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A Decision Support System for Credit Granting Using the Simple Additive Weighting (SAW) Method

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***Abstract*— CodeArtisan Auto Finance is a rural savings and loan institution whose creditworthiness assessment process is still performed manually through document verification, field surveys, and subjective evaluation. This process requires one to five days and increases the risk of human error. This study applies the Simple Additive Weighting (SAW) method within a Decision Support System (DSS) to improve the speed and accuracy of credit decision-making. The proposed system evaluates prospective customers based on ten criteria: collateral, loan term, domicile status, employment status, social obligations, relationship with savings products, loan amount, expenditure-to-income ratio, planned installment-to-income ratio, and credit history. Evaluation on 37 historical customer records achieved an accuracy of 81.08%, precision of 90.32%, and recall of 87.50%, demonstrating that the SAW method provides objective and consistent creditworthiness recommendations. Therefore, the implementation of the SAW method can support faster, more transparent, and reliable credit decision-making at CodeArtisan Auto Finance.**

***Intisari*— CodeArtisan Auto Finance merupakan lembaga keuangan simpan pinjam yang melayani masyarakat di wilayah pedesaan. Proses penilaian kelayakan kredit masih dilakukan secara manual melalui verifikasi dokumen, survei lapangan, dan evaluasi subjektif, sehingga membutuhkan waktu satu hingga lima hari serta berpotensi menimbulkan kesalahan akibat faktor manusia. Penelitian ini menerapkan metode Simple Additive Weighting (SAW) dalam Sistem Pendukung Keputusan (SPK) untuk meningkatkan kecepatan dan akurasi pengambilan keputusan kredit. Penilaian dilakukan berdasarkan sepuluh kriteria, yaitu jaminan, jangka waktu pinjaman, status domisili, status pekerjaan, tanggungan sosial, hubungan dengan produk simpanan, jumlah pinjaman, rasio pengeluaran terhadap pendapatan, rasio angsuran terhadap pendapatan, dan riwayat kredit. Pengujian terhadap 37 data historis nasabah menghasilkan akurasi sebesar 81,08%, presisi sebesar 90,32%, dan recall sebesar 87,50%. Hasil tersebut menunjukkan bahwa metode SAW mampu memberikan rekomendasi kelayakan kredit secara objektif, konsisten, dan lebih efisien dibandingkan dengan penilaian manual. Dengan demikian, penerapan metode SAW dapat mendukung proses pengambilan keputusan kredit yang lebih cepat, transparan, dan andal di CodeArtisan Auto Finance.**

***Kata Kunci*— Decision Support System; Simple Additive Weighting; Credit Granting; Multi-Criteria Decision Making.**

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I. INTRODUCTION

CodeArtisan Auto Finance is a company engaged in the financial sector, specifically providing savings and loan services to rural communities, where access to funding remains limited. Since its establishment in 2000, the company has contributed to supporting local economic activities by providing credit facilities, thereby playing an important role in the development of the financial sector in underserved areas. In 2019, CodeArtisan Auto Finance received 322 loan applications from customers, reflecting the high demand for its financing services. In this context, the effectiveness of the loan disbursement process is highly dependent on the accuracy and consistency of loan eligibility assessments for prospective borrowers [1][2].

Creditworthiness assessment is one of the most critical stages in the loan disbursement process at CodeArtisan Auto Finance. However, this process is still primarily conducted manually, including document verification, field surveys, and evaluations based on several criteria that heavily rely on the subjective judgment of officers. This condition often leads to longer decision-making times, increases the risk of human errors, and causes inconsistencies in assessment results. Consequently, service quality and customer satisfaction regarding credit decisions may be negatively affected. Therefore, a more objective, standardized, and systematic assessment mechanism is required to support faster and more accurate decision-making [3][4].

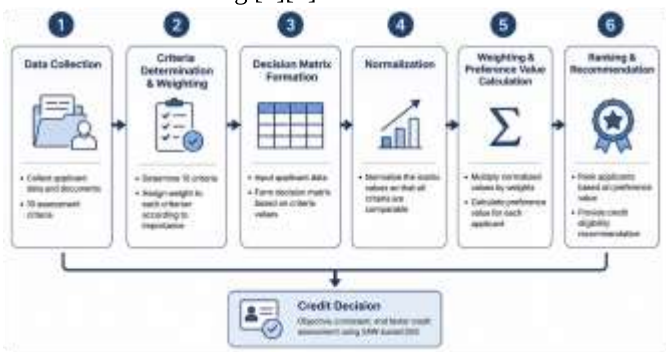

Figure 1: Overview of Creditworthiness Assessment.

One approach that can be used to address this problem is the implementation of a Decision Support System (DSS). A DSS provides a structured and data-driven framework to support the evaluation and decision-making process. Through a DSS, organizations can systematically integrate quantitative data with expert knowledge, thereby reducing dependence on intuition and subjective judgment [5].

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Among the various methods used in a Decision Support System (DSS), Simple Additive Weighting (SAW) is one of the most widely applied methods in multi-criteria decision-making. This method works by normalizing the value of each alternative for each criterion, assigning weights according to their importance, and then aggregating the values into a single final preference value [6][7]. SAW is considered suitable for the creditworthiness evaluation process because it offers high efficiency, simple computation, transparency in calculations, and the ability to evaluate multiple alternatives simultaneously [8]. Recent studies in the same journal have also demonstrated that SAW-based decision support remains an actively developed approach for operational decision-making in the electrical and information technology domains [9][10]. This trend is further supported by a growing body of studies published between 2022 and 2025 that continue to apply SAW to various institutional decision-making problems, including pension credit approval [11], student achievement selection [12], school selection [13], scholarship selection [14], and public health center selection combined with the Weighted Product method [15]. These findings confirm that SAW remains a relevant and actively researched method rather than an outdated technique.

Considering this, CodeArtisan Auto Finance has the opportunity to implement a credit assessment system using a Decision Support System, as illustrated in Figure 1. The proposed system utilizes ten key credit assessment criteria: collateral, loan term, domicile status, employment status, social obligations, relationship with savings products, loan amount, expenditure ratio, installment ratio, and credit history. The SAW method was selected to develop a DSS capable of providing objective, consistent, and accurate credit decisions [16][17]. By implementing SAW, CodeArtisan Auto Finance is expected to improve the speed and objectivity of credit assessments, enhance operational efficiency, and reduce subjectivity in officer evaluations. Therefore, this approach can support the company’s vision and mission while improving customer satisfaction.

II. Related Works

Several previous studies have applied the Simple Additive Weighting (SAW) method in the context of loan or creditworthiness assessment. Rosad [16] developed a decision support system for loan provision in a multi-purpose cooperative, where the main issue addressed was that loan application assessments were still subjective and did not consider measurable eligibility percentages. The proposed system assisted cooperative leaders in determining loan eligibility based on predefined criteria.

Another study by Wiryawan et al. [17] implemented the SAW method for a decision support system in debtor acceptance at a savings and loan cooperative, resulting in a web-based system for ranking and selecting prospective debtors. A related SAW-based ranking system for public procurement decisions was also reported for the Denpasar city government [18], confirming that the method can be generalized beyond the financial sector. More recently, Isabella and Sardjono [11] applied SAW specifically for pension-credit approval at a bank branch office, while Khaliq et al. [14] and Setyani and Sipayung [12] used SAW for scholarship and student-achievement selection, and Suhartono et al. [13] applied SAW for school selection. However, these 2023–2024 studies still rely on four to six generic criteria and mainly report ranking results without quantitative validation against actual decision outcomes. Overall, these studies indicate that the SAW method is suitable for selecting the best alternatives based on multi-criteria evaluation in financial and lending domains [17, 6].

Furthermore, Iskandar et al. [19] highlighted the importance of big data processing in modern decision-making, particularly how data analysis techniques can improve evaluation objectivity across various fields. In another study, Iskandar and Supartha [20] applied Fuzzy C-Means and Fuzzy Subtractive methods to identify hidden patterns in large datasets, demonstrating that computational approaches can enhance analytical accuracy. These findings support the application of the SAW method in this study as a systematic approach for generating more objective and data-driven decisions.

Beyond SAW, the same author group has previously investigated other multi-criteria and optimization-based decision-support techniques for institutional decision problems, including a nonformal test-based gamification model to improve student motivation [21], a Profile Matching approach for determining outstanding educational staff [22], and a genetic-algorithm-based approach for optimizing final-project examination scheduling [23]. Positioning this SAW-based credit assessment study within this research trajectory demonstrates a consistent effort toward applying and comparing computational decision-support techniques, including SAW, Profile Matching, genetic algorithms, and clustering, across various institutional decision problems. This background motivates the criteria design and validation strategy adopted in this study, which is also aligned with similar profile-matching applications for scholarship and personnel-related decision-making [24].

Novelty of this study. Unlike previous SAW-based studies that generally employ four to six generic criteria for cooperative or personnel selection problems, this study develops and validates a decision model using ten domain-specific credit assessment criteria that integrate customer profile attributes (e.g., domicile, employment status, and social obligations) with quantitative financial indicators (e.g., expenditure-to-income ratio, installment-to-income ratio, and credit history) for a rural auto-finance institution. Furthermore, the proposed SAW model is evaluated using 37 historical loan decisions through confusion-matrix analysis, providing accuracy, precision, and recall measurements that are rarely reported in comparable SAW-based credit assessment studies. Therefore, the primary contribution of this work lies in the development of a domain-specific decision model and its empirical validation rather than in modifying the SAW algorithm itself.

The SAW computation presented in Equations (1)–(2) follows the standard formulation of the standard normalization and weighted-summation procedure established in the literature is adopted in this study [25][26]. The methodological novelty instead lies in two aspects: (i) the use of an empirically validated decision threshold ($V_i \geqslant 0.50$), derived from CodeArtisan Auto Finance’s operational policy and verified through confusion-matrix analysis against historical decisions, and (ii) the integration of ten qualitative and quantitative credit-risk indicators into a unified SAW decision matrix, extending the narrower criterion sets commonly adopted in previous studies [16][12[13]. Although recent studies have proposed genuine extensions to the SAW algorithm itself, such as sub-alternative preference aggregation [27], algorithm modification is beyond the scope of this work.

A. Decision Support System

A Decision Support System (DSS) is an information system designed to assist decision-makers in addressing semi-structured and unstructured problems through the provision of information, modeling, and flexible analytical tools [5][28]. DSS is not intended to replace decision-makers but rather to enhance their capabilities in processing information and evaluating various decision alternatives [17].

The advantages of DSS include accelerating the resolution of complex problems, improving decision-making consistency, providing various alternative solutions, and increasing decision-makers' confidence in the policies adopted [5][29]. In the context of credit provision, DSS can assist financial institutions in assessing customer creditworthiness more objectively and systematically through documented evaluation processes, thereby reducing dependence on manual assessments.

B. Definition of Credit

Etymologically, the term credit originates from the Latin word credere, which means trust. Credit represents the lender's confidence that borrowed funds will be repaid according to the agreed terms [1]. Banking Law Number 10 of 1998 defines credit as the provision of money or equivalent claims based on an agreement between a bank and another party, in which the borrower is required to repay the debt within a specified period along with interest [2].

Credit serves several important functions in the economy, including increasing the utility of money, facilitating money circulation, improving the utility of goods, supporting economic stability, encouraging entrepreneurship, and promoting income distribution through the creation of new employment opportunities [1][3]. The effectiveness of credit management is strongly influenced by the quality of creditworthiness analysis, as this process plays an essential role in reducing credit default risks and maintaining the sustainable performance of financial institutions.

C. Simple Additive Weighting (SAW) Method

The Simple Additive Weighting (SAW) method, also known as the weighted-sum method, is used to determine the preference value of an alternative by calculating the sum of the products between the performance rating of each alternative on each criterion and the predetermined weight of each criterion [6]. The basic principle of this method begins with the construction of a decision matrix, followed by normalization according to the criterion type, namely benefit or cost attributes. The normalized values are then multiplied by the corresponding criterion weights to obtain the final preference score for each alternative [7][8].

In general, the implementation stages of the SAW method include identifying alternatives and criteria, determining criterion weights, constructing the decision matrix, normalizing values based on benefit or cost attributes, and calculating the final preference values to rank alternatives [25][26]. The detailed steps applied in this study are presented in Section III.C. The SAW method provides several advantages, including simple implementation, ease of interpreting computational results, and the ability to generate clear rankings of alternatives based on the obtained scores [30].

In the context of credit provision at CodeArtisan Auto Finance, the SAW method is applied to integrate ten evaluation criteria, including collateral, loan term, domicile status, employment status, social obligations, relationship with savings products, loan amount, expenditure ratio, installment ratio, and credit history, into a single preference value representing the customer's credit eligibility.

III. Methodology

This study applies the Simple Additive Weighting (SAW) method to support decision-making in creditworthiness assessment at CodeArtisan Auto Finance. The research stages follow the workflow presented in Figure 2, consisting of data collection, requirements analysis, system design, implementation, and testing [5].

A. Research Stages

The research stages are described as follows:

1. Problem Identification
   The credit provision process at CodeArtisan Auto Finance was observed and analyzed. The current process is still conducted manually and requires a relatively long time to verify customer creditworthiness, which may affect the efficiency and consistency of credit decisions [3].
2. Data Collection
   The criteria and subcriteria data were obtained from CodeArtisan Auto Finance's credit assessment policies. The collected data consist of ten main criteria, including collateral, loan term, domicile status, employment status, social obligations (KSK), relationship with savings products, loan amount, expenditure ratio, installment ratio, and credit history [16].
3. System and SAW Model Design
   The SAW mathematical model is designed by normalizing the value of each criterion and calculating the final preference score based on the assigned criterion weights.
4. System Implementation
   The system is implemented as a web-based application to facilitate the management of criteria, alternatives, decision matrices, normalization processes, and alternative ranking.
5. Testing and Evaluation

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The system was evaluated using 37 actual customer credit records. The SAW calculation results were compared with the actual credit decisions using a confusion matrix analysis to measure accuracy, precision, and recall.

B. Research Workflow

The research workflow refers to the process illustrated in Figure 2, which describes the main stages involved in developing a SAW-based Decision Support System [6]. The workflow consists of four main stages: (1) Data Collection, which involves collecting relevant data from customers, credit histories, financial records, and other supporting sources; (2) System Design, which includes the design of the system architecture, database structure, user interface, and SAW calculation module; (3) System Implementation, which involves developing the system based on the designed specifications; and (4) Testing and Evaluation, which aims to measure the accuracy and effectiveness of the system in supporting credit decision-making.

Figure 2: Research workflow for developing a SAW-based decision support system.

C. Simple Additive Weighting (SAW) Algorithm

The SAW method is a weighted-sum approach used to determine the best alternative based on normalized values and criterion weights. The fundamental concept of this method is to calculate the sum of the products between normalized performance ratings and the corresponding preference weights [7] [8]. The steps of the SAW algorithm applied in this study are as follows:

1. Determine the set of alternatives (A_i).
2. Determine the set of evaluation criteria (C_j).
3. Determine the preference weights of each criterion W = (w_1, w_2, ..., w_n) according to their relative importance.
4. Construct the decision matrix X = [x_{ij}], which contains the performance ratings of each alternative for every criterion.
5. Normalize the decision matrix X to obtain the normalized matrix R using Equation (1).
6. Calculate the preference value V_i for each alternative using Equation (2).

D. Normalization Formula

The decision matrix is normalized to ensure that criteria with different units, scales, and measurement directions become comparable within the range of [0, 1]. The normalization process applies two rules depending on the attribute type. A benefit attribute, where a higher value indicates a better alternative (e.g., collateral and credit history), uses the maximum value in the criterion column as the divisor. Meanwhile, a cost attribute, where a lower value represents a better alternative (e.g., expenditure-to-income ratio), uses the minimum value in the criterion column as the numerator.

$$R_{ij} = \begin{cases} \dfrac{x_{ij}}{\max\limits_{k} x_{kj}}, & \text{if } C_j \text{ is benefit,} \\ \dfrac{\min\limits_{k} x_{kj}}{x_{ij}}, & \text{if } C_j \text{ is cost.} \end{cases} \tag{1}$$

where x_{ij} represents the attribute value of alternative A_i for criterion C_j. The term $\max_k x_{kj}$ represents the maximum value of criterion j among all alternatives, while $\min_k x_{kj}$ represents the minimum value of criterion j among all alternatives.

E. Preference Value Calculation

After obtaining the normalized matrix R, the preference value of each alternative is calculated as follows:

$$V_i = \sum_{j=1}^{n} w_j R_{ij} \tag{2}$$

where V_i represents the preference value of the i-th alternative, w_j represents the weight of the j-th criterion, and R_{ij} represents the normalized rating of alternative A_i for criterion C_j. A higher value of V_i indicates a higher level of creditworthiness, and this value is used to rank the alternatives.

F. SAW Calculation Example (Case Study)

The following section presents a manual calculation example using Equations (1)–(2) for 10 alternatives (A_1–A_{10}) and 10 criteria (C_1–C_{10}) based on the case-study data presented in Tables 5.16–5.19. The decision matrix X and weight vector W are adopted from the source document.

Decision Matrix *X*

$$X = \begin{bmatrix} 2 & 3 & 4 & 2 & 3 & 1 & 3 & 2 & 2 & 3 \\ 3 & 3 & 3 & 2 & 2 & 3 & 2 & 3 & 1 & 3 \\ 3 & 4 & 4 & 3 & 3 & 4 & 4 & 2 & 3 & 1 \\ 4 & 2 & 4 & 4 & 4 & 4 & 4 & 2 & 3 & 1 \\ 2 & 3 & 2 & 2 & 2 & 2 & 2 & 4 & 3 & 4 \\ 0 & 2 & 4 & 2 & 3 & 3 & 2 & 3 & 2 & 1 \\ 0 & 3 & 4 & 2 & 2 & 1 & 3 & 2 & 2 & 2 \\ 2 & 3 & 1 & 2 & 2 & 3 & 2 & 3 & 3 & 4 \\ 1 & 3 & 3 & 2 & 3 & 3 & 3 & 3 & 4 & 4 \\ 2 & 3 & 3 & 2 & 3 & 2 & 2 & 4 & 4 & 2 \end{bmatrix} \tag{3}$$

Preference Weights *W* The weights according to CodeArtisan Auto Finance policy are:

$$W = \begin{bmatrix} 0.25 & 0.10 & 0.05 & 0.05 & 0.05 \\ 0.10 & 0.10 & 0.10 & 0.10 & 0.10 \end{bmatrix} \tag{4}$$

The sum of all criterion weights is equal to 1. Criteria C_1–C_6 are categorized as benefit attributes, where higher values indicate

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better alternatives, while criteria C_7–C_{10} are categorized as cost attributes, where lower values indicate better alternatives.
Normalized Matrix R (rounded to 4 decimals)

$$R \approx \begin{bmatrix} 0.5000 & 0.7500 & 1.0000 & 0.5000 & 0.7500 & 0.2500 & 0.3333 & 0.5000 & 0.5000 & 0.3333 \\ 0.7500 & 0.7500 & 0.7500 & 0.5000 & 0.5000 & 0.7500 & 0.5000 & 0.3333 & 1.0000 & 0.3333 \\ 0.7500 & 1.0000 & 1.0000 & 0.7500 & 0.7500 & 1.0000 & 0.2500 & 0.5000 & 0.3333 & 1.0000 \\ 1.0000 & 0.5000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 0.2500 & 0.5000 & 0.3333 & 1.0000 \\ 0.5000 & 0.7500 & 0.5000 & 0.5000 & 0.5000 & 0.5000 & 0.5000 & 0.2500 & 0.3333 & 0.2500 \\ 0.0000 & 0.5000 & 1.0000 & 0.5000 & 0.7500 & 0.7500 & 0.5000 & 0.3333 & 0.5000 & 1.0000 \\ 0.0000 & 0.7500 & 1.0000 & 0.5000 & 0.5000 & 0.2500 & 0.3333 & 0.5000 & 0.5000 & 0.5000 \\ 0.5000 & 0.7500 & 0.2500 & 0.5000 & 0.5000 & 0.7500 & 0.5000 & 0.3333 & 0.3333 & 0.2500 \\ 0.2500 & 0.7500 & 0.7500 & 0.5000 & 0.7500 & 0.7500 & 0.3333 & 0.3333 & 0.2500 & 0.2500 \\ 0.5000 & 0.7500 & 0.7500 & 0.5000 & 0.7500 & 0.5000 & 0.5000 & 0.2500 & 0.2500 & 0.5000 \end{bmatrix} \tag{5}$$

Preference Value Calculation Example For alternative $A1$ (row 1), applying Equation (2) :

$$\begin{aligned} V_1 &= 0.25(0.5000) + 0.10(0.7500) + 0.05(1.0000) + 0.05(0.5000) \\ &\quad +0.05(0.7500) + 0.10(0.2500) + 0.10(0.3333) \\ &\quad +0.10(0.5000) + 0.10(0.5000) + 0.10(0.3333) \\ &\approx 0.5042. \end{aligned} \tag{6}$$

Table 1. Preference Values (V_i) and Decision Results (Threshold = 0.50)

Alternative	V_i	**Decision**
A_1	0.5042	Recommended
A_2	0.6417	Recommended
A_3	0.7208	Recommended
A_4	0.7583	Recommended
A_5	0.4583	Not Recommended
A_6	0.4708	Not Recommended
A_7	0.3833	Not Recommended
A_8	0.4792	Not Recommended
A_9	0.4292	Not Recommended
A_{10}	0.5000	Threshold (Policy: $V_i \geq 0.50$)

Preference Values for All Alternatives

G. System Evaluation

System evaluation is conducted using the confusion matrix method with three main performance metrics [31]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

Testing on 37 customer data records resulted in an accuracy of 81.08%, a precision of 90.32%, and a recall of 87.50%, indicating that the SAW method can provide effective credit decision recommendations [17]. The detailed confusion matrix results are presented in Section IV.D.

To provide an additional descriptive analysis of the decision matrix, a Pearson correlation heatmap was generated based on the ten evaluation criteria, as presented in Figure 3. The visualization illustrates the linear relationships between each pair of criteria. Overall, the correlations are generally low to moderate, indicating that each criterion provides complementary information rather than representing redundant measurements. This finding supports the preferential independence assumption commonly adopted in the Simple Additive Weighting (SAW) method, in which each criterion is evaluated independently before the weighted aggregation process.

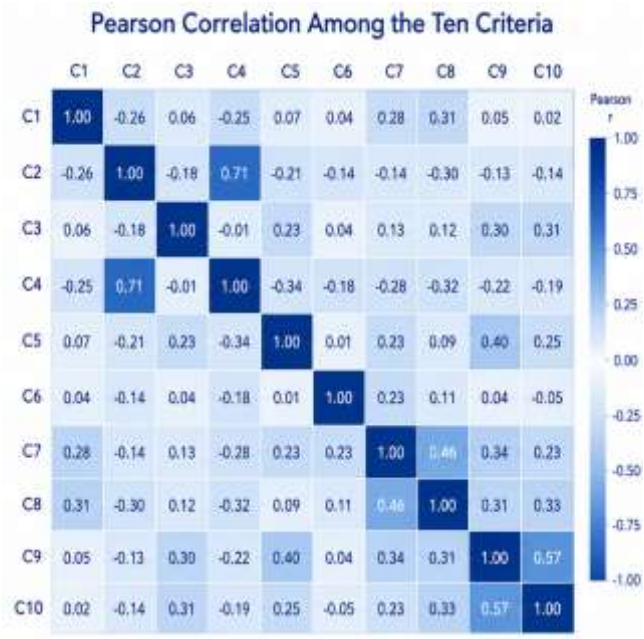

Figure 3: Pearson Correlation Heatmap.

IV. RESULT AND DISCUSSION

This section presents the results of implementing the Simple Additive Weighting (SAW) method in the credit decision support system developed for CodeArtisan Auto Finance. Testing was conducted using 37 historical customer data records, each containing actual credit decision labels. The SAW method was implemented as a web-based application. The following subsections describe the main system interfaces, decision matrix, normalization results, preference scores, and evaluation metrics.

The Login Page (Figure 4) serves as the initial access point for users to enter the system. Users are required to provide valid credentials to ensure that only authorized personnel can access administrative functions and data-processing features.

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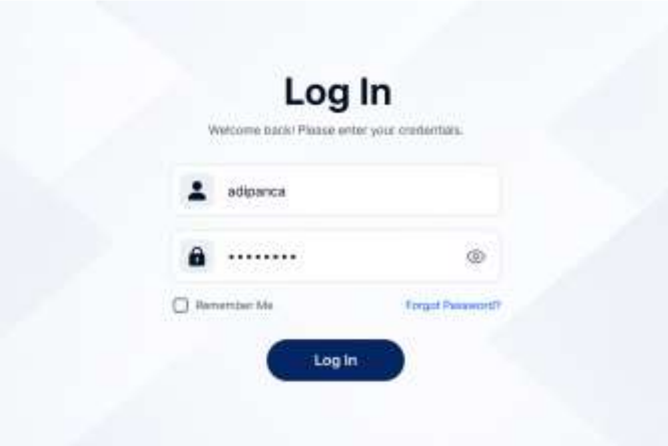

Figure 4: Login Page.

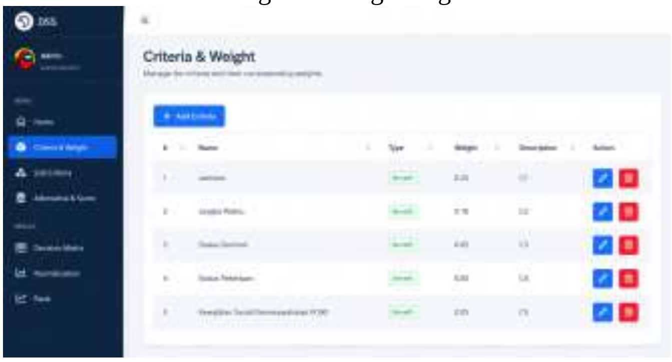

Figure 5: Criteria and weight page for setting criteria and weights.

The Criteria & Weight Page (Figure 5) is used to define the evaluation criteria required for decision-making. Users can assign weights to each criterion, which is an essential component in SAW calculations because the weights represent the relative importance of each criterion in the overall evaluation process.

Figure 6: Sub-criteria page for defining sub-criteria for each criterion.

The criteria are accompanied by rating scales used to classify evaluation scores, providing a structured assessment scheme that enables each alternative to be evaluated consistently. The Alternative & Score Page (Figure 7) allows users to input the list of alternatives to be evaluated and assign scores to each alternative based on the predefined criteria.

Figure 7: Alternative and score page for entering alternatives and scores foreach criterion

Figure 8: Decision matrix page used as the basis for normalization and preference-value calculations.

The Decision Matrix Page (Figure 8) displays the decision matrix containing the values of each alternative across all evaluation criteria. This matrix serves as the basis for the normalization process and preference-value calculation. Previously entered customer data are transformed into a matrix format to enable computational processing using the SAW method. This implementation enables automated, consistent, and more accurate calculations compared with conventional manual processes.

A. Decision Matrix

The decision matrix is the fundamental component in the SAW calculation process, containing the values of each alternative (customer) for all credit assessment criteria. Each element x_{ij} represents the performance value of alternative i with respect to criterion j, obtained by transforming qualitative assessment data into numerical scores according to CodeArtisan Auto Finance’s credit evaluation policy.

The creditworthiness evaluation in this study is performed based on ten criteria: collateral, loan term, domicile status, employment status, social obligations (KSK), relationship with savings products (HDPS), loan amount, expenditure-to-income ratio, installment-to-income ratio, and credit history. Mathematically, the decision matrix can be represented as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \tag{10}$$

where, in Equation (10), m represents the number of alternatives (customers) and n represents the number of criteria. The decision matrix is generated on the Alternatives and Scores page based on the credit officer's assessment results and the mapping of predefined sub-criteria. This matrix serves as the primary basis for producing objective and measurable creditworthiness evaluations.

B. Matrix Normalization

Normalization is performed to ensure that criteria with different units, scales, and measurement directions are standardized within the same range [0, 1] using Equation (1). This process prevents criteria with larger numerical scales from dominating the calculation and ensures that each criterion contributes proportionally to the final preference score. The normalization process produces matrix R, where $0 \leqslant R_{ij} \leqslant 1$. Values closer to 1 indicate better relative performance among alternatives. A complete calculation example is provided in Section III.F.

C. Preference Value Calculation and Ranking

After normalization, the preference score for each customer is calculated using Equation (2), where w_j represents the weight of criterion C_j determined by CodeArtisan Auto Finance, and R_{ij} represents the normalized score of alternative A_i for criterion C_j. In this study, collateral receives the highest weight (0.25), while the remaining nine criteria, including loan term, domicile status, employment status, social obligations, relationship with savings products, loan amount, expenditure ratio, installment ratio, and credit history, are assigned weights ranging from 0.05 to 0.10 [17].

A higher preference value (V_i) indicates a higher level of creditworthiness, representing a comprehensive evaluation of customer performance across all evaluated criteria. The preference values for the first ten sampled customers are presented in Figure 9. These values are used as the quantitative basis for ranking customers from the highest to the lowest creditworthiness.

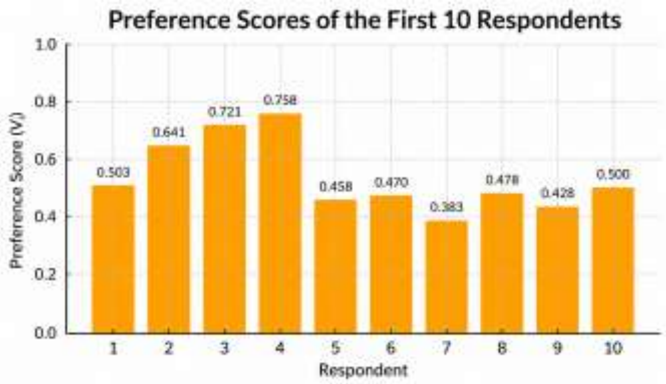

Figure 9: Preference values V_i for the first 10 customers.

To interpret the results, a threshold value of 0.50 is applied as the decision boundary: $V_i > 0.50$ indicates that a customer is recommended for credit approval, while $V_i \leqslant 0.50$ indicates that a customer is not recommended for credit approval. This threshold is defined based on CodeArtisan Auto Finance's policy to ensure that only customers demonstrating an adequate level of creditworthiness according to all evaluation criteria are recommended for credit approval.

The generated result represents a system recommendation rather than a final decision, as the final approval decision remains under the authority of the decision-maker. Overall, the ranking results demonstrate that the obtained preference scores are consistent with the actual credit decisions implemented by CodeArtisan Auto Finance. This indicates that the SAW method is effective as a foundation for objective and data-driven decision-making in customer creditworthiness evaluation.

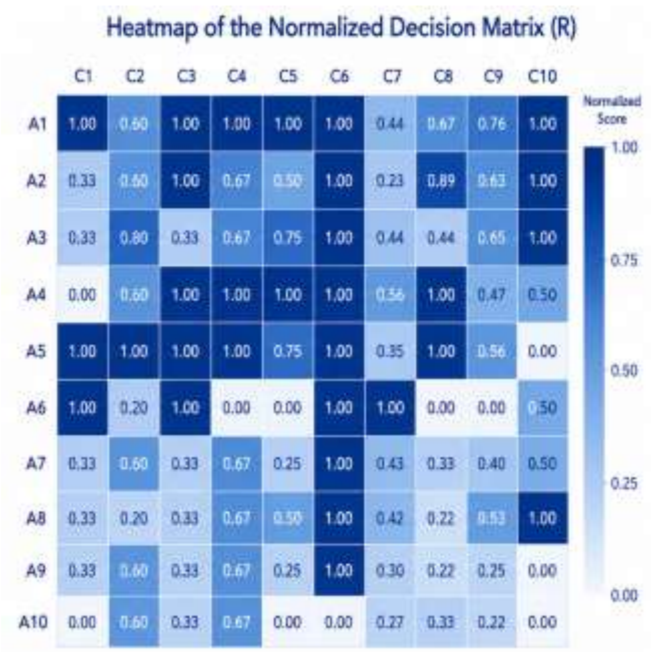

Figure 10: Heatmap of the normalized decision matrix (R).

Figure 10 presents the normalized decision matrix in the form of a heatmap. Brighter cells indicate higher normalized scores, whereas darker cells represent lower values after the normalization process. This visualization enables readers to identify the relative strengths and weaknesses of each customer across all evaluation criteria before the weighted preference calculation is performed. The heatmap also demonstrates that the normalization process successfully transforms heterogeneous criterion values into a comparable scale ranging from 0 to 1.

D. Evaluation Using Confusion Matrix

The performance of the SAW-based credit decision support system was evaluated by comparing the system classification results with the actual credit decisions recorded at CodeArtisan Auto Finance. A total of 37 historical customer records were used as test samples, and the results are presented in Table 2

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Table 2. Confusion Matrix of Testing Results

	Predicted Eligible	**Predicted Not Eligible**
Actual Eligible	28 (TP)	4 (FN)
Actual Not Eligible	3 (FP)	2 (TN)

Applying Equations (7)–(9) to the values presented in Table 2 results in an accuracy of 81.08%, a precision of 90.32%, and a recall of 87.50%, as summarized in Figure 11.

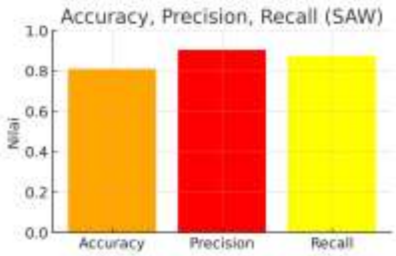

Figure 11: Confusion-matrix result of the SAW model.

The evaluation results can be interpreted as follows:

- Accuracy (81.08%) indicates that the system correctly classified the majority of customers, demonstrating the overall reliability of the SAW method in creditworthiness evaluation.
- Precision (90.32%) indicates that most customers predicted as eligible were indeed creditworthy, reducing the risk of recommending credit approval for customers who do not meet the eligibility requirements.
- Recall (87.50%) demonstrates that the system successfully identified a high proportion of customers who were actually eligible, ensuring that qualified applicants were not overlooked.

These results confirm that the SAW method provides a reliable and data-driven mechanism for credit decision-making, with results that closely align with the actual decisions implemented at CodeArtisan Auto Finance. The high precision and recall values indicate that the system is capable of recommending qualified customers while minimizing the risk of inappropriate credit recommendations, thereby supporting consistent, objective, and fair credit evaluation.

V. *Conclusion*

Based on the implementation of the Simple Additive Weighting (SAW) method in the creditworthiness assessment decision support system at CodeArtisan Auto Finance, the proposed approach was successfully applied to evaluate customer creditworthiness using ten company-defined criteria: collateral, loan term, domicile status, employment status, social obligations, relationship with savings products, loan amount, expenditure ratio, installment ratio, and credit history. Through the weighting and normalization processes, the SAW method integrates all criteria into a single preference value that is measurable, objective, and easy to interpret.

The developed decision support system generates a ranking of potential customers based on the obtained preference values (V_i). Customers with preference values exceeding thepredefined threshold are considered to have a higher level of credit eligibility. System performance evaluation using a confusion matrix on 37 historical customer records achieved an accuracy of 81.08%, a precision of 90.32%, and a recall of 87.50%, demonstrating that the SAW method is effective in supporting the credit decision-making process. As discussed in Section II, the main contribution of this study lies in the development of a domain-specific ten-criterion decision matrix and its empirical validation using confusion-matrix analysis, rather than in modifying the underlying SAW formulation itself.

The implementation of the SAW-based decision support system also accelerates the credit analysis process and reduces subjectivity in officer evaluations, thereby improving operational efficiency while producing more consistent and standardized credit assessments within the CodeArtisan Auto Finance environment.

For future research, this study can be extended by integrating SAW with objective criterion-weighting techniques, such as Entropy or the Analytical Hierarchy Process (AHP), instead of relying solely on policy-defined weights. In addition, future studies may explore sub-alternative-level aggregation approaches recently proposed for SAW extensions [27], as well as hybridizing SAW with other decision-making methods, such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and machine-learning models, to potentially improve credit assessment accuracy.

The integration of additional external data sources, such as national credit history information and digital transaction behavior data, may further enhance the quality of evaluation results. Furthermore, the system can be expanded for broader operational deployment through real-time database integration, decision-monitoring features, and automated data-validation mechanisms. Continuous testing in the CodeArtisan Auto Finance production environment is also required to ensure that the system remains adaptive to changing customer-data characteristics over time.

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References

[1] B. Catur, "Pengamanan pemberian kredit bank dengan jaminan hak guna bangunan," Jurnal Cita Hukum, vol. II, no. 9, pp. 1689–1699, 2014.

[2] H. R. E. Efendhi, "Analysis of company financial statements in terms of providing credit to prospective customers," Jurnal EMBA, vol. 7, no. 3, pp. 4144–4153, 2019.

[3] N. N. Sudiyani and A. A. P. G. B. A. Susandya, "Fungsi sistem pengendalian intern dalam mencegah kredit macet," Jurnal Riset Akuntansi, vol. 8, no. 2, pp. 112–116, 2018.

[4] J. K. Karisma, "Sistem informasi kredit sahabat pada BUMDes Semamung berbasis web," Jurnal Inovasi Teknologi, vol. 2, no. 1, pp. 42–49, 2020.

[5] W. Setiyaningsih, Konsep Sistem Pendukung Keputusan. Yayasan Edelweis, 2015.

[6] Frieyadie, "Penerapan metode simple additive weight (SAW) dalam sistem pendukung keputusan promosi kenaikan jabatan," Jurnal Pilar Nusa Mandiri, vol. 12, no. 1, pp. 37–45, 2016.
[7] A. Supriyatna and D. Ekaputra, "Metode fuzzy simple additive weighting dalam pemilihan ketua OSIS," Jurnal PETIR, vol. 10, no. 1, pp. 71–76, 2017.
[8] E. Churchill and A. Singh, "A review of simple additive weighting method in decision support systems," International Journal of Decision Support Systems, vol. 5, no. 2, pp. 45–52, 2019.
[9] A. H. Hardiansyah, I. N. S. Kumara, and R. S. Hartati, "IoT berbasis NodeMCU ESP8266 sebagai decision support system pengelolaan energi gedung Telkomsel Renon," Majalah Ilmiah Teknologi Elektro, vol. 23, no. 1, pp. 103–116, 2024.
[10] S. Pramana, R. S. Hartati, and Y. Divayana, "Analisis metode sistem pendukung keputusan pemilihan waktu terbaik perubahan harga dinamis hotel," Majalah Ilmiah Teknologi Elektro, vol. 18, no. 2, 2019.
[11] S. Isabella and S. Sardjono, "Sistem pendukung keputusan pemberian kredit pensiun menggunakan metode SAW pada BNI Talang Banjar Jambi," Jurnal Manajemen Sistem Informasi, vol. 8, no. 2, pp. 287–298, 2023.
[12] I. A. Setyani and Y. R. Sipayung, "Sistem pendukung keputusan menentukan siswa berprestasi dengan metode SAW (Simple Additive Weighting)," Jurnal Sistem Komputer dan Informatika (JSON), vol. 4, no. 4, pp. 632–641, 2023.
[13] W. H. Suhartono, R. K. Niswatin, and R. Wulanningrum, "Pengembangan sistem pendukung keputusan untuk pemilihan sekolah menengah atas menggunakan metode Simple Additive Weighting," JATI (Jurnal Mahasiswa Teknik Informatika), vol. 8, no. 5, pp. 10051–10059, 2024.
[14] N. A. Khaliq, A. Josi, and L. Fujiyanti, "Sistem informasi pendukung keputusan seleksi beasiswa menggunakan metode SAW," JSITIK: Jurnal Sistem Informasi dan Teknologi Informasi Komputer, vol. 1, no. 2, pp. 94–108, 2023.
[15] A. Irawan, S. Ipnuwati, A. Tardiansyah, and A. Maseleno, "Decision support system for selecting the best public health center using Simple Additive Weighting (SAW) and Weighted Product (WP) methods," Journal of Artificial Intelligence, Machine Learning and Neural Network, no. 21, pp. 9–26, 2022.
[16] S. Rosad, "Sistem pendukung keputusan pemberian pinjaman menggunakan metode SAW," 2019.
[17] R. Ristiana and Y. Jumaryadi, "Sistem pendukung keputusan pemilihan paket wedding organizer menggunakan metode SAW," Jurnal Teknologi Informasi, vol. 10, pp. 25–30, 2021.
[18] W. Sanjaya, I. N. Sukajaya, and I. G. Gunadi, "Sistem pendukung keputusan pemilihan pemenang pengadaan jasa konstruksi pada Pemerintah Kota Denpasar dengan metode SAW berbasis fuzzy," Majalah Ilmiah Teknologi Elektro, vol. 18, no. 1, p. 15, 2019.
[19] A. P. S. Iskandar et al., Teknologi Big Data: Pengantar dan Penerapan Teknologi Big Data di Berbagai Bidang. PT Green Pustaka Indonesia, 2024.
[20] I. K. D. G. Supartha and A. P. S. Iskandar, "Analisis kinerja Fuzzy C-Means (FCM) dan Fuzzy Subtractive (FS) dalam clustering data alumni STMIK STIKOM Indonesia," INFORMAL: Informatics Journal, vol. 6, no. 1, pp. 41–51, 2021.
[21] A. P. S. Iskandar, M. Sudarma, and K. O. Saputra, "Nonformal test-based gamification model to improve student motivation," in 2018 International Conference on Smart Green Technology in Electrical and Information Systems (ICSGTEIS). IEEE, 2018, pp. 215–220.
[22] A. P. S. Iskandar and I. Pratistha, "Penentuan tenaga kependidikan berprestasi dengan menggunakan metode Profile Matching," INFORMAL: Informatics Journal, vol. 8, no. 1, pp. 1–11, 2023.
[23] A. P. S. Iskandar, "Optimasi penjadwalan ujian tugas akhir dengan menggunakan algoritma genetika," Journal of Computer Science and Informatics Engineering (J-Cosine), vol. 5, no. 1, pp. 40–48, 2021.
[24] S. Retno and N. Hasdyna, "Profile matching in government scholarship acceptance system for student in Aceh Utara," Journal of Informatics and Telecommunication Engineering, vol. 5, no. 2, pp. 268–275, 2022.
[25] K. Yoon and C. L. Hwang, Multiple Attribute Decision Making: An Introduction. SAGE Publications, 1995.
[26] E. Triantaphyllou, Multi-Criteria Decision Making Methods: A Comparative Study. Springer, 2000.
[27] P. Zandi, M. Ajalli, and N. S. Ekhtiyati, "An extended Simple Additive Weighting decision support system with application in the food industry," Decision Analytics Journal, vol. 14, p. 100553, 2025.
[28] L. Meilina, I. N. S. Kumara, and I. N. Setiawan, "Literature review klasifikasi data menggunakan metode cosine similarity dan artificial neural network," Majalah Ilmiah Teknologi Elektro, vol. 20, no. 2, pp. 307–314, 2021.
[29] D. O. Sumadya and H. H. Ginardi, "Perancangan dan implementasi basis data aplikasi web Fotokita," Jurnal Teknik ITS, vol. 5, no. 2, pp. 2–5, 2016.
[30] Salmon and B. Harpad, "Komparasi metode SAW dan AHP untuk pemilihan staf laboratorium," Jurnal Penelitian Komunikasi dan Opini Publik, vol. 22, no. 1, 2018.
[31] L. Meilina, N. P. Sastra, and D. M. Wiharta, "Lecturers admissions selections model using fuzzy k-nearest neighbor method," Jurnal Teknik Informatika (JUTIF), vol. 4, no. 2, pp. 449–456,

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