A Nonlinear Utility-Based GDSS Model for Village Development Priority Determination

Ubaidilah Aminuddin Thoyieb[1], Dyah Aruming Tyas[2*], Sri Mulyana[3]

[1] *Master of Computer Science, Universitas Gadjah Mada, Yogyakarta, Indonesia*
[2,3] *Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada, Yogyakarta, Indonesia*

*corr-author: dyah.aruming.t@ugm.ac.id

Abstract - The determination of village development priorities through Village Development Planning Deliberation often faces subjectivity, limited analytical instruments, and difficulties in evaluating multiple alternatives and criteria simultaneously. Conventional approaches such as Simple Additive Weighing (SAW) and TOPSIS exhibit different characteristics in distinguishing alternatives with similar evaluation profiles. This study proposed a group decision support system model based on nonlinear utility for adaptive collective decision-making. The model integrated the Analytical Hierarchy Process (AHP) for sector weighing, the Simple Multi-Attribute Rating Technique (SMART) with nonlinear utility functions for alternative evaluation, and the Borda method for preference aggregation. The proposed model was compared with AHP–SAW–Borda and AHP–TOPSIS–Borda using a case study involving 24 development program alternatives classified into 5 development sectors and evaluated using 6 assessment parameters. The results showed that the proposed model maintained globally consistent ranking structures across both comparison approaches. Spearman correlation coefficients reached 0.9389 for SMART versus SAW and 0.9519 for SMART versus TOPSIS, indicating strong consistency across additive and distance-based evaluation paradigms. Ranking variations mainly occurred among mid-ranked alternatives, while dominant priorities remained stable. The findings indicate that nonlinear utility transformation improves adaptive ranking sensitivity while preserving overall decision stability.

Keywords: AHP, SMART, borda, nonlinear utility, village priority.

I. INTRODUCTION

The determination of village development priorities through Village Development Planning Deliberation represents a collective decision-making process involving multiple stakeholders. However, in practice, this process still faces several limitations, including the dominance of subjectivity, the absence of analytical instruments, and difficulties in evaluating multiple alternatives and criteria simultaneously [1]. In addition, existing decision support models often have limited capability in accommodating multi-stakeholder preferences [2], resulting in decisions that tend to be inconsistent and difficult to justify rationally. Similar challenges have also been identified in processes such as beneficiary selection, which require intelligent system approaches to improve objectivity and consistency [3].

MCDM approaches such as the AHP, SAW, TOPSIS, and the Borda method have been widely applied to support such processes. The development of MCDA methods has shown improvements in handling the complexity of multi-criteria decision problems [4]. Decision support systems have also been implemented in various application contexts, including optimization of alternative selection in tourism systems [5] and suitability assessment of alternatives against multi-criteria conditions [6]. AHP can produce consistent sector weights and has been applied to multi-criteria content and resource selection problems [7, 8], while the Borda method effectively aggregates individual preferences into group decisions [9].SAW applies proportional linear aggregation, whereas TOPSIS evaluates alternatives according to their relative distance from ideal positive and ideal negative solutions. Both approaches have been widely used in MCDM contexts because they represent different evaluation paradigms for ranking alternatives.

Previous studies have demonstrated the integration of AHP, SAW, TOPSIS, and Borda to support structured priority determination in various decision-making contexts [10]. In addition, the integration of AHP with utility-based approaches such as SMART has been applied to improve preference representation [11].

Linear additive approaches such as SAW preserve proportional relationships between original values and normalized scores, whereas TOPSIS evaluates alternatives based on their relative distance to ideal solutions. However, both approaches remain dependent on fixed transformation structures that may reduce flexibility in representing heterogeneous preference characteristics across parameter-specific utility configurations [12].

As a result, alternatives with similar evaluation profiles may remain difficult to distinguish under conventional additive or ideal-solution-based approaches, particularly in competitive decision-making conditions [13].

Utility-based approaches provide a more adaptive transformation mechanism for representing nonlinear preferences and heterogeneous evaluation behavior [14]. The SMART method adopts this concept, allowing value distributions to be adjusted according to preference characteristics [15]. Nevertheless, studies that explicitly investigate the role of nonlinear utility functions within a group decision-making framework for village development priority determination remain limited. Previous studies have also implemented SMART in decision support systems to improve decision accuracy and transparency in evaluation processes [16], including comparative evaluations of service quality where SMART demonstrated superior discriminative performance over alternative methods [17].

Therefore, this study proposed a group decision support system model integrating AHP for sector weighing, SMART based on nonlinear utility functions for adaptive alternative evaluation, and the Borda method for preference aggregation. The novelty of this study lies in the use of parameter-specific nonlinear utility configurations (α) to represent heterogeneous evaluation characteristics across evaluation parameters, enabling more adaptive preference transformation compared with fixed additive and ideal-solution-based evaluation mechanisms. Furthermore, this study compared the proposed AHP–SMART–Borda model with AHP–SAW–Borda and AHP–TOPSIS–Borda to evaluate ranking behavior across additive, distance-based, and nonlinear utility evaluation paradigms in participatory village planning contexts.

II. METHOD

A. Decision Model Architecture

The group decision-making model integrates sector weighing, alternative evaluation, and preference aggregation into a structured computational process for determining village development priorities. The model combines AHP to derive sector weights, SMART with nonlinear utility functions to evaluate alternatives, and the Borda method to aggregate group preferences into a collective ranking. This integration enables strategic sector prioritization, operational alternative evaluation, and collective preference aggregation to be processed within a unified decision-making framework.

As illustrated in Fig. 1, the process begins with input data consisting of sectors, alternatives, and decision makers from multiple domains. Sector weights are first determined using pairwise comparisons in AHP. These weights are then used in the SMART evaluation process, where alternative values are transformed through nonlinear utility functions to produce utility scores. Finally, individual rankings are aggregated using the Nested Borda approach to generate the final collective priority ranking of village development programs.

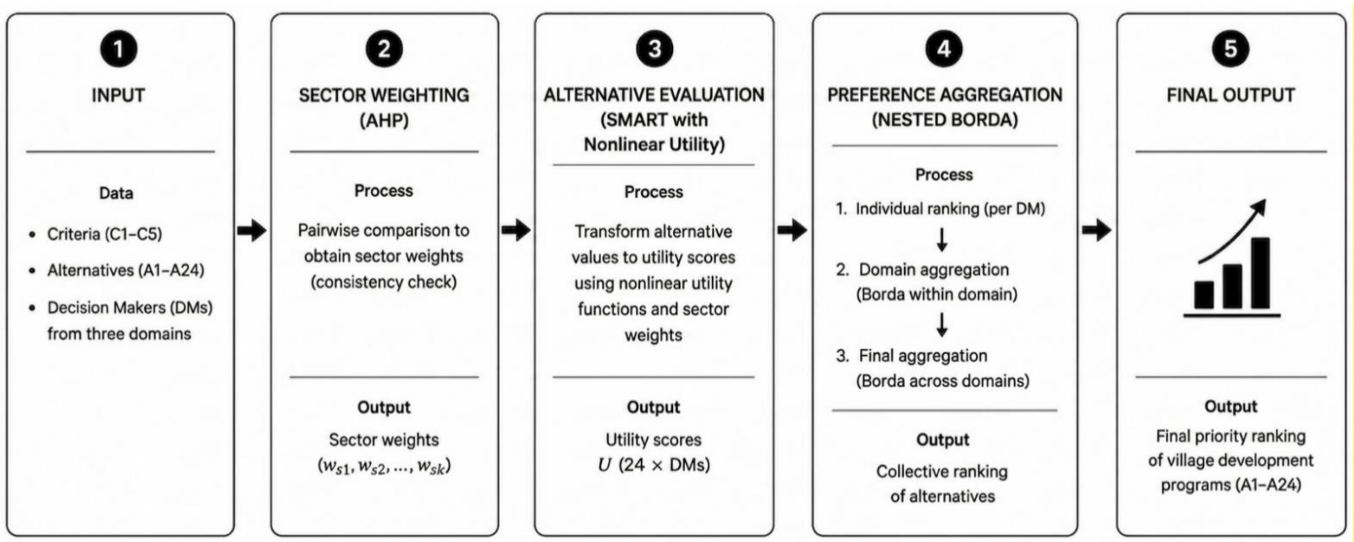

Fig. 1 Computational workflow of the group decision-making model

This architecture enables the decision-making process to be conducted systematically while preserving the functional separation between weighing, evaluation, and aggregation processes.

B. Decision-Maker Structure

The decision-making process involved nine decision makers representing three functional domains within the village development planning context. The technical domain consisted of one administrative operator responsible for providing and validating proposal data. The strategic domain consisted of one village head responsible for assessing policy alignment and development priorities. The participatory domain consisted of seven community representatives reflecting public preferences and local development needs.

Each domain contributed evaluations according to its functional perspective within the planning process. The technical domain focused on data feasibility and administrative consistency, the strategic domain emphasized policy and governance considerations, while the participatory domain represented community-based preferences.

In this study, all domains were treated with equal importance during the aggregation process to preserve balance among administrative, strategic, and participatory perspectives in collective decision-making. Therefore, the Nested Borda aggregation was performed without additional inter-domain weighing.

C. Sector Weighing Using AHP

Sector weighing was performed using the AHP method through pairwise comparisons to produce priority weights among development sectors [18]. The sector weights were calculated and normalized based on the eigenvector approach, as formulated in (1) [19].

$$w_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}{\sum_{k=1}^{n}\left(\prod_{j=1}^{n} a_{kj}\right)^{\frac{1}{n}}} \quad (1)$$

where w_i denotes the sector weight of sector i, a_{ij} represents the pairwise comparison value between sector i and j, and n is the number of sectors.

AHP was selected for sector weighing because it provides a structured mechanism for translating qualitative judgments into quantitative weights through pairwise comparisons. Compared with direct numerical scoring, this approach enables decision makers to assess the relative importance among sectors more consistently within collective decision-making contexts.

In village development planning, all decision makers participated in the weighing process to represent collective development priorities. To reduce cognitive burden and maintain assessment consistency, the process was limited to a focused set of sectors relevant to the planning context.

The consistency ratio was used to ensure that judgments remained logical and non-contradictory. In the group decision-making process, aggregation was performed at the comparison matrix level before deriving the final sector weights, which were subsequently applied to alternatives based on their associated development sector.

D. Nonlinear Utility Modelling

Alternative evaluation was conducted using the SMART method with a nonlinear utility function to transform parameter values into preference scales. This transformation was used to accommodate differences in parameter characteristics, so that the relationship between initial values and preference values was not strictly linear, as explained in multi-attribute utility theory [20]. The utility function is formulated in (2).

$$u(x) = \left(\frac{x - x_{min}}{x_{max} - x_{min}}\right)^{\alpha} \quad (2)$$

where $u(x)$ is the utility value of parameter x, x_{min} and x_{max} denote the minimum and maximum values of the parameter, respectively, and α is the parameter controlling the shape of the utility function.

The parameter α acted as a control for the shape of the utility curve representing collective preferences. A value of $0< \alpha<1$ produced a concave function that emphasized equalization effects by increasing sensitivity at lower values, while $\alpha>1$ produced a convex function that delayed score increases until values approached the upper bound. When $\alpha=1$, the function became linear as a special case.

The α values for each parameter were determined by the researchers based on the theoretical characteristics of each parameter, validated through deliberation with decision makers. To maintain consistency and reduce uncontrolled subjectivity, the selection was limited to three standard function types, as summarized in Table I.

TABLE I
UTILITY FUNCTION PARAMETER CONFIGURATION

Code	Parameter	Attribute	Function	α
P1	Budget (RAB)	Cost	Convex	4
P2	Beneficiaries	Benefit	Concave	0.2
P3	Coverage Area	Benefit	Concave	0.2
P4	Vision–Mission Alignment	Benefit	Linear	1
P5	Impact	Benefit	Convex	4
P6	Urgency	Benefit	Concave	0.2

The configuration in Table I reflects the different evaluation characteristics across parameters. Budget (RAB) and impact use a convex function with α = 4 because the penalty becomes significant only when the value approaches extreme limits. Beneficiaries, coverage area, and urgency use a concave function with α = 0.2 because initial achievements in these parameters already provide meaningful contributions, so the dominance of higher values needs to be moderated.

E. Alternative Evaluation Model

Each alternative was mapped to a single dominant development sector corresponding to the sector weighed using AHP. These weights represent strategic development priorities within the decision-making process. Subsequently, alternatives were evaluated operationally using SMART based on nonlinear utility functions applied to assessment parameters such as budget, beneficiaries, urgency, and impact.

The evaluation value of each alternative was calculated by integrating parameter utility scores with the corresponding sector weight obtained from AHP. The evaluation value is expressed in (3).

$$V_i = w_{s(i)} \cdot \left(\frac{1}{k}\sum_{j=1}^{k} u_j(a_i)\right) \tag{3}$$

where V_i represents the evaluation score of alternatives i, $w_{s(i)}$ denotes the weight of the sector associated with alternative i, $u_j(a_i)$ is the utility value of parameter j for alternatives i, and k is the number of parameters.

This approach uses the average utility without parameter weighing to maintain model simplicity while preserving the focus on the influence of the utility function shape on the evaluation results.

F. Preference Aggregation using Nested Borda

Preference aggregation was performed using the Nested Borda method to combine ranking results from multiple decision-maker domains. This approach is an extension of the Borda method in social choice theory, which is used to aggregate individual preferences into a group decision [21]. It preserves priority ranking information while reducing bias caused by differences in value scales across domains. The final consensus score was calculated by accumulating ranking points across domains, as expressed in (4).

$$TB_i = \sum_{d=1}^{3} B_{id} \tag{4}$$

where TB_i represents the total Borda score of alternatives i, B_{id} denotes the Borda score of alternatives i in domain d, and d represents the decision-making domain.

The aggregation process was conducted hierarchically, where individual rankings were first consolidated at the domain level and then combined to produce the final collective decision. This approach ensures that each domain contributes proportionally without eliminating its preference characteristics.

G. Comparison Methods using SAW and TOPSIS

The Simple Additive Weighing (SAW) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods were used as comparison models to evaluate the behavior of the proposed nonlinear utility-based approach under different evaluation paradigms.

In both comparison schemes, the SMART nonlinear utility transformation was replaced while the sector weighing process using AHP and the preference aggregation process using Nested Borda remained consistent with the proposed model. The evaluation value of each alternative was calculated by integrating normalized parameter values with the corresponding sector weight obtained from AHP, as expressed in (5).

$$V_i = w_{s(i)} \cdot \left(\frac{1}{n}\sum_{j=1}^{n} r_{ij}\right) \tag{5}$$

where V_i represents the evaluation score of alternatives i, $w_{s(i)}$ denotes the weight of the sector associated with alternative i, r_{ij} is the normalized value of parameter j for alternative i, and n is the number of evaluation parameters.

Meanwhile, the TOPSIS method evaluates alternatives according to their relative distance from the ideal positive and ideal negative solutions. The weighted normalized matrix was first constructed using vector normalization, as formulated in (6).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{6}$$

The weighted normalized value was then calculated as expressed in (7).

$$y_{ij} = w_j \cdot r_{ij} \tag{7}$$

where w_j denotes the weight of parameter j derived from the AHP sector weighing process.

The separation measures from the ideal positive and ideal negative solutions were calculated using Euclidean distance, as formulated in (8) and (9).

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(y_{ij} - y_j^+\right)^2} \tag{8}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(y_{ij} - y_j^-\right)^2} \tag{9}$$

Finally, the preference score of each alternative in the AHP–TOPSIS–Borda scheme was calculated using the relative closeness coefficient, as expressed in (10).

$$C_i{}' = w_{s(i)} \cdot C_i \quad (10)$$

where C_i represents the final weighted preference score.

The ranking results obtained from the AHP–SAW–Borda and AHP–TOPSIS–Borda schemes were subsequently compared with those of the proposed AHP–SMART–Borda model to analyze differences in ranking behaviour between additive, distance-based, and nonlinear utility-based evaluation approaches.

H. Model Evaluation Design

The evaluation design was structured to analyze ranking behavior differences between the proposed nonlinear utility-based model and the comparison methods representing additive and distance-based evaluation approaches. The evaluation scenarios used in this study are summarized in Table II.

The evaluation was conducted by comparing ranking distributions produced by the nonlinear utility-based approach against linear additive and distance-based approaches. Ranking differences and Spearman correlation analysis were used to observe the consistency and behavioral variation among the evaluated models.

I. Model Configuration

The experimental configuration involved 24 development program alternatives classified into 5 development sectors and evaluated using 6 assessment parameters. The evaluation process involved 9 decision makers representing technical, strategic, and participatory domains.

Each alternative was represented using codes (A1–A24) corresponding to village development proposals across infrastructure, economic, social, and public service sectors. This configuration was used to analyze the effect of nonlinear utility transformation on collective ranking behavior compared with additive linear normalization and distance-based evaluation approaches.

III. RESULTS AND DISCUSSION

A. Sector Weighing Results

The results of sector weighing are presented in Table III, showing the relative priority distribution among sectors in the decision model.

The weight distribution indicates a dominance of the productive economy and security sectors. As a result, alternatives with strong performance in these aspects contribute more significantly to the overall evaluation score. This finding confirms that sector weighing acts as a primary control factor influencing ranking sensitivity within the decision model.

B. Alternative Evaluation Results

The alternative evaluation process involved 24 alternatives, 6 evaluation parameters, and assessments from 9 decision makers, resulting in many utility transformation records. Representative examples were selected to illustrate the behavior of nonlinear utility transformation under different parameter characteristics and utility function types. Alternatives evaluated using concave utility functions tend to experience amplification at moderate raw values, whereas convex functions suppress utility values unless the raw scores approach the upper bound, as presented in Table IV.

TABLE II
SYSTEM EVALUATION SCENARIOS

No	Evaluation Type	Testing Scenario	Measurement Parameter
1	Comparative Evaluation	Comparison between AHP–SMART–Borda and AHP–SAW–Borda	Ranking Difference (Δ)
2	Comparative Evaluation	Comparison between AHP–SMART–Borda and AHP–TOPSIS–Borda	Ranking Difference (Δ)
3	Correlation Analysis	Correlation of ranking results among methods	Spearman Correlation Coefficient (ρ)

TABLE III
SECTOR WEIGHING RESULTS

Code	Sector	Weight
C1	Basic Services	0.1040
C2	Infrastructure and Environment	0.2183
C3	Productive Economy and Agriculture	0.2551
C4	Appropriate Technology	0.1690
C5	Security and Public Order	0.2536

TABLE IV
REPRESENTATIVE NONLINEAR UTILITY TRANSFORMATION RESULTS

Alternative	Parameter	Raw Value	Min-Max	Normalization	Type	α	Utility Value
A5	P5	2	1–5	0.2500	Convex	4	0.0039
A5	P6	4	1–5	0.7500	Concave	0.2	0.9441
A8	P5	5	1–5	1.0000	Convex	4	1.0000
A13	P5	1	1–5	0.0000	Convex	4	0.0000
A16	P1	15000000	5000000–150000000	0.9310	Convex	4	0.7514
A20	P2	100	50–800	0.0667	Concave	0.2	0.5818
A24	P3	2	1–5	0.2500	Concave	0.2	0.7579
A8	P4	3	1–5	0.5000	Linear	1	0.5000

The nonlinear transformation caused score differences to become non-proportional to the original parameter values, resulting in a more adaptive utility distribution.

The transformed utility values were subsequently integrated with development sector weights obtained from AHP to produce weighted evaluation scores across decision makers. Alternatives such as A7, A17, and A20 consistently achieved relatively high weighted evaluation scores across multiple decision makers, indicating stable collective preferences, while alternatives such as A5 and A13 exhibit greater score variation across decision-making domains, as presented in Table V.

The score distribution indicates that alternatives such as A7, A17, and A20 consistently achieved high values across multiple decision makers, reflecting stable evaluation performance across highly weighted sector priorities. In contrast, alternatives such as A5 and A13 exhibit greater variation in scores, indicating differences in perception across decision-making domains.

The transformation using nonlinear utility functions caused the differences in scores to become non-proportional to the original values. Score differences may be attenuated or amplified depending on the function characteristics, resulting in a more adaptive distribution. Consequently, alternatives with similar initial values can be distinguished more contextually, while dominant alternatives remain stable.

C. Preference Aggregation Results

After obtaining the utility scores, preference aggregation was performed using the Nested Borda method to produce a collective ranking through the integration of participatory, strategic, and technocratic domains. The final ranking of alternatives is presented in Table VI, which shows the top-ranked alternatives.

The ranking distribution shows that A20 occupies the first position with a score of 62.0, followed by A16 in second place with 60.5, and A7 in third place with 58.5. The fourth position is jointly held by A8 and A17, both with identical scores of 57.5, indicating an equivalent level of collective preference for these alternatives. In cases of identical Borda scores, tie-breaking was resolved by comparing the raw evaluation scores prior to Borda aggregation, where the alternative with the higher average weighted utility score across decision makers was assigned the superior rank.

Meanwhile, the lower-ranked group remains relatively stable, indicating that the overall decision structure is not significantly affected by local fluctuations during the evaluation stage.

The Nested Borda approach enables the integration of preferences without dominance from any single domain, as each domain contributes equally to the formation of the final ranking. This results in a decision that is more representative of collective preferences while maintaining consistency with the underlying evaluation structure.

TABLE V
WEIGHTED EVALUATION SCORES ACROSS DECISION MAKERS

Code	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	DM9
A5	0.2551	0.0972	0.1209	0.2551	0.1190	0.1190	0.1190	0.1608	0.0341
A7	0.2551	0.1115	0.1280	0.2551	0.1115	0.1608	0.1284	0.1115	0.1402
A8	0.1268	0.2536	0.1276	0.1109	0.1598	0.1598	0.1276	0.1598	0.1324
A9	0.0260	0.0523	0.0485	0.0455	0.0396	0.0655	0.0655	0.0485	0.0612
A13	0.0423	0.0000	0.0640	0.0644	0.0000	0.0788	0.0788	0.0644	0.1077
A17	0.2551	0.1115	0.1280	0.2551	0.1115	0.1608	0.1284	0.1115	0.1256
A20	0.2551	0.1115	0.1280	0.2551	0.1115	0.1608	0.1608	0.1115	0.1198

TABLE VI
FINAL AGGREGATION RESULTS OF ALTERNATIVES

Rank	Alternative	Final Score
1	A20	62
2	A16	60.5
3	A7	58.5
4.5	A8	57.5
4.5	A17	57.5
6	A24	55.5

D. Comparison of SMART, SAW, and TOPSIS Methods

Differences in characteristics among methods within the multi-criteria decision-making framework have been widely discussed in the literature, particularly regarding sensitivity and ranking behavior [19]. To evaluate the effect of nonlinear utility functions, comparisons were conducted between the proposed AHP–SMART–Borda model and the AHP–SAW–Borda as well as AHP–TOPSIS–Borda models. The comparison focused on ranking differences (Δ) to identify variations in ranking behaviour between nonlinear utility-based, additive, and distance-based evaluation approaches. A summary of the comparison results is presented in Table VII.

The comparison results indicate that the proposed AHP–SMART–Borda model produced ranking patterns generally consistent with both SAW- and TOPSIS-based approaches. Most alternatives maintained relatively similar positions across methods, particularly the top-ranked alternatives such as A20, A16, A7, and A17.

Several alternatives experienced moderate ranking shifts between methods, particularly in middle-ranked alternatives with relatively similar evaluation profiles. These variations indicate differences in how additive, distance-based, and nonlinear utility-based approaches interpret parameter distributions and preference structures.

The SAW method preserves proportional relationships through linear aggregation, while TOPSIS evaluates alternatives according to their relative distance from ideal positive and ideal negative solutions. In contrast, the SMART approach applies parameter-specific nonlinear utility transformations that adjust score sensitivity according to the evaluation characteristics of each parameter.

Despite several local ranking variations, the overall priority structure remained relatively stable across methods. This result indicates that the nonlinear utility-based approach refines ranking discrimination without substantially altering the collective decision structure.

E. Rank Correlation Analysis (Spearman)

The correlation analysis was conducted using the Spearman rank correlation coefficient to evaluate the consistency of ranking patterns among the evaluated methods [22]. The Spearman rank correlation coefficient was calculated across all 24 alternatives to ensure full representativeness of the ranking comparison. The results show a coefficient of 0.9389 between the AHP–SMART–Borda and AHP–SAW–Borda models, and 0.9519 between the AHP–SMART–Borda and AHP–TOPSIS–Borda models.

These results indicate that the proposed nonlinear utility-based model preserves the overall priority structure across both additive and distance-based evaluation approaches. The higher correlation with TOPSIS suggests that the ranking behavior of the proposed SMART model is relatively closer to the distance-based evaluation mechanism than to proportional linear aggregation.

Although several local ranking variations occurred among middle-ranked alternatives, dominant alternatives consistently maintained their positions across methods. Therefore, the nonlinear utility approach remains structurally consistent with conventional MCDM approaches while providing more adaptive preference representation through parameter-specific utility transformations.

TABLE VII
RANKING COMPARISON BETWEEN SMART, SAW, AND TOPSIS METHODS

ID	Alternative Program	Rank (SMART)	Rank (SAW)	Rank (TOPSIS)
A20	Job skills training	1	3	1
A16	Disaster preparedness simulation	2	1	2
A7	MSME management training	3	2	3
A8	Road safety signs	4.5	6	5
A17	Business legality assistance	4.5	5	4
A24	Public street lighting	6	7	6
A14	Agricultural cultivation assistance	7	4	8
A5	Livestock production facilities	8	11.5	10.5
A15	Public building rehabilitation	9	11.5	9
A12	Drainage channel normalization	10	8	7

IV. CONCLUSION

The proposed group decision-making model integrating AHP, SMART based on nonlinear utility functions, and Nested Borda produced ranking results that remained structurally consistent with both additive and distance-based evaluation approaches. The Spearman correlation analysis showed strong correlations between the AHP–SMART–Borda model and the comparison models, with coefficients of 0.9389 against AHP–SAW–Borda and 0.9519 against AHP–TOPSIS–Borda.

The comparison results indicate that most alternatives maintained relatively stable ranking positions across methods, particularly dominant alternatives such as A20, A16, and A7. Several ranking variations occurred among middle-ranked alternatives, indicating that nonlinear utility transformation affects ranking sensitivity without substantially altering the overall priority structure.

From a methodological perspective, the findings confirm that the form of value transformation influences how evaluation differences are translated into decision outcomes. The proposed nonlinear utility approach provides more adaptive preference representation through parameter-specific utility configurations while remaining consistent with conventional MCDM approaches.

However, this study has several limitations. The model was evaluated using a single case study with a specific configuration, so its generalizability requires validation in different village contexts. In addition, the α values were determined through collective agreement without a data-driven calibration mechanism. Future research may explore systematic approaches for α calibration, broader implementation scenarios, and dynamic preference adaptation across planning periods.

ACKNOWLEDGEMENT

The authors would like to thank all parties who contributed to this research, including the decision makers and stakeholders involved in the evaluation process, as well as those who provided support in data collection and system development. This work was supported by the Department of Computer Science and Electronics, Universitas Gadjah Mada under the Publication Funding Year 2026.

REFERENCES

[1] E. Triantaphyllou, *Multi-Criteria Decision Making Methods: A Comparative Study*. New York: Springer, 2000.

[2] A. Saoud, G. Benmessaoud, and A. Chikh, “decideXpert: A collaborative decision support platform integrating AHP and TOPSIS,” *SoftwareX*, 2025, doi: 10.1016/j.softx.2024.101597.

[3] A. Anggrawan, “Sistem aplikasi cerdas klasterisasi penerima bantuan,” *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 22, no. 2, 2022.

[4] J. Wieckowski, “Recent advances in multi-criteria decision analysis: A comprehensive review of applications and trends,” *International Journal of Knowledge-Based and Intelligent Engineering Systems*, vol. 27, no. 4, pp. 367–393, 2023, doi: 10.3233/KES-230487.

[5] D. Setiadi and Y. I. Mukti, “Electronic tourism using decision support systems to optimize the trips,” *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 23, no. 1, pp. 183–200, 2023, doi: 10.30812/matrik.v23i1.3331.

[6] P. Wolo, S. Mulyana, and R. Wardoyo, “Decision Support System for Suitability of Horticultural Agricultural Plant Types with Land Conditions Using Interpolation Profile Matching,” *JUITA: Jurnal Informatika*, vol. 11, no. 1, p. 133, May 2023, doi: 10.30595/juita.v11i1.16546.

[7] T. L. Saaty, “Decision making with the analytic hierarchy process,” *International Journal of Services Sciences*, vol. 1, no. 1, pp. 83–98, 2008.

[8] C. Wiguna, S. Mulyana, and R. Wardoyo, “Selection of TikTok Content Based on User Engagement Criteria Using the Analytic Hierarchy Process,” *JUITA: Jurnal Informatika*, vol. 11, no. 1, pp. 125–131, May 2023, doi: 10.30595/juita.v11i1.16314.

[9] D. G. Saari, *Decisions and Elections: Explaining the Unexpected*. Cambridge: Cambridge University Press, 2001.

[10] D. Trisnawarman, “Pemodelan Sistem Pendukung Keputusan Kelompok untuk Penentuan Prioritas Pembangunan dalam Sistem E-Governance Partisipatif Pemerintahan Desa,” Universitas Gadjah Mada, Yogyakarta, Indonesia, 2018. [Online]. Available: https://etd.repository.ugm.ac.id/penelitian/detail/155464

[11] N. Afriza, N. Siti, and I. Sahputra, “Decision support system for human resource program prioritization using AHP–SMART,” *JITE*, vol. 9, no. 2, 2026, doi: 10.31289/jite.v9i2.16999.

[12] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-Matos, “Assessing Normalization Techniques for Simple Additive Weighing Method,” *Procedia Comput. Sci.*, vol. 199, pp. 1229–1236, 2022, doi: 10.1016/j.procs.2022.01.156.

[13] C. L. Hwang and K. Yoon, *Multiple Attribute Decision Making: Methods and Applications*. Springer-Verlag, 1981.

[14] J. S. Dyer and R. Sarin, "Measurable multiattribute value functions," *Oper. Res.*, vol. 27, no. 4, pp. 810–822, 1979, doi: 10.1287/opre.27.4.810.

[15] W. Edwards, "How to Use Multiattribute Utility Measurement for Social Decision Making," *IEEE Trans. Syst. Man Cybern.*, vol. SMC-7, no. 5, pp. 326–340, 1977.

[16] G. Permana, A. Rahmatulloh, and R. Rianto, "Sistem Pendukung Keputusan Layanan Verifikator Pengadaan dengan Metode Simple Multi Attribute Rating Technique (SMART)," *JUITA: Jurnal Informatika*, vol. 6, no. 2, pp. 99–111, 2018, doi: 10.30595/juita.v6i2.3204.

[17] Y. Lestari and others, "Decision Support System for Service Quality Using SMART and Fuzzy ServQual Methods," *JUITA: Jurnal Informatika*, vol. 9, no. 1, May 2021, doi: 10.30595/juita.v9i1.9644.

[18] E. H. Forman and K. Peniwati, "Aggregating Individual Judgments and Priorities with the Analytic Hierarchy Process," *Eur. J. Oper. Res.*, vol. 108, no. 1, pp. 165–169, 1998.

[19] T. L. Saaty and L. G. Vargas, *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process*. New York: Springer, 2012.

[20] R. L. Keeney and H. Raiffa, *Decisions with Multiple Objectives: Preferences and Value Trade-Offs*. Cambridge: Cambridge University Press, 1993. doi: 10.1017/CBO9781139174086.

[21] D. Black, *The Theory of Committees and Elections*. Berlin: Springer, 1958. doi: 10.1007/978-94-015-7853-8.

[22] C. Spearman, "The proof and measurement of association between two things," *American Journal of Psychology*, vol. 15, no. 1, pp. 72–101, 1904, doi: 10.2307/1412159.