic already familiar to credit analysts [12], [14], whereas ARAS performs proportional normalization relative to the sum of all alternatives' values, which is inherently more robust to extreme individual values [13], [16]. Prior studies have applied SMART or ARAS independently within the credit and financing domain [5], [6], [12] or compared ARAS against other methods such as TOPSIS and ELECTRE in non-financing contexts [3], [8], but none has directly juxtaposed SMART and ARAS specifically for motorcycle financing eligibility assessment. Because the two methods' normalization mechanisms are expected to yield systematically different selectivity behavior, a direct comparison is needed to reveal which method's risk profile, conservative versus inclusive, is better aligned with a given financing company's credit approval policy. This methodological contrast, rather than the mere availability of the two techniques, constitutes the research gap and the novelty addressed by the present study.

Based on these considerations, this study aims to implement and compare the SMART and ARAS methods within a decision support system for evaluating motorcycle financing eligibility at PT MCF Lhokseumawe Branch. Furthermore, the study seeks to identify the method that is more suitable for supporting the company's credit assessment policy. The primary contribution of this research is to provide comparative empirical evidence regarding the characteristics of two widely used MCDM methods using real-world data from the motorcycle financing sector, while offering practical recommendations for financing companies in selecting an appropriate applicant evaluation method according to their risk management policies.

II. METHODS

A. Research Type and Location

This study employed a comparative research design with a quantitative approach to compare the results of applicant eligibility assessments using the SMART and ARAS methods. The research was conducted at PT Mega Central Finance (MCF) Lhokseumawe Branch, Aceh Province, Indonesia, which was selected as the study site due to its motorcycle financing eligibility assessment process, making it an appropriate case for evaluating and comparing multi-criteria decision-making methods.

B. Data Collection and Sampling

The study utilized primary data obtained through interviews with credit analysts and documentation of motorcycle financing application records from prospective loan applicants during the 2024 to 2025 period. A total sampling (census sampling) technique was employed, in which all financing applications that met the research criteria, including complete records, the absence of missing values, and verification by credit analysts, were included as research samples. As a result, a total of 223 loan applicants were selected as the alternatives in the decision-making process.

Because the sample selection criteria described above already required complete records, the absence of missing values, and verification by credit analysts, the dataset did not require additional preprocessing; no missing-value imputation, duplicate-record removal, or outlier treatment was necessary, and each of the 223 records was independently verified prior to inclusion. Table II presents the descriptive characteristics of the 223 loan applicants included in this study.

TABLE II
DESCRIPTIVE CHARACTERISTICS OF THE 223 LOAN APPLICANTS

Variable	Value
Age (years)	Mean = 38.4, SD = 10.1 (range 21–55)
Monthly Income (IDR)	Mean = 3,870,404, SD = 1,175,510 (range 2,500,000–7,500,000)
Occupation	Daily: 85 (38.1%); Contract: 70 (31.4%); Permanent: 68 (30.5%)
Marital Status	Married: 120 (53.8%); Unmarried: 103 (46.2%)
Number of Dependents	Mean = 2.47, SD = 2.28 (range 0–7)
Outstanding Debt Balance (IDR)	Mean = 25,002,940, SD = 7,542,289 (range 15,058,000–39,974,000)
Down Payment (IDR)	Mean = 4,460,796, SD = 1,804,954 (range 1,882,000–8,883,000)
Down Payment Percentage	10%: 69 (30.9%); 15%: 77 (34.5%); 20%: 77 (34.5%)

As shown in Table II, the average applicant age was 38.4 years (SD = 10.1; range 21–55), consistent with the productive-age range defined for Criterion C1. The average monthly income was IDR 3,870,404 (SD = IDR 1,175,510), with occupations distributed across daily-wage work (38.1%), contract employment (31.4%), and permanent employment (30.5%). Slightly more than half of the applicants (53.8%) were married, and the average number of dependents was 2.47 (SD = 2.28). The average outstanding debt balance was IDR 25,002,940 and the average down payment was IDR 4,460,796, corresponding to down payment percentages of 10%, 15%, or 20% of the vehicle price.

C. Criteria and Weighting

The applicant eligibility assessment was based on seven criteria, namely age (C1), monthly income (C2), occupation (C3), marital status (C4), number of dependents (C5), remaining outstanding debt (C6), and down payment (DP) (C7). These seven criteria were not derived solely from the interview with the credit analyst; rather, the interview was used to confirm and locally calibrate a criterion set that is grounded in the 5C principle of credit analysis (Character, Capacity, Capital, Collateral, and Condition), which is widely adopted by lending institutions to assess borrower creditworthiness. Within this framework, marital status (C4) and age (C1) correspond to the Character and stability dimension; monthly income (C2), occupation (C3), and outstanding debt balance (C6) correspond to the Capacity dimension, reflecting the applicant's ability and existing financial burden in meeting repayment obligations; the down payment (C7) corresponds to the Capital dimension, reflecting the applicant's own financial commitment to the transaction; and the number of dependents (C5) corresponds to the Condition dimension, reflecting household financial exposure. The same set of variables, particularly income, occupation, marital status, dependents, and existing debt, has also been consistently used as eligibility criteria in prior SMART- and ARAS-based credit and financing decision support studies [5], [6], [12], which further supports their relevance for the present case. Criteria C1 to C4 and C7 were classified as benefit criteria, whereas C5 and C6 were classified as cost criteria. The weight of each criterion was determined using an expert judgment approach based on structured interviews with a single domain expert, Mr. Muchsin, who serves as a Senior Credit Analyst at PT Mega Central Finance (MCF) Lhokseumawe Branch and is directly responsible for evaluating motorcycle financing applications at the study site. The expert was asked to rate the relative importance of each of the seven criteria, after which the ratings were normalized so that their total equaled 1, as presented in Table I. Because the weighting process relied on a single expert who holds direct operational authority over credit approval decisions at the study site, inter-rater consistency testing was not applicable; the authors acknowledge this reliance on a single expert as a source of subjectivity in the weighting process, further discussed in Section III.E.

TABLE I
CRITERIA, WEIGHTS, AND ASSESSMENT DIRECTIONS

Code	Criterion	Type	Weight (%)	Assessment Direction
C1	Age	Benefit	10	Productive age (21 to 55 years) is considered more stable
C2	Monthly Income	Benefit	25	Higher income is preferred
C3	Occupation	Benefit	20	Permanent employment > Contract employment > Daily employment
C4	Marital Status	Benefit	10	Married applicants are considered more stable
C5	Number of Dependents	Cost	10	A higher number of dependents increases financial risk
C6	Outstanding Debt Balance	Cost	15	A higher outstanding balance increases the financial burden

C7	Down Payment (DP)	Benefit	10	A higher down payment reduces the financing burden
Total			**100**	

D. SMART Method Calculation

The SMART (Simple Multi-Attribute Rating Technique) method was implemented through several stages, including defining the evaluation criteria and their corresponding weights, determining sub-criteria and scores, establishing the decision value standards, calculating the utility values, applying the criterion weights, and computing the final preference scores. The overall workflow of the SMART method is illustrated in Figure 1 [12].

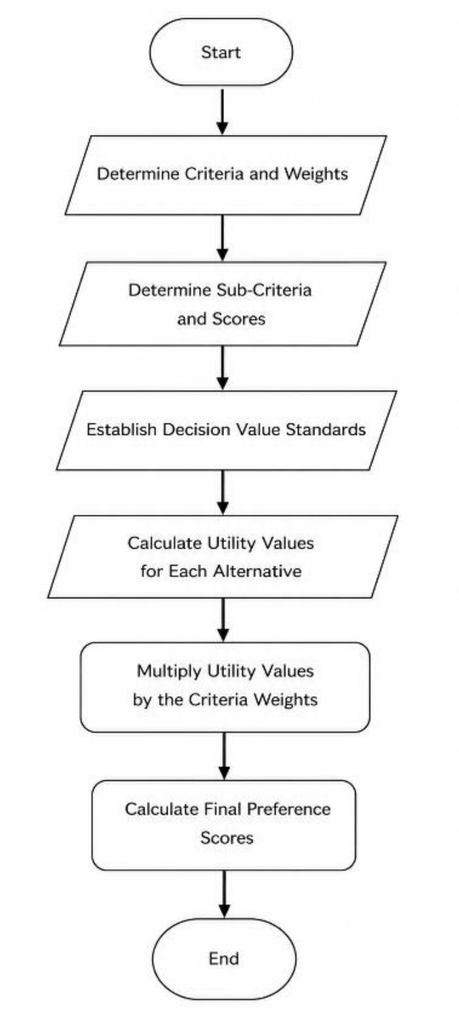

Figure 1. Flowchart of the SMART Method

The utility value $(u_{ij})$was calculated by transforming each criterion value into a scale ranging from 0 to 1. For benefit criteria, the utility value was calculated using Equation (1), whereas for cost criteria, Equation (2) was applied [14].

$$u_{ij} = \frac{x_{\max} - x_{ij}}{x_{\max} - x_{\min}} \qquad (2)$$

where u_{ij}represents the utility value of the i-th alternative for the j-th criterion, $x_{ij}$is the original criterion value, and $x_{\min}$and $x_{\max}$denote the minimum and maximum values of the j-th criterion, respectively.

The final preference score for each alternative was calculated using Equation (3) [15].

$$S_i = \sum_{j=1}^{n} (w_j \times r_{ij}) \qquad (3)$$

where $S_i$is the final preference score of the i-th alternative, $w_j$is the weight of the j-th criterion, $r_{ij}$is the utility value of the i-th alternative for the j-th criterion, and $n$is the total number of criteria. The alternative with the highest preference score was considered the most eligible for motorcycle financing.

E. ARAS Method Calculation

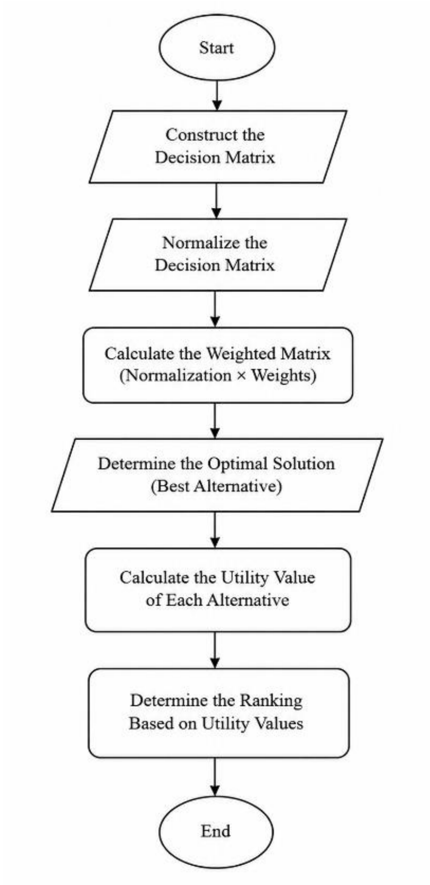

Figure 2. Flowchart of the ARAS Method

The ARAS (Additive Ratio Assessment) method evaluates the eligibility of each alternative based on its degree of closeness to the optimal solution. The calculation process consists of constructing and normalizing the decision matrix, applying criterion weights, calculating the optimality function, and determining the utility degree. The overall procedure of the ARAS method is illustrated in Figure 2 [13].For the benefit and cost criteria, the normalized values were calculated using Equations (4) and (5), respectively [16].

$$x'_{ij} = \frac{x_{ij}}{\max(x_j)} \quad (4)$$

$$x'_{ij} = \frac{\min(x_j)}{x_{ij}} \quad (5)$$

The optimality function $(S_i)$for each alternative was calculated using Equation (6) by summing the products of the normalized criterion values and their corresponding weights [17].

$$S_i = \sum_{j=1}^{n} (w_j \times x'_{ij}) \quad (6)$$

Subsequently, the utility degree $(K_i)$was determined using Equation (7) as the ratio between the optimality function value of the i-th alternative $(S_i)$and the optimality function value of the optimal alternative (S_0)[18].

$$K_i = \frac{S_i}{S_0} \quad (7)$$

where $x'_{ij}$is the normalized value of the i-th alternative for the j-th criterion, $S_i$is the optimality function value of the i-th alternative, $S_0$is the optimality function value of the optimal alternative, $w_j$is the weight of the j-th criterion, and $K_i$represents the utility degree of the i-th alternative. An alternative with the highest $K_i$value was considered the closest to the ideal solution and therefore the most eligible for motorcycle financing.

In this study, an applicant was classified as eligible if the final score, either $V_i$for the SMART method or $K_i$for the ARAS method, was greater than or equal to 0.60. This threshold value was determined by the researchers themselves rather than derived from a formal credit policy of PT Mega Central Finance (MCF); it was set above the general decision-support-system benchmark of 0.50, at which a score is generally considered to indicate only a satisfactory level of conformity with the evaluation criteria, in order to reflect a moderately conservative eligibility standard appropriate for credit risk evaluation. The absence of a company-mandated threshold and of empirical calibration against actual credit outcomes is acknowledged as a limitation of this study, discussed further in Section III.E.

III. Result and discussion

A. Dataset and Criteria Value Conversion

The dataset used in this study consisted of 223 loan applicants, each described by the attributes of age, monthly income, occupation, marital status, number of dependents, outstanding debt balance, down payment (DP), and DP percentage. As an illustration, one applicant, ABD MANAF, was 24 years old, had a monthly income of Rp3,700,000, worked under a contract, was unmarried, had one dependent, had an outstanding debt balance of Rp22,840,000, and made a down payment of Rp4,030,000 (15%). Each raw attribute was converted into a corresponding criterion score (C1 to C7) according to the scoring scheme presented in Table III, resulting in the criterion value sample shown in Table III.

TABLE III
SAMPLE OF CRITERIA VALUE CONVERSION

Debtor	C1	C2	C3	C4	C5	C6	C7
ABD MANAF	1	3	2	1	3	1	2
ABDILLAH	1	2	2	1	3	3	2
ABDUL HAMID	3	3	3	1	3	1	2
ADNAN	1	3	2	2	1	1	3
ADNAN FADLI	3	3	3	2	1	1	3
AFRIZAL MURFI	3	4	1	1	2	2	1
MIN	1	1	1	1	1	1	1
MAX	3	4	3	2	3	3	3

The minimum and maximum values of each criterion across all 223 alternatives were used as the reference values for the normalization process in the subsequent SMART and ARAS calculations.

B. SMART Method Calculation Results

As an illustration, the applicant ABD MANAF obtained the initial criterion scores of C1 = 1, C2 = 3, C3 = 2, C4 = 1, C5 = 3, C6 = 1, and C7 = 2. Based on Equations (1) and (2), the corresponding utility values were calculated as [0.000, 0.667, 0.500, 0.000, 0.000, 1.000, 0.500]. These utility values were then multiplied by the criterion weights presented in Table I and summed using Equation (3), resulting in a final preference score of 0.4667, as presented in Table IV.

TABLE IV
PREFERENCE SCORE CALCULATION FOR APPLICANT ABD MANAF

Kriteria	Utility (rij)	Bobot (wj)	wj × rij
C1	0,000	0,10	0,000
C2	0,667	0,25	0,167
C3	0,500	0,20	0,100
C4	0,000	0,10	0,000
C5	0,000	0,10	0,000
C6	1,000	0,15	0,150
C7	0,500	0,10	0,050
Total (Vi)			0,4667

The same calculation was carried out for all 223 alternatives, resulting in a distribution of preference values (Vi) and rankings as illustrated in Table V. The highest value was obtained by ADNAN FADLI with Vi=0.9167 (rank 1), while the lowest value in this subset was obtained by ABDILLAH with Vi=0.2333 (rank 223).

TABLE V
SNIPPET OF RANKING RESULTS USING THE SMART METHOD

Debtor	Vi	Rank
ADNAN FADLI	0,9167	1
ADNAN	0,7167	32
ABDUL HAMID	0,6667	52
AFRIZAL MURFI	0,4750	151
ABD MANAF	0,4667	168
ABDILLAH	0,2333	223

C. Results of ARAS Method Calculations

The alternative values in the ARAS decision matrix are identical to the criteria values after conversion (Table III), with the total value of each criterion across all alternatives used as the normalization divisor (Equations 4 and 5). After normalization and weighting, the optimal function values (Si) and utility degrees (Ki) were obtained, as shown in Table VI. The highest Si value was again achieved by ADNAN FADLI at 0.0060 with Ki=0.94 (rank 1), consistent with the results from the SMART method.

TABLE VI
EXCERPTS OF SI, KI, AND RANKINGS OF THE ARAS METHOD

Debtor	Si	Ki	Rank
ADNAN FADLI	0,0060	0,94	1
AKBAR FIRDAUS	0,0059	0,93	7
ADNAN	0,0051	0,80	31
ABDUL HAMID	0,0050	0,78	49
ABD MANAF	0,0041	0,65	148
AFRIZAL MURFI	0,0040	0,62	171
ABDILLAH	0,0032	0,50	222

D. Comparison of the Feasibility of SMART and ARAS Methods

Based on a minimum feasibility threshold of 0.60, the SMART method classifies 96 debtors as feasible and 127 debtors as not feasible, while the ARAS method classifies 181 debtors as feasible and 42 debtors as not feasible, as summarized in Table VII and visualized in Figures 3 and 4.

TABLE VII
COMPARISON OF FEASIBILITY RESULTS BETWEEN SMART AND ARAS METHODS

Category	SMART	ARAS
Eligible	96	181
Not Eligible	127	42
Total	223	223

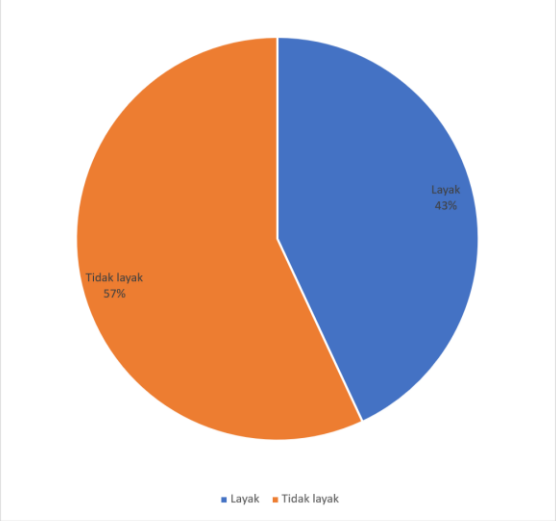

Figure 3. Debtor Eligibility Distribution – SMART

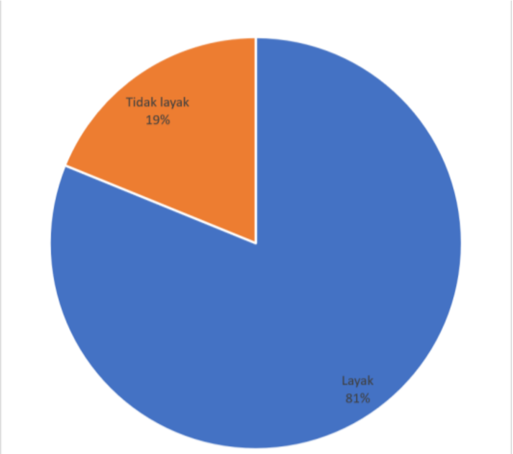

Figure 4. Debtor Eligibility Distribution – ARAS Method

The difference in the number of applicants classified as eligible by the two methods is primarily attributed to their different normalization and aggregation mechanisms. In the SMART method, utility values are calculated based on the distance between the minimum and maximum values of each criterion, as defined in Equations (1) and (2). Consequently, alternatives receiving low scores on highly weighted criteria, particularly monthly income (weight = 0.25) and occupation (weight = 0.20), experience a substantial reduction in their final preference scores. This characteristic makes SMART more sensitive to variations among criterion values, resulting in a more selective evaluation process. These findings are consistent with the observations of Taherdoost and Mohebi, who reported that SMART is highly influenced by criterion weights while remaining transparent and easy to interpret [9].

In contrast, the ARAS method normalizes criterion values based on their ratios to the total values of all alternatives for each criterion, as described in Equations (4) and (5). As a result, every alternative receives a contribution from each criterion without experiencing a significant decrease in the final score due to a single low criterion value. This optimal solution approach produces a more balanced distribution of preference scores, allowing a larger number of applicants to exceed the eligibility threshold. This finding is consistent with the study by Pinem *et al.*, which reported that ARAS achieved higher accuracy than SMART and ELECTRE in a priority determination problem [8]. It also agrees with the results of Goswami and Behera, who demonstrated the robustness of the ARAS method under various data conditions [11].

Despite these differences, both methods consistently ranked ADNAN FADLI as the highest-ranked applicant and ABDILLAH as the lowest-ranked applicant. This indicates that both methods produce consistent results for applicants with clearly distinguishable characteristics. Such consistency supports the validity of both methods in identifying applicants who are clearly eligible or clearly ineligible for financing. The differences between the methods mainly occur for applicants with mixed criterion profiles, commonly referred to as borderline cases, as also reported by Brata *et al.* in their comparative study of TOPSIS and ARAS [3].

From a practical perspective, the more stringent evaluation mechanism of SMART is appropriate when PT Mega Central Finance (MCF) aims to minimize the risk of loan default through a more conservative applicant selection process. Conversely, the more flexible evaluation approach of ARAS, which considers the contribution of all criteria in a balanced manner, is better suited for organizations seeking to expand the number of eligible applicants without overlooking credit risk considerations. This observation is consistent with the application of ARAS for motorcycle financing eligibility assessment by Azzahra *et al.* [5] and for sustainable supplier evaluation by Ahmed and Rezaei [17].

E. Sensitivity Analysis

To address the concern that the reported comparison between SMART and ARAS might be an artifact of the specific criterion weights and eligibility threshold chosen by the researchers, a quantitative sensitivity analysis was conducted on the full dataset of 223 applicants using three complementary tests: (i) a weight-perturbation test, in which the weight of each criterion was individually increased or decreased by 10% and 20% while the remaining six weights were rescaled proportionally to preserve a total of 1.00; (ii) a threshold-sweep test, in which the eligibility threshold was varied from 0.50 to 0.70 in increments of 0.05; and (iii) a structural extreme-value test, in which a single applicant's score on one criterion at a time was shifted from the observed minimum to the observed maximum while holding all other criterion values fixed, in order to directly quantify each method's responsiveness to an extreme value.

Table VIII summarizes the weight-perturbation results. Across all seven criteria and both perturbation magnitudes (±10% and ±20%), the number of applicants classified as eligible changed by at most 6 out of 223 (2.7%) for either method, and the Spearman rank-order correlation between the perturbed ranking and the baseline ranking remained above 0.99 in every case. This indicates that the SMART and ARAS rankings, and consequently the practical eligibility decision, are robust to plausible imprecision in the expert-elicited weights, which mitigates the subjectivity concern raised regarding the single-expert weighting procedure described in Section II.C.

TABLE VIII
WEIGHT-PERTURBATION SENSITIVITY (±10% AND ±20% PER CRITERION, OTHERS RESCALED)

Criterion perturbed	**Weight change**	**SMART eligible (Δ vs. baseline 96)**	**ARAS eligible (Δ vs. baseline 181)**	**Rank correlation ρ (SMART)**	**Rank correlation ρ (ARAS)**
C1 (Age)	−20%	96 (0)	178 (−3)	0.996	0.998
C1 (Age)	+20%	96 (0)	183 (+2)	0.997	0.998
C2 (Income)	−20%	101 (+5)	176 (−5)	0.996	0.997
C2 (Income)	+20%	95 (−1)	181 (0)	0.993	0.996
C3 (Occupation)	−20%	92 (−4)	182 (+1)	0.992	0.990
C3 (Occupation)	+20%	93 (−3)	175 (−6)	0.991	0.992
C4–C7 (remaining criteria)	−20% to +20%	95–97 (−1 to +1)	178–183 (−3 to +2)	≥0.996	≥0.996

The largest eligible-count movements occur for C2 (Income, weight = 0.25) and C3 (Occupation, weight = 0.20), the two most heavily weighted criteria, which is expected and consistent with the criteria's intended influence rather than indicating instability.

TABLE IX
ELIGIBILITY THRESHOLD SENSITIVITY (223 APPLICANTS)

Threshold	**SMART eligible**	**SMART %**	**ARAS eligible**	**ARAS %**
0.50	145	65.0%	221	99.1%
0.55	119	53.4%	211	94.6%
0.60 (used in this study)	96	43.0%	181	81.2%
0.65	68	30.5%	145	65.0%
0.70	47	21.1%	104	46.6%

Table IX shows that the eligible proportion under ARAS remains consistently higher than under SMART at every threshold level examined, confirming that the more inclusive behavior of ARAS reported in Section III.D is not an artifact of the particular 0.60 cut-off but a persistent property of its normalization mechanism. As expected, both methods become more conservative as the threshold increases, and the gap between the two methods narrows at the highest threshold (0.70), where fewer applicants of either method retain a sufficiently high score.

To directly test the claim that SMART is more sensitive to extreme criterion values than ARAS, rather than relying on interpretation alone, the structural extreme-value test described above was applied to every criterion. For each criterion, a single applicant's score was moved from the sample minimum to the sample maximum while all other criterion values were held fixed, and the resulting change in the final preference score (ΔVi for SMART, Ki for ARAS) was recorded. The results are presented in Table X.

TABLE X
STRUCTURAL SENSITIVITY OF SMART AND ARAS TO A SINGLE EXTREME CRITERION VALUE

Criterion	**Weight (wj)**	**Δ SMART score (min→max)**	**Δ ARAS score (min→max)**	**Ratio (SMART / ARAS)**
C1 (Age)	0.10	+0.1000	+0.0637	1.57×
C2 (Income)	0.25	+0.2500	+0.1875	1.33×
C3 (Occupation)	0.20	+0.2000	+0.1450	1.38×
C4 (Marital status)	0.10	+0.1000	+0.0453	2.21×
C5 (Dependents, cost)	0.10	−0.1000	−0.0753	1.33×
C6 (Outstanding debt, cost)	0.15	−0.1500	−0.0867	1.73×
C7 (Down payment)	0.10	+0.1000	+0.0686	1.46×

Table X provides direct numerical evidence for the claim discussed in Section III.D. For every one of the seven criteria, moving a single applicant from the observed minimum to the observed maximum produces a larger absolute change in the SMART preference score than in the ARAS utility degree, with the SMART-to-ARAS sensitivity ratio ranging from 1.33× to 2.21× (mean 1.57×) across criteria. This occurs because the SMART utility value is rescaled linearly between the sample minimum and maximum for every criterion (Equations 1–2), so that an applicant occupying either extreme always receives the full weight wj regardless of how the other 222 applicants are distributed; in ARAS, by contrast, a criterion value is normalized as a ratio to the sum of all 223 applicants' (plus the optimal alternative's) values (Equations 4–5), so the same extreme value is diluted by the aggregate magnitude of the remaining data and therefore shifts the final score by a smaller amount. This structural difference is also reflected at the distribution level: the standard deviation of the final scores relative to their mean (coefficient of variation) is 26.1% for SMART (Vi) versus 14.4% for ARAS (Ki), and the observed score range across all 223 applicants is 0.683 for SMART versus 0.463 for ARAS. Both the per-criterion extreme-value test and the overall score-dispersion statistics therefore provide converging, data-driven confirmation that SMART produces a more spread-out and extreme-value-sensitive score distribution than ARAS, rather than this being solely an interpretive claim.

F. Study Limitations

This study has several limitations that should be considered when interpreting the findings. First, the dataset was obtained from a single branch office of PT Mega Central Finance (MCF) during the 2024–2025 period; consequently, the generalizability of the findings to other branches, financing companies, or time periods may be limited. Second, as noted in Section II.C, the criterion weights were derived from the judgment of a single credit analyst; although this reflects direct operational expertise, it introduces a degree of subjectivity that could not be cross-validated against multiple raters. Third, the eligibility threshold of 0.60 was set by the researchers based on a general decision-support-system evaluation concept rather than a formal policy of PT MCF or an empirically calibrated cut-off; although Section III.E shows that the relative behavior of SMART and ARAS is stable across threshold values from 0.50 to 0.70, the specific cut-off itself was not derived from or validated against actual credit outcomes. Fourth, and most notably, this study did not have access to the applicants' actual credit repayment status (e.g., current, delinquent, or default); consequently, the eligibility classifications produced by the SMART and ARAS methods could not be validated against real-world credit outcomes, and accuracy, precision, recall, and F1-score metrics could not be computed. Future research is encouraged to incorporate actual repayment performance data as ground truth and to involve multiple experts with a formal consistency-check procedure such as pairwise comparison in the Analytic Hierarchy Process, building on the weight- and threshold-sensitivity evidence already established in Section III.E of this study.

IV. CONCLUSION

This study implemented and compared the SMART and ARAS methods in a decision support system for motorcycle financing eligibility assessment using data from 223 loan applicants at PT Mega Central Finance (MCF) Lhokseumawe Branch based on seven evaluation criteria. The results showed that the SMART method classified 96 applicants as eligible and 127 applicants as not eligible, whereas the ARAS method classified 181 applicants as eligible and 42 applicants as not eligible using an eligibility threshold of 0.60. These differences are primarily attributed to the distinct normalization mechanisms employed by the two methods. SMART calculates utility values based on the minimum and maximum range of each criterion, making it more sensitive to variations in criterion values and therefore more selective. In contrast, ARAS normalizes criterion values based on the ratio of each alternative to the total value of all alternatives, resulting in a more balanced distribution of preference scores and a more flexible eligibility assessment.

The main contribution of this study is the provision of comparative empirical evidence regarding the characteristics of two widely used Multi-Criteria Decision-Making (MCDM) methods using real-world data from the motorcycle financing sector. The findings provide practical guidance for financing companies in selecting an appropriate credit eligibility evaluation method according to their risk management policies. Specifically, the SMART method is more suitable for organizations adopting a conservative lending strategy with stricter applicant selection, whereas the ARAS method is more appropriate for organizations seeking a more inclusive evaluation process while maintaining a structured assessment of credit risk.

ACKNOWLEDGMENT

The authors gratefully acknowledge PT Mega Central Finance (MCF) Lhokseumawe Branch for granting permission to conduct this study and for providing the data and support necessary for the completion of this research.

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