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Artificial intelligence for personalized and ethical political campaign decision-making

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ABSTRACT

The increasing use of artificial intelligence (AI) in evaluating political campaign strategies has enhanced data-driven decision-making; however, existing studies often treat sentiment analysis and multi-criteria decision-making (MCDM) as separate processes, resulting in fragmented and less transparent evaluations. To address this gap, this study proposes a novel hybrid AI-MCDM framework that integrates optimized sentiment analysis directly into the decision-making process as an explicit evaluation criterion, rather than treating it as a standalone analytical output. The framework combines support vector machine (SVM) optimized by salp swarm optimization (SSO) for sentiment analysis, logarithmic percentage change-driven objective weighting (LOPCOW) for objective criteria weighting, and preference ranking organization method for enrichment evaluations (PROMETHEE II) for strategy ranking. The main methodological novelty lies in unifying sentiment classification, objective weighting, outranking-based strategy evaluation, and ranking robustness analysis within a single transparent decision-support pipeline. Experimental results demonstrate that the SVM-SSO model achieves 93.33% accuracy, while the PROMETHEE II analysis identifies branding and candidate image (BCI) as the most preferred strategy based on net flow values. Sensitivity analysis further confirms the robustness of the ranking results. The proposed framework provides a transparent, data-driven, and ethically grounded decision-support approach for evaluating political campaign strategies.

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1. INTRODUCTION

Elections constitute a fundamental mechanism of democratic systems through which citizens select political representatives and influence governance [1]. Understanding electoral dynamics is therefore essential to address inequalities in political representation and improve voter participation [2]. For candidates and political parties, campaign effectiveness depends not only on communicating political programs but also on understanding voter behavior within complex social, economic, and political environments [3]. This complexity has increased the need for data-driven approaches that support more systematic, responsive campaign strategies.

Advances in artificial intelligence (AI) and machine learning (ML) provide new opportunities for political campaign analysis. ML can process voter preferences, demographic characteristics, social-media interactions, and public opinion to support personalized communication and strategic decision-making [4]. AI-based approaches can also adapt campaign messages to voter characteristics and evolving behavioral patterns, potentially improving political engagement [5], [6]. However, their application raises concerns regarding privacy, algorithmic bias, misinformation, and political manipulation [7]. Responsible adoption therefore requires balancing campaign effectiveness with transparency, accountability, and the protection of democratic values [8]–[10].

The growing availability of digital and social-media data has encouraged the use of computational techniques for voter analysis and election prediction [11]. ML can identify patterns and classify public sentiment, while multi-criteria decision-making (MCDM) provides a structured mechanism for evaluating strategic alternatives across multiple, potentially conflicting criteria [12], [13]. Despite these complementary capabilities, existing studies commonly treat voter prediction, sentiment classification, content personalization, and campaign evaluation as separate analytical tasks. MCDM-based evaluations are also often disconnected from ML outputs, rely on subjective criterion weights, and offer limited assessment of ranking robustness. More importantly, public sentiment is often treated as a descriptive output rather than incorporated directly into the formal strategy-evaluation process. This creates a methodological gap in linking optimized sentiment classification, objective criterion weighting, and preference-based strategy ranking within a unified and transparent decision-support framework.

To address this gap, this study proposes a hybrid AI-MCDM framework that integrates a support vector machine (SVM) optimized by salp swarm optimization (SSO), logarithmic percentage change-driven objective weighting (LOPCOW), and the preference ranking organization method for enrichment evaluations II (PROMETHEE II). As shown in Figure 1, SVM-SSO extracts sentiment from public textual responses, LOPCOW determines objective criterion weights, and PROMETHEE II evaluates and ranks campaign alternatives. The classified sentiment is incorporated directly into the decision matrix as an explicit criterion, enabling public responses to influence strategy prioritization rather than remaining an independent analytical output.

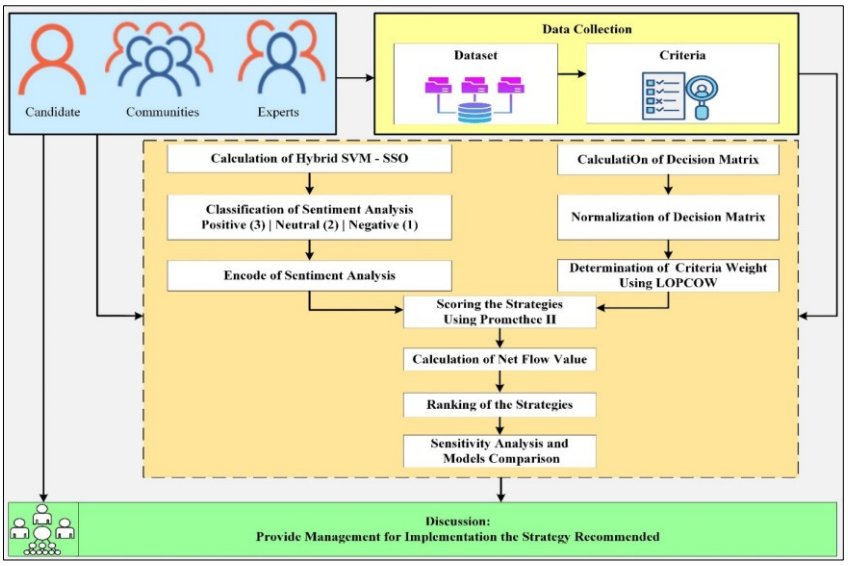


Figure 1. Research design

The main contribution of this study is the explicit integration of ML-based sentiment classification with multi-criteria preference reasoning in a single decision-support pipeline. Unlike approaches that analyze sentiment and campaign strategies separately, the proposed framework connects optimized sentiment classification, sentiment-informed decision matrices, objective weighting, and preference-based ranking, while sensitivity analysis evaluates ranking stability under variations in criterion weights. Ethical considerations related to fairness, transparency, accountability, privacy, and democratic values are incorporated as governance principles for responsible interpretation and implementation of AI-assisted recommendations. Consequently, the proposed framework provides an integrated, interpretable, and robustness-aware approach for evidence-based political campaign strategy evaluation.

2. RELATED WORKS

2.1. Artificial intelligence and machine learning in political campaigning

AI, particularly ML, has become integral to modern political campaigns [14]. Political actors increasingly rely on ML algorithms to analyze large-scale data, including voter demographics, social media interactions, and historical voting behavior, to predict voter preferences and tailor campaign messages [15]. AI-based tools enable the generation of highly personalized content, such as targeted advertisements and customized social media messaging, which have been shown to enhance voter engagement [16], [17]. However, the growing use of AI in political campaigning has raised significant ethical and societal concerns. AI-generated content can facilitate the spread of misinformation and deepfakes, potentially undermining public trust and democratic integrity [18]. Empirical studies indicate that AI-driven political communication may exacerbate polarization and reinforce cognitive biases among voters [19], [20]. Furthermore, excessive personalization risks narrowing voters' exposure to diverse viewpoints, which may negatively affect informed political participation [21]. Despite their predictive capabilities, most AI-based approaches remain focused on opinion classification and content personalization, offering limited support for structured and transparent strategic decision-making.

2.2. Multi-criteria decision-making in political strategy

MCDM methods provide a systematic framework for evaluating political strategies that involve multiple and often conflicting criteria [22]. In the context of political campaigns, MCDM has been applied to resource allocation, policy prioritization, and candidate positioning based on voter preferences [23]–[25]. These approaches improve transparency by enabling explicit trade-off analysis and structured comparison among strategic alternatives [26]. Nevertheless, many existing MCDM-based political studies rely heavily on subjective weighting schemes or expert judgment, which may introduce bias and limit reproducibility [27], [28]. Even when objective weighting techniques are employed, public sentiment is typically treated as an auxiliary analytical outcome rather than being formally integrated as a decision criterion [29], [30]. Moreover, robustness and sensitivity analyses are often neglected, reducing confidence in the stability of strategy rankings under changing conditions. These limitations reveal a clear research gap in the development of an integrated, transparent, and robustness-aware framework that unifies optimized sentiment analysis, objective criteria weighting, and outranking-based strategy evaluation within a single decision-support system. To address this gap, the present study proposes a hybrid AI-MCDM framework that explicitly incorporates sentiment analysis as a formal decision criterion and evaluates ranking stability through sensitivity analysis.

2.3. Explainable artificial intelligence and intelligent decision support

Recent studies demonstrate the growing role of AI in political analytics. ML models have been applied to electoral forecasting by integrating social-media engagement with polling data, indicating that heterogeneous digital indicators can provide complementary evidence for understanding electoral dynamics [31]. In election-related opinion mining, previous research compared long short-term memory (LSTM), bidirectional encoder representations from transformers (BERT), and linear support vector classifiers using large-scale political discourse data, demonstrating the ability of natural language processing to identify candidate-related sentiment and engagement patterns [32]. Similarly, Hassija *et al.* [33] developed election-focused bidirectional encoder representations from transformers (ElecBERT) to improve sentiment classification in election-specific conversations by capturing contextual political language more effectively than general-purpose language models. Collectively, these studies demonstrate that ML can transform unstructured political communication into analytically useful information. Nevertheless, their outputs remain primarily predictive or descriptive such as sentiment labels, engagement patterns, and electoral forecasts, which is not systematically operationalized within a multi-criteria decision process for evaluating and ranking campaign strategies.

2.4. Theoretical contribution

The theoretical contribution of this study lies in conceptualizing political campaign strategy evaluation as an integrated learning-to-decision process that bridges predictive intelligence and prescriptive decision support. The proposed framework combines SVM-SSO to transform unstructured political discourse into quantified sentiment, LOPCOW to objectively determine criterion weights, and PROMETHEE II to generate interpretable strategy rankings. Its key theoretical advancement is the operationalization of ML-derived sentiment as an explicit decision criterion rather than a separate descriptive output. This integration enables public responses to directly influence multi-criteria strategy evaluation while preserving transparency in the weighting and ranking processes. Sensitivity analysis further examines ranking stability under criterion-weight variations. Consequently, the framework extends isolated AI analysis into a traceable, interpretable, and robustness-aware architecture for evaluating campaign strategies involving multiple and potentially conflicting criteria.

3. METHOD

3.1. Data collection

The case study data were collected from two primary sources. First, campaign strategy evaluation data were obtained through structured questionnaires completed by respondents to assess predefined campaign alternatives against the selected decision criteria. Expert opinions and insights from political analysts and campaign strategists were also considered to support the identification and prioritization of key campaign factors. Second, textual public opinion data related to the evaluated campaign strategies were collected from relevant online and social media sources and used for sentiment classification. The collected data supported two interconnected analytical components: the questionnaire-based decision matrix was processed using LOPCOW and PROMETHEE II, while the textual data were analyzed using the SVM-SSO model to classify sentiment into positive, neutral, and negative.

Before analysis, the textual data underwent preprocessing to improve data quality and consistency. The preprocessing stages included duplicate removal, removal of irrelevant content, text normalization, lowercase conversion, tokenization, stop-word removal, and stemming or lemmatization, as appropriate to the dataset's language characteristics [34]. The cleaned text was then transformed into numerical feature representations and used as input to the SVM-SSO classifier. The resulting sentiment scores were subsequently incorporated into the decision-making framework as an additional input for evaluating campaign strategies. This preprocessing workflow ensured that the textual data were consistently prepared before model training and evaluation.

3.2. Proposed hybrid artificial intelligence -multi criteria decision making model

This study proposes an integrated hybrid AI-MCDM framework for evaluating and ranking political campaign strategies. The framework combines ML-based sentiment analysis, objective criterion weighting, and outranking-based decision analysis within a single, coherent pipeline. The workflow of the proposed framework is illustrated in Figure 2.

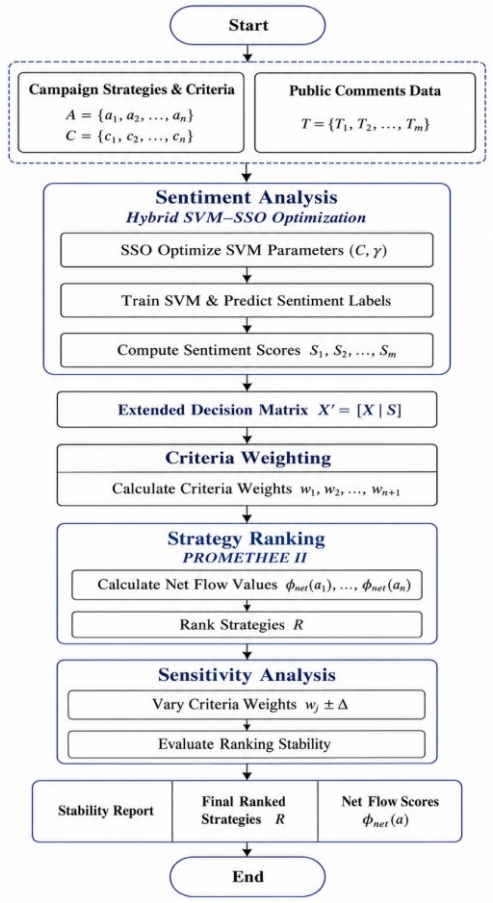


Figure 2. Workflow of the proposed hybrid AI-MCDM decision support framework

3.3. Logarithmic percentage change-driven objective weighting method

An objective weighting method called LOPCOW can eliminate gaps due to data size, produce more reasonable weightings, and consider positive and negative data in the weighting process [35]. The LOPCOW method provides weighting based on the data structure of the decision matrix to eliminate various problems, including negative values and dimensional disparities, that come from different criterion structures [36]. This approach makes decision-makers more responsive to market or environmental dynamics while reducing subjective bias in assigning relative weights to criteria. The LOPCOW provides a structured and robust MCDM framework that enhances accuracy, responsiveness, and precision in decision-making [35]. Stages of the LOPCOW are as follows.

i) Decision matrix construction consists of decision variables arranged systematically.

ii) Normalization ensures comparability of criteria using (1).

$$n_{ij} = \frac{x_{ij}}{m+\sum_{i=1}^{m} {x_{ij}}^2} \tag{1}$$

iii) The preference value is derived using logarithmic transformations using (2).

$$PV_{ij} = 100 \times \left| \frac{\sqrt{\sum_{i=1}^{m} {n_{ij}}^2}}{ln\frac{m}{\sigma}} \right| \tag{2}$$

iv) The final weight (wj) for each criterion is calculated using (3).

$$w_j = \frac{PV_{ij}}{\sum_{j=1}^{n} PV_{ij}} \tag{3}$$

The LOPCOW method offers several advantages. Firstly, it minimizes bias by applying mathematical transformations rather than relying on subjective evaluations. Secondly, it effectively manages uncertainty by utilizing logarithmic percentage changes, providing greater stability than absolute values. Lastly, adjusting to data variations and fluctuations enhances decision accuracy in dynamic environments.

3.4. Hybrid support vector machine - salp swarm optimization

The combination of SVM and SSO provides a promising hybrid framework for improving classification accuracy, predictive performance, and optimization efficiency. SSO, initially introduced by Zhang *et al.* [37], has been reported to perform well at solving complex global optimization problems, making it particularly useful for tuning SVM parameters and improving model performance in high-dimensional feature spaces. In a related context, Yildiz and Erdaş [38] examined the application of hybrid optimization techniques to engineering problems, highlighting their relevance for developing robust and efficient optimization-based engineering solutions. SSO itself is an advanced metaheuristic algorithm inspired by the collective foraging behavior of salps, a type of marine invertebrate, and has gained attention as a recent optimization approach for complex search problems [39]. In this study, sentiment analysis is performed using an SVM classifier, with hyperparameters optimized via SSO to improve classification accuracy and generalization.

Given a training dataset $\{(x_i, y_i)\}_{i=1}^{N}$, the SVM aims to solve the following optimization problem using (4) and (5) [40].

$$\min_{w,b,\xi} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{N} \xi_i \tag{4}$$

Subject to:

$$y_i(w \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0 \tag{5}$$

Where C is the penalty parameter and ξ_i denotes the slack variables. A radial basis function (RBF) kernel is adopted and defined using (6) [41].

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2) \tag{6}$$

The SSO algorithm is employed to optimize the SVM hyperparameters Cγ by minimizing the classification error through cross-validation. The predicted sentiment labels are mapped to numerical

sentiment scores: positive: 3, neutral: 2, and negative: 1. A majority voting mechanism is then applied to obtain a single sentiment score S_i for each campaign strategy.

3.5. Preference ranking organization method for enrichment evaluations II method

Several MCDM methods, including analytic hierarchy process (AHP), technique for order preference by similarity to ideal solution (TOPSIS), multi-criteria optimization and compromise solution or *višekriterijumsko kompromisno rangiranje* (VIKOR), and PROMETHEE II, were considered. AHP relies on hierarchical and judgment-based pairwise comparisons, while TOPSIS ranks alternatives according to their relative distance from ideal and anti-ideal solutions. VIKOR emphasizes compromise solutions for decision problems involving conflicting criteria.

In contrast, PROMETHEE II uses an outranking mechanism to generate a complete ranking through positive, negative, and net preference flows [42]. This approach is well suited to heterogeneous campaign criteria and enables the direct integration of LOPCOW-derived weights and SVM-SSO sentiment scores. Therefore, PROMETHEE II provides a transparent and interpretable ranking mechanism consistent with the proposed AI-MCDM framework.

One of the key advantages of PROMETHEE II is its ability to avoid compensation effects among criteria, thereby ensuring that no single criterion disproportionately affects the overall assessment [43]. The PROMETHEE II method is used to rank campaign strategies based on the weighted criteria [44]. For each pair of strategies ab, the aggregated preference index is computed using (7).

$$\pi(a,b) = \sum_{j=1}^{n+1} w_j \, P_j(a,b) \tag{7}$$

Where $P_j(a,b)$ denotes the preference function for the criterion c_j. The leaving flow, entering flow, and net flow are calculated using (8) to (10).

$$\Phi^{+}(a) = \frac{1}{m-1} \sum_{b \neq a} \pi(a,b) \tag{8}$$

$$\Phi^{-}(a) = \frac{1}{m-1} \sum_{b \neq a} \pi(b,a) \tag{9}$$

$$\Phi_{\text{net}}(a) = \Phi^{+}(a) - \Phi^{-}(a) \tag{10}$$

Strategies are ranked in descending order of $\Phi_{\text{net}}(a)$. The PROMETHEE II method can incorporate decision-maker preferences, perform sensitivity analysis, and provide clear and understandable results, thus facilitating decision interpretation and communication [45].

3.6. Integration of machine-learning predictions into the multi-criteria decision-making process

For each campaign strategy A_i, the SVM-SSO model classifies the associated public-opinion texts as negative, neutral, or positive. These predicted classes are encoded as 1, 2, and 3, respectively. The sentiment criterion for strategy A_i is then determined using majority voting, as written in (11).

$$S_i = \text{mode}\left(\hat{y}_{i1}, \hat{y}_{i2}, \ldots, \hat{y}_{iN_i}\right), \ \hat{y}_{it} \in \{1,2,3\} \tag{11}$$

Where $\hat{y}_{it}$ denotes the predicted sentiment class of text t, N_i is the number of texts associated with strategy A_i, and a higher S_i represents more favorable public sentiment. The resulting sentiment score is incorporated as an additional benefit criterion C_{n+1} in the structured decision matrix, as written in (12).

$$\mathrm{X}^{*} = \begin{bmatrix} x_{11} & \cdots & x_{1n} & S_1 \\ x_{21} & \cdots & x_{2n} & S_2 \\ \vdots & \ddots & \vdots & \vdots \\ x_{m1} & \cdots & x_{mn} & S_m \end{bmatrix} \tag{12}$$

Where x_{ij} represents the performance of campaign strategy A_i with respect to structured criterion C_j. The extended matrix X^{*}, containing m alternatives and $n+1$ criteria, is subsequently processed using the LOPCOW weighting procedure and PROMETHEE II ranking equations presented in the preceding subsections. Thus, the ML output is quantitatively integrated into the MCDM process without repeating the mathematical formulations of the individual methods.

The extended matrix X^*, comprising m campaign alternatives and $n+1$ criteria, was processed using the LOPCOW procedure defined in (1) to (3) to obtain the normalized criterion weights, including the weight of the sentiment criterion. These weights and the corresponding criterion values were subsequently incorporated into PROMETHEE II preference aggregation and net-flow calculations defined in (4) to (10). The alternatives were then ranked in descending order of their net-flow values. The SVM-SSO predictions serve as an operational input to the MCDM model rather than as a separate descriptive output.

3.7. Ethical considerations and evaluation framework

The use of AI in political campaigning requires ethical safeguards to ensure that data-driven strategies remain consistent with responsible and democratic practices. In the proposed framework, ethical considerations are operationalized through two main dimensions: fairness and transparency. Fairness focuses on avoiding discriminatory targeting and ensuring reasonable accessibility of campaign information across voter groups, while transparency emphasizes the explainability and traceability of AI-assisted analysis and decision-making processes.

To maintain consistency with the predefined dataset and decision criteria, these ethical dimensions are implemented as an ethical audit layer rather than as additional criteria in the LOPCOW-PROMETHEE II decision matrix. Therefore, they do not alter the calculated criterion weights or strategy rankings but provide complementary indicators for evaluating the responsible interpretation and implementation of AI-assisted campaign recommendations. The ethical dimensions and corresponding audit indicators are shown in Table 1.

Table 1. Ethical audit indicators for the proposed AI-MCDM framework

Ethical dimension	Audit indicator	Assessment principle
Fairness	Non-discriminatory targeting	Campaign recommendations should not systematically exclude or disadvantage specific voter groups.
Fairness	Equal information accessibility	Campaign information should remain reasonably accessible across relevant voter segments.
Transparency	Model explainability	The rationale underlying AI-generated sentiment classifications should be interpretable.
Transparency	Decision traceability	Criteria, weights, sentiment outputs, and ranking processes should be traceable.
Transparency	AI disclosure	The use of AI-assisted analysis and personalization should be appropriately disclosed.

3.8. Experimental setup and implementation details

The sentiment dataset contained 500 public-opinion comments associated labeled as positive, neutral, or negative. The dataset was divided into training and testing sets using a stratified 70 : 30 split, corresponding to 350 and 150 observations, respectively. Preprocessing included duplicate and irrelevant-content removal, text normalization, lowercasing, tokenization, Indonesian stop-word removal, and stemming using the Sastrawi stemmer.

The cleaned texts were transformed into numerical features using TF-IDF with unigram and bigram features (ngram_range = (1, 2)), a maximum of 10000 features, min_df = 2, and max_df = 0.95. Sentiment classification was performed using an SVM with RBF kernel. The regularization parameter C and kernel coefficient γ were optimized using SSO within the search ranges $C \in [0.1, 100]$ and $\gamma \in [10^{-4}, 1]$. SSO employed 30 search agents over 50 iterations, with macro-averaged F1-score on the validation set used as the fitness function. A fixed random seed of 42 was applied to data partitioning and stochastic optimization to improve experimental repeatability. All experiments were implemented in Python 3.11 using scikit-learn 1.5 and Sastrawi 1.0.1, with SSO implemented as a custom Python optimization routine.

4. RESULTS AND DISCUSSION

4.1. Definition of criteria and strategy

This study conducted interviews with stakeholders about the strategies used in the campaign process, where all strategies from several sources were summarized as branding and candidate image (BCI), voter segmentation and targeting (VST), digital and traditional campaigning (DTC), team and volunteer management (TVM), debate and public speaking (DPS), positive or negative campaigning (PNC), and voter mobilization (VM). Furthermore, this study identifies the criteria that are used to determine the ideal strategy in implementation as campaign effectiveness (CE), implementation cost (IC), voter reach (VR), impact speed (IS), risks and barriers (RB), public trust level (PTL), flexibility and adaptation (FA), long-term influence (LTI), ease of implementation (EI), and stakeholder support (SS). Guidelines for using the criteria for the scoring process are shown in Table 2.

Table 2. Criteria and subcriteria score

No	Criteria	Score: 9	Score: 7	Score: 5	Score: 3
1	CE	Very effective (> 20% increase)	Effective (10-20%)	Quite effective (5-10%)	Less effective (<5%)
2	IC	Very cheap (< 5% of budget)	Cheap (5-15%)	Moderate (15-30%)	Expensive (30-50%)
3	VR	National reach (> 75%)	Wide reach (50-75%)	Medium range (30-49%)	Limited reach (7-29%)
4	IS	Impact < 1 month	Impact 1-3 months	Impact 3-6 months	Impact 6-12 months
5	RB	Very low risk	Low risk	Moderate risk	High risk
6	PTL	Highly trusted	Trusted	Moderate trusted	Less trusted
7	FA	Highly flexible	Flexible	Moderate flexible	Less flexible
8	LTI	Long (> 5 years)	Medium (3-5 years)	Moderate (1-3 years)	Short (6-12 months)
9	EI	Very easy to implement	Easy to implement	Moderate to implement	Difficult to Implement
10	SS	Full	Majority	Moderate	Minimal

4.2. Determining the criteria weights logarithmic percentage change-driven objective weighting

In the initial stage of applying the LOPCOW method, the objective weights for each evaluation criterion are determined from the decision matrix in Table 3. This matrix summarizes the performance of each campaign strategy against the defined criteria and serves as the primary input to the weighting process. By analyzing the dispersion of criterion values, the LOPCOW method objectively captures the relative importance of each criterion without relying on subjective judgment.

Based on the decision matrix data, the normalized maximum values are calculated to convert all criterion values to a comparable scale. This normalization process ensures that differences in measurement units and value ranges across criteria do not bias the subsequent weighting and ranking procedures. The results of the normalization process are presented in Table 4.

Table 4 presents the normalized decision matrix values, scaled to 0 - 1 relative to each criterion's maximum value. This normalization ensures that all criteria are represented on a comparable scale and eliminates differences in measurement units. Based on the normalized values, the final criterion weights calculated using the LOPCOW method are presented in Table 5. The weights obtained using the LOPCOW method are subsequently used in the scoring process to determine the ranking of each campaign strategy. By incorporating LOPCOW-derived weights into the evaluation process, the resulting strategy rankings better reflect data-driven priorities and reduce subjective bias in decision-making.

Table 3. Result of scoring for each criterion

No	Strategy	CE	IC	VR	IS	RB	PTL	FA	LTI	EI	SS
1	BCI	3	7	3	5	7	9	7	7	7	7
2	VST	3	5	5	7	5	5	3	3	5	9
3	DTC	5	3	9	5	7	7	5	7	5	5
4	TVM	5	5	5	7	9	5	5	5	3	3
5	DPS	7	7	7	7	7	3	7	9	5	7
6	PNC	3	5	7	9	3	7	7	7	5	5
7	VM	5	5	3	5	9	7	5	5	7	3

Table 4. Results of the normalization value of the decision matrix

Strategy	CE	IC	VR	IS	RB	PTL	FA	LTI	EI	SS
BCI	0.429	1.000	0.333	0.556	0.778	1.000	1.000	0.875	1.000	0.778
VST	0.429	0.714	0.556	0.778	0.556	0.556	0.429	0.375	0.714	1.000
DTC	0.714	0.429	1.000	0.556	0.778	0.778	0.714	0.875	0.714	0.556
TVM	0.714	0.714	0.556	0.778	1.000	0.778	0.714	0.625	0.429	0.333
DPS	1.000	1.000	0.778	0.778	0.778	0.333	1.000	1.000	0.714	0.778
PNC	0.429	0.714	0.333	1.000	0.333	0.778	1.000	0.875	1.000	0.556
VM	0.714	0.714	0.333	0.556	1.000	0.778	0.714	0.625	1.000	0.333

Table 5. The criteria weights using the LOPCOW method

Criteria	CE	IC	VR	IS	RB	PTL	FA	LTI	EI	SS
Weight	0.1001	0.0993	0.1013	0.0988	0.1004	0.1000	0.0994	0.0998	0.0994	0.1013

4.3. Sentiment analysis score

The sentiment analysis value is a representation of the response of prospective voters, which is set as a special criterion, as set by the sentiment values positive = 3, neutral = 2, and negative = 1. Calculating sentiment values using hybrid SVM-SSO results in a majority decision of voter sentiment in a region against the strategy scenario. This study collected a dataset of 500 comments for each ideal strategy used to win a

candidate. The sample dataset containing public and stakeholder comments on the BCI strategy is shown in Table 6, and the predicted sentiment results are presented in Table 7.

Table 6. Dataset of potential voters

No	Text	Source	Topic category	Keywords
1	I really appreciate how this candidate listens to the people. We need more like them! #Leadership	Blog	Predictive analytics	Ethics, engagement, AI
2	Not convinced by their promises. We've heard this all before.	LinkedIn	Voter influence	Campaign, prediction, misinformation
3	They have a solid plan for education reform. This is exactly what we need!	LinkedIn	Predictive analytics	Voter, misinformation, AI
499	…	..	..	..
500	Another candidate is making promises they can't keep. Not falling for it this time.	Blog	Democracy and AI	Prediction, campaign, misinformation

Table 7. Result of predicting sentiment analysis using SVM-SSO

No	Text	Sentiment	Predicted sentiment
1	We finally have a candidate who stands up for the working class!	Neutral	Positive
2	They understand digital transformation and how it affects jobs. Smart policies!	Negative	Negative
3	Why are they suddenly changing their stance on important issues? Feels calculated.	Neutral	Neutral
4	I'm voting for them because they actually take the time to listen to us.	Positive	Positive
149	..	..	..
150	This is the kind of leader we need for the future. Let's support them!	Positive	Positive
Optimized C:			5.1460
Optimized gamma:			0.7602
Model accuracy:			0.9333

To further evaluate the performance and reliability of the proposed SVM–SSO model, its classification results were compared with SVM, random forest (RF), and bidirectional long short-term memory (BiLSTM) using accuracy, precision, recall, and F1-score. In addition, 95% confidence intervals (CIs) were calculated for classification accuracy to quantify the uncertainty associated with the performance estimates. Table 8 summarizes the comparative results of the evaluated models.

Table 8 presents a comparative evaluation of the proposed SVM-SSO model against conventional ML, ensemble learning, and deep learning baselines under the same experimental protocol. SVM, RF, and BiLSTM achieved accuracies of 92.67%, 91.33%, and 92.00%, respectively, whereas SVM-SSO achieved the highest observed accuracy of 93.33% (95% CI: 88.16 - 96.34%), together with the highest precision (0.934), recall (0.929), and F1-score (0.931). Although the improvement over conventional SVM is modest, SVM-SSO consistently achieved the highest observed values across the evaluated performance metrics. The CI further quantifies the uncertainty associated with the accuracy estimate, supporting a more reliable interpretation of model performance. These results indicate that SSO-based hyperparameter optimization provides an incremental improvement in SVM performance while maintaining balanced predictive capability across the evaluated sentiment classes.

Table 8. Performance comparison between the conventional SVM and the proposed SVM-SSO models

Model	Accuracy (%)	Precision	Recall	F1-score	95% CIs (accuracy)
SVM	92.67	0.928	0.923	0.925	87.35 - 95.86
RF	91.33	0.914	0.909	0.911	85.74 - 94.87
BiLSTM	92.00	0.921	0.916	0.918	86.54 - 95.36
Proposed SVM–SSO	93.33	0.934	0.929	0.931	88.16 - 96.34

The improved performance of the SVM-SSO model indicates that metaheuristic optimization can enhance the selection of SVM hyperparameters and consequently improve sentiment classification performance. This finding is consistent with previous studies demonstrating that optimization-assisted SVM models can achieve better predictive performance than conventional SVM configurations [46], [47]. However, the moderate improvement observed in this study also suggests that optimization should be evaluated not only in terms of accuracy gains but also in relation to computational complexity and model stability [48]. Finally, Figure 3 presents the sentiment classification results for each campaign strategy, namely BCI as in Figure 3(a), VST as in Figure 3(b), DTC as in Figure 3(c), TVM as in Figure 3(d), DPS as

in Figure 3(e), PNC as in Figure 3(f), and VM as in Figure 3(g). Based on the calculation results, public sentiment towards the proposed strategy varies, with the majority giving a neutral response.

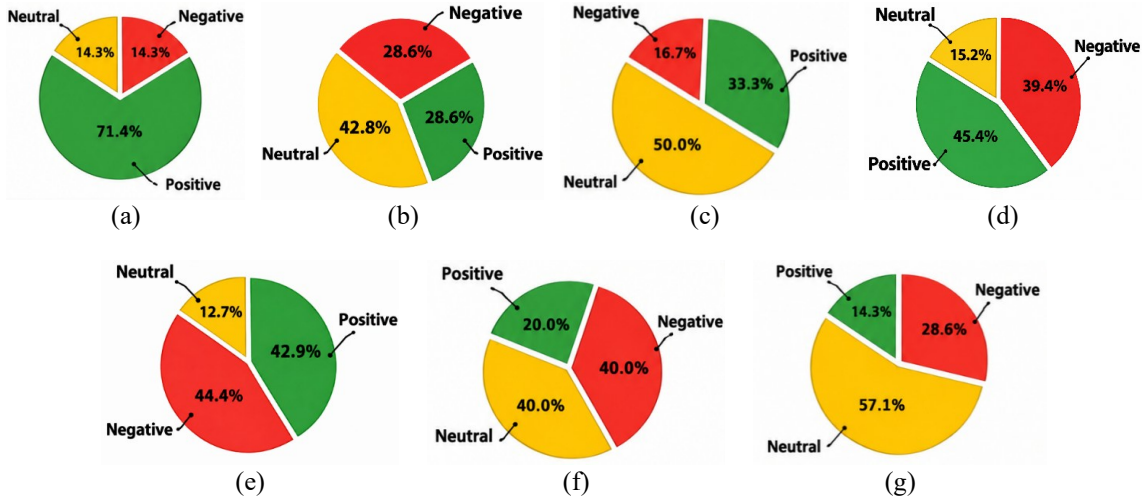


Figure 3. Sentiment distributions across the evaluated campaign strategies: (a) BCI, (b) VST, (c) DTC, (d) TVM, (e) DPS, (f) PNC, and (g) VM

4.4. Ranking of campaign strategies using the PROMETHEE II method

The strategy ranking process involves all criteria to produce an objective conclusion, with all interested parties participating in decision-making. The input score for the strategy is presented in Table 9. Based on the values of each criterion in Table 9, the positive, negative, and net flow values are calculated. Furthermore, the total and relative values are calculated to determine each strategy's ranking. The calculation results are shown in Table 10.

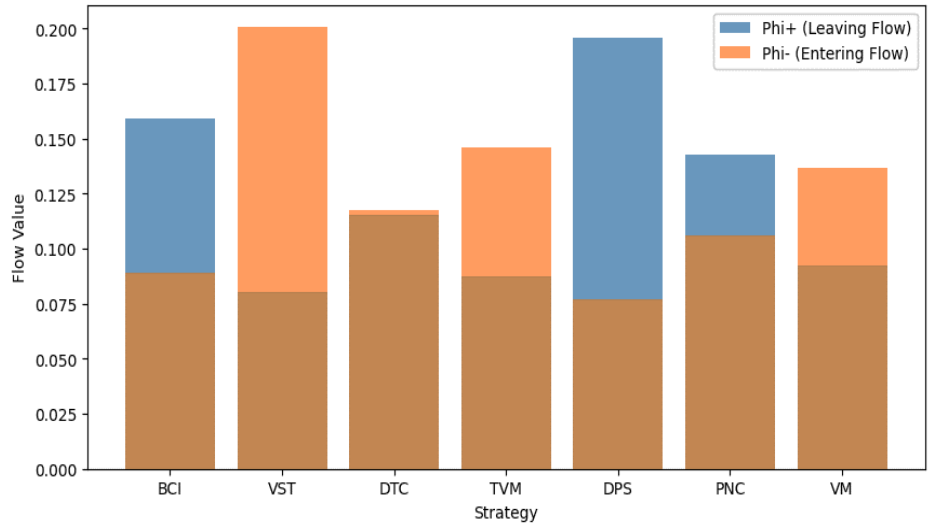
Table 9. Overall criterion input value

No	Strategy	CE	IC	VR	IS	RB	PTL	FA	LTI	EI	SS	Sentiment score
1	BCI	3	7	3	5	7	9	7	7	7	7	3
2	VST	3	5	5	7	5	5	3	3	5	9	2
3	DTC	5	3	9	5	7	7	5	7	5	5	2
4	TVM	5	5	5	7	9	5	5	5	3	3	3
5	DPS	7	7	7	7	7	3	7	9	5	7	1
6	PNC	3	5	7	9	3	7	7	7	5	5	2
7	VM	5	5	3	5	9	7	5	5	7	3	2

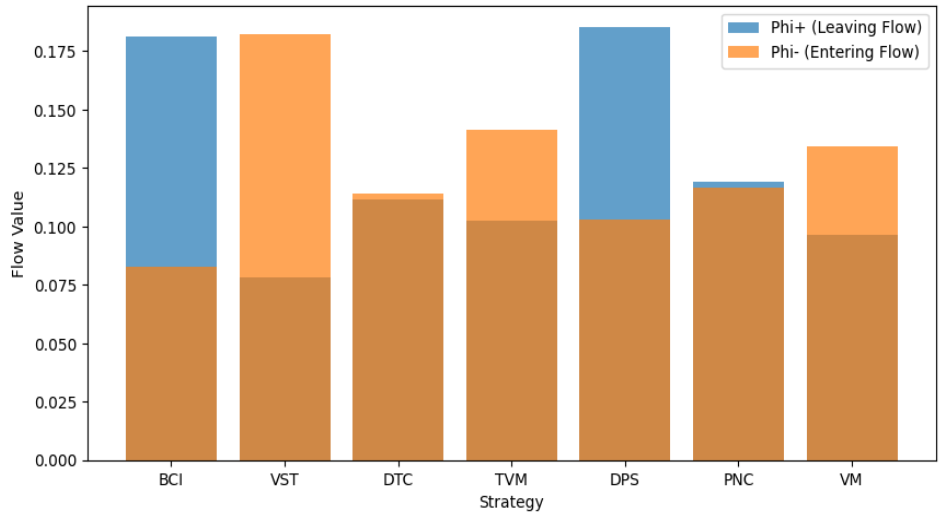
Table 10. The results of the calculation of the value of each strategy using the PROMETHEE II

No	Strategy	Phi+ (positive flow)	Phi- (negative flow)	Net flow (Phi)	Total score	Relative score	Rank
1	BCI	0.1812	0.0825	0.0987	0.7858	1.0000	1
2	VST	0.0781	0.1823	-0.1041	0.6119	0.7788	7
3	DTC	0.1115	0.1141	-0.0026	0.6990	0.8895	4
4	TVM	0.1025	0.1416	-0.0390	0.6677	0.8498	6
5	DPS	0.1853	0.1031	0.0823	0.7717	0.9821	2
6	PNC	0.1193	0.1167	0.0027	0.7035	0.8952	3
7	VM	0.0963	0.1342	-0.0379	0.6687	0.8510	5

Figure 4 presents a comparative visualization of the PROMETHEE II leaving and entering flow values under two evaluation scenarios, namely without and with the integration of public sentiment as an additional decision criterion. Figure 4(a) illustrates the leaving and entering flow values generated by the PROMETHEE II method without incorporating sentiment scores, while Figure 4(b) shows the corresponding flow values after integrating sentiment scores as an additional decision criterion. Based on the leaving and entering flow values, the ranking changes across strategies. The results are shown in Table 11.



(a)



(b)

Figure 4. PROMETHEE II preference flows of the evaluated campaign strategies (a) without sentiment integration and (b) with SVM-SSO-derived sentiment integration

Table 11. Comparison of strategy ranking results

No	Strategy	Without sentiment score		With sentiment score	
		Net flow	Ranking	Net flow	Ranking
1	BCI	0.0702	2	0.0987	1
2	VST	-0.1203	7	-0.1041	7
3	DTC	-0.0023	4	-0.0026	4
4	TVM	-0.0587	6	-0.0390	6
5	DPS	0.1187	1	0.0823	2
6	PNC	0.0366	3	0.0027	3
7	VM	-0.0442	5	-0.0379	5

Based on the PROMETHEE II results presented in Table 11, the contribution of AI-derived sentiment to the MCDM process was examined by comparing campaign strategy rankings with and without the sentiment criterion. Without sentiment integration, DPS ranked first, followed by BCI. After incorporating sentiment information generated by the SVM-SSO model, BCI became the highest-ranked strategy with a net flow of 0.0987, while DPS moved to second place with a net flow of 0.0823. The remaining strategies maintained their relative ranking positions, indicating that sentiment integration primarily influenced the prioritization of the leading alternatives while preserving the overall stability of the

ranking structure. This shift demonstrates that the ML component provides decision-relevant information that materially influences the final MCDM outcome and suggests that strengthening candidate image and branding may offer a more effective strategic focus when public perceptions are explicitly incorporated into campaign strategy evaluation.

4.5. Sensitivity analysis

The sensitivity analysis further demonstrates that the ranking results remain relatively stable under variations in criterion weights, providing additional evidence of the robustness of the proposed decision framework. Assessing ranking stability is particularly important in MCDM applications because changes in criterion importance can potentially alter the ordering of alternatives and affect the reliability of decision recommendations [49]. Therefore, the observed stability strengthens confidence in the proposed framework as a decision-support approach for evaluating campaign strategy. To improve decision reliability and flexibility, sensitivity tests are used to stabilize strategies across scenarios, identify the criteria with the greatest influence, and make it easier to demonstrate objectives in decision-making. The analyst's sensitivity test is performed by adding 0.5 to each criterion. The calculation results are shown in Figure 5.

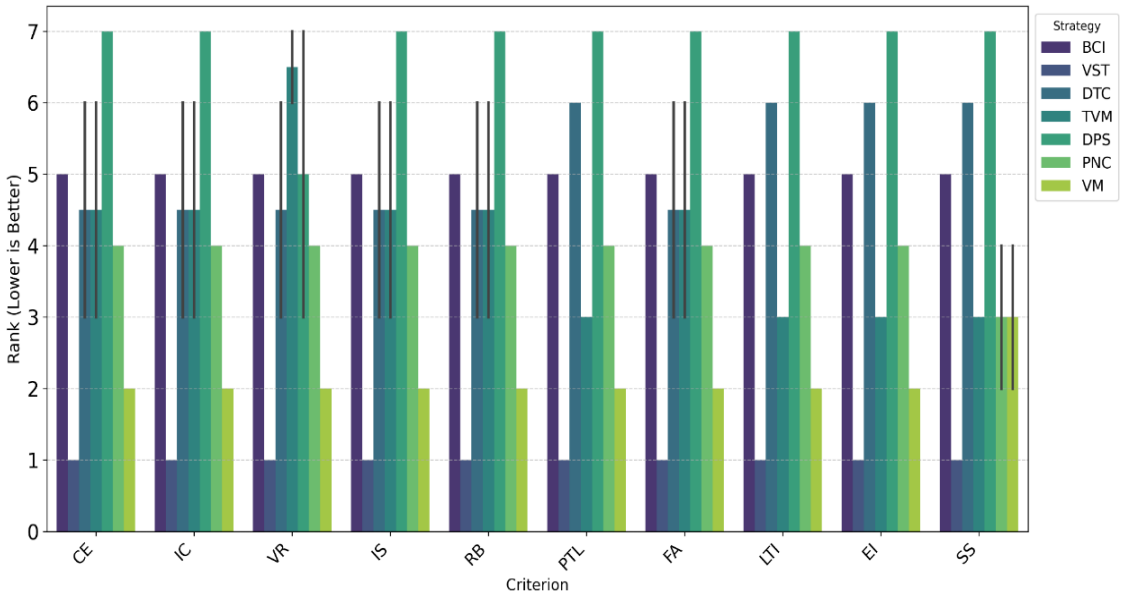


Figure 5. Sensitivity analysis of campaign strategy rankings across the evaluated decision criteria

Based on the results of the sensitivity analysis of the test, it is known that the PTL, LTI, and EI criteria greatly influence the change in strategy ratings. Furthermore, the DPS and TVM strategies are very sensitive to changes in the weight of the criteria, so in-depth evaluation is needed in decision-making. It is stated that BCI and PNC are more stable strategies and are not much affected by changes in the weight of the criteria, so they are ideal to implement. This study implies that independent watchdog organizations should be established to monitor AI usage in elections, ensuring compliance with ethical and legal standards and preventing undue influence on the democratic process.

4.6. Comparative analysis with recent AI-Based political decision-support approaches

To evaluate the relative contribution of the proposed framework, a comparative analysis was conducted against recent AI-based approaches in political analytics and decision support. Table 12 summarizes the comparative characteristics, advantages, and limitations of these approaches. Table 12 compares the proposed framework with recent AI-based political decision-support approaches using consistent functional criteria. While existing approaches primarily focus on predictive or descriptive political analytics, the proposed framework integrates SVM-SSO sentiment classification with LOPCOW weighting and PROMETHEE II ranking to support prescriptive strategy selection. Its main advantage lies in combining public-opinion intelligence with a traceable MCDM process. However, its effectiveness remains context-dependent and requires validation across broader electoral settings.

Table 12. Comparison with recent AI-based political decision-support approaches

Study	AI/analytical method	Sentiment analysis	Multi-criteria evaluation	Objective weighting	Strategy ranking	Decision traceability	Main limitation
[50]	BERT, SBERT, topic modeling	Limited	No	No	Relevance-based suggestions	Moderate	Focused on improving voting advice applications statements
[51]	Deep learning	Yes	No	No	No	Limited	Primarily sentiment classification
[52]	ML-based social-media analysis	Yes	No	No	No	Moderate	Focuses on digital campaign analysis
Proposed framework	SVM-SSO + LOPCOW + PROMETHEE II	Yes	Yes	Yes	Yes	High	Context-dependent data; strategy-level sentiment aggregation may lose distributional information

4.7. Computational efficiency and scalability

The computational characteristics of the proposed framework should also be considered for real-world deployment. The SVM-SSO component represents the most computationally demanding stage because SSO iteratively searches for optimal SVM hyperparameters, requiring repeated model training and evaluation. However, this optimization is primarily performed during model development or during periodic retraining, whereas sentiment prediction using the optimized SVM can be executed more efficiently in operational use. In comparison, the LOPCOW and PROMETHEE II components involve relatively straightforward matrix-based calculations, making them computationally manageable for evaluating a moderate number of campaign strategies and decision criteria. From a scalability perspective, the framework's modular architecture enables sentiment analysis, criteria weighting, and strategy ranking to be processed as interconnected yet separable components. This design facilitates parallel or distributed data preprocessing and sentiment classification when handling larger volumes of public opinion data. Nevertheless, real-world deployment involving continuous social media streams, multilingual data, and large voter populations may increase computational and storage requirements.

4.8. Limitations

Despite its advantages, the proposed framework has several limitations. Firstly, scalability may become challenging when substantially larger numbers of campaign alternatives, criteria, and social-media observations are processed, particularly because SSO optimization and PROMETHEE II require iterative and pairwise computations. Secondly, the findings are context-dependent and cannot be directly generalized to political environments with different electoral systems, voter behavior, cultural characteristics, languages, or digital-media ecosystems. Cross-country and multilingual validation is therefore required before broader deployment. Thirdly, algorithmic bias may arise from imbalanced or non-representative public-opinion data, subjective sentiment labels, and unequal representation of demographic or political groups. Such biases may propagate from the SVM-SSO sentiment predictions into the MCDM ranking. Majority-voting aggregation may obscure differences in sentiment distributions among campaign strategies.

5. CONCLUSION

This study demonstrates that integrating AI-based sentiment analysis with MCDM provides a systematic approach for evaluating political campaign strategies by combining public opinion with multiple decision criteria. The findings indicate that AI-derived sentiment provides decision-relevant information that can influence campaign strategy prioritization, with BCI emerging as the highest-ranked strategy after sentiment integration. This highlights the value of incorporating public sentiment into data-driven campaign decision support. The main contribution of this study is an integrated AI-MCDM framework that connects sentiment analysis, objective criteria weighting, and multi-criteria strategy evaluation within a unified decision-support process. The framework is intended to support rather than replace human judgment, enabling campaign decision-makers to evaluate alternatives using both structured assessment information and public responses. In practical terms, it can support more evidence-based, adaptive, and transparent campaign planning while promoting responsible use of AI in politically sensitive decision-making. Nevertheless, the findings should be interpreted within the scope of the evaluated electoral, linguistic, and data contexts. Future research should validate the framework using larger, multilingual, cross-country, and multi-platform datasets to assess its generalizability and transferability. Further investigation should also address fairness, privacy protection, potential data and algorithmic.

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C : **C**onceptualization
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [I], upon reasonable request.

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