

Article

A Hybrid NSGA-II and Machine Learning Framework for Multi-Objective Marketing Budget Optimization in Kazakhstan's Agro-Industrial Complex

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Abstract

The agro-industrial complex of Kazakhstan faces increasing pressure to improve the efficiency of marketing activities under conditions of limited budgets, regional heterogeneity, seasonal demand, and uneven digital infrastructure. Traditional marketing planning methods often rely on expert judgment or single-objective optimization and therefore cannot adequately address the conflicting objectives of maximizing marketing effectiveness, expanding audience coverage, and minimizing campaign expenditure. This study proposes a hybrid decision-support framework that combines the Non-dominated Sorting Genetic Algorithm II (NSGA-II) with machine learning-based clustering for multi-objective marketing budget optimization in the agro-industrial sector. The model considers five major promotion channels: digital media, television, radio, print media, and events. NSGA-II is used to generate Pareto-optimal budget allocation strategies, while K-means clustering classifies the resulting solutions into interpretable strategy groups. The framework was evaluated using synthetic data and enterprise-level data reflecting marketing conditions in Kazakhstan. Results show that strategies combining digital media and television achieve the highest marketing effectiveness and audience coverage, although they require greater campaign expenditure. Radio and print media remain relevant for cost-sensitive strategies, particularly for enterprises with limited resources. Cluster analysis identified three main strategy groups: cost-efficient, balanced, and high-performance configurations. The findings confirm that marketing budget allocation in the agro-industrial sector should be treated as a multi-objective optimization problem rather than a single-criterion decision. The proposed framework provides both computational optimization and managerial interpretability, supporting data-driven, adaptive, and resource-aware marketing planning for agro-industrial enterprises in Kazakhstan.



Received: 28 April 2026

Revised: 6 July 2026

Accepted: 17 July 2026

Published: 27 July 2026

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Keywords: marketing budget optimization; machine learning; K-means clustering; Pareto optimization; multi-objective optimization

1. Introduction

The rapid development of digital technologies has significantly changed modern marketing practices across many industries, including the agro-industrial sector [1,2]. Agro-industrial enterprises increasingly use digital platforms, online advertising, and data-driven marketing strategies to improve customer engagement, increase product visibility, and strengthen market competitiveness [3]. However, effective marketing budget allocation remains a complex challenge, especially under conditions of limited financial resources, changing market demand, and regional heterogeneity [4].

In Kazakhstan's agro-industrial complex, these challenges are even more important due to differences in digital infrastructure, unequal regional market accessibility, and varying enterprise capacities [5]. Many agricultural enterprises operate with limited marketing budgets and therefore require effective strategies that can maximize marketing impact while controlling campaign costs. As a result, intelligent decision-support systems and optimization methods are becoming increasingly important for improving marketing efficiency in this sector [6].

Marketing budget allocation is inherently a multi-objective optimization problem. Enterprises must simultaneously maximize marketing effectiveness and audience coverage while minimizing financial expenditure. These objectives are often conflicting, making traditional single-objective optimization methods insufficient for solving real-world marketing planning problems [7]. Therefore, multi-objective optimization approaches have attracted growing attention in recent years.

Previous studies have applied machine learning, evolutionary algorithms, and optimization techniques for resource allocation and marketing strategy analysis [8–10]. Among these approaches, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) has become one of the most widely used methods for solving multi-objective optimization problems due to its stable convergence behavior, ability to preserve Pareto diversity, and relatively low computational complexity [11]. NSGA-II has been successfully applied in engineering, operations research, scheduling, and resource allocation problems involving conflicting objectives [12].

In the proposed study, NSGA-II was selected because the marketing budget optimization problem includes three conflicting objectives: marketing effectiveness, audience coverage, and campaign cost. Compared with many-objective optimization algorithms such as NSGA-III, NSGA-II is more suitable for problems with a limited number of objectives while maintaining computational efficiency and stable Pareto-front generation [13].

Although NSGA-II can effectively generate Pareto-optimal solutions, the obtained Pareto front may contain many alternative strategies that are difficult for practitioners and managers to interpret directly. In practical agro-industrial environments, decision-makers require not only mathematically optimal solutions, but also understandable strategic categories that can support real managerial decisions under different budget conditions.

To address this issue, K-means clustering was integrated into the proposed framework as a post-optimization analysis tool. The purpose of clustering is not to replace optimization, but to organize similar Pareto-optimal solutions into interpretable strategy groups such as cost-efficient, balanced, and high-performance marketing strategies [14]. This improves the practical usability and interpretability of the optimization results.

K-means clustering was selected because of its computational simplicity, fast convergence, and easy interpretation of clustering results. Compared with more complex clustering methods such as Gaussian Mixture Models (GMM), K-means provides simpler centroid-based grouping and lower computational complexity, making it suitable for practical decision-support applications in the agro-industrial sector.

Based on these considerations, this study proposes a hybrid NSGA-II and K-means framework for multi-objective marketing budget optimization in Kazakhstan's agro-industrial complex. The proposed framework combines optimization and clustering to provide both efficient resource allocation and practical managerial interpretation of the obtained strategies.

The main contributions of this study are summarized as follows:

- Development of a hybrid optimization and clustering framework for marketing budget allocation;
- Application of NSGA-II for solving conflicting marketing objectives;
- Integration of K-means clustering for interpretable categorization of Pareto-optimal strategies;
- Adaptation of the framework to the specific conditions of Kazakhstan's agro-industrial sector;
- Improvement of practical decision-support capability for marketing strategy planning.

The remainder of this paper is organized as follows. Section 2 reviews related studies on marketing optimization and machine learning approaches. Section 3 presents the proposed methodology and hybrid framework. Section 4 discusses the experimental results and analysis. Finally, Section 5 concludes the paper and outlines future research directions.

2. Literature Review

The optimization of marketing strategies has been widely investigated in the fields of management science [15], digital marketing [16], operations research [17], and decision-support systems [18]. Previous studies have shown that marketing performance depends not only on the total amount of financial resources allocated to promotional activities, but also on how these resources are distributed among different communication channels [19], consumer segments [20], and regional markets [21]. In the context of agro-industrial enterprises, this problem becomes more complex because marketing decisions are affected by seasonality, logistical constraints, product perishability, regional demand heterogeneity, and the limited availability of reliable market data [1,3,4].

Traditional approaches to marketing planning have often relied on expert assessment, historical sales data, heuristic rules, or single-objective optimization models [7–9]. Such methods are useful when the number of decision variables is small and when the main objective is clearly defined, for example, maximizing sales volume or minimizing advertising cost. However, these approaches are limited in complex environments where several objectives must be achieved simultaneously. In agro-industrial marketing, decision-makers usually need to increase audience reach, improve campaign effectiveness, and control marketing expenditure at the same time [8,9]. These objectives are interdependent and often conflicting, which makes single-criterion optimization insufficient for practical decision-making [12,13].

In recent years, multi-objective optimization methods have increasingly been applied to marketing and resource allocation problems [19–21]. These methods allow researchers and practitioners to identify a set of compromise solutions rather than a single optimal answer. This is particularly important for marketing budget allocation, where each solution may represent a different strategic scenario. For example, one solution may provide high

audience coverage at a higher cost, another may minimize expenditure with moderate effectiveness, while a third may offer a balanced compromise between cost, reach, and efficiency.

Evolutionary algorithms have become one of the most effective tools for solving multi-objective optimization problems. Among them, the Non-dominated Sorting Genetic Algorithm II, commonly known as NSGA-II, has received considerable attention due to its ability to approximate Pareto-optimal solution sets [10,11]. The algorithm uses non-dominated sorting to rank candidate solutions and a crowding-distance mechanism to preserve diversity within the population [22,23]. These properties make NSGA-II suitable for problems where the objective functions are nonlinear, mutually conflicting, and difficult to optimize using classical mathematical programming methods [13,14]. In marketing applications, NSGA-II can be used to generate alternative budget allocation strategies across different promotional channels.

Despite these advantages, optimization algorithms alone do not always provide sufficient interpretability for managerial decision-making. A Pareto front may include a large number of solutions, each representing a different combination of budget shares and performance indicators. Without additional analytical tools, it may be difficult for decision-makers to understand which strategies are suitable for specific segments, budget levels, or regional conditions. Therefore, the integration of machine learning methods with multi-objective optimization has become an important direction in modern decision-support research [24–26].

Machine learning methods can strengthen marketing optimization in several ways. Clustering algorithms can be used to group similar strategies and identify dominant patterns in the Pareto-optimal solution set. Predictive models can estimate the expected effectiveness of promotion channels based on previous campaign data, market characteristics, and consumer behavior. Segmentation methods can help distinguish groups of customers or regions with different demand profiles [27,28]. In this study, K-means clustering is used as a post-optimization tool to structure the Pareto-optimal solutions generated by NSGA-II and to make the results more interpretable for practical use.

In agricultural and agro-industrial contexts, digital marketing and intelligent analytics are still developing unevenly. Many studies emphasize the importance of digital transformation, information and consulting services, and marketing infrastructure for improving the competitiveness of agricultural producers. However, fewer studies provide a formal optimization framework that simultaneously considers multiple marketing performance criteria. In particular, the existing literature often discusses agricultural marketing, digitalization, or decision-support tools separately, while integrated approaches combining evolutionary optimization and machine learning remain limited.

Another important limitation of previous studies is that marketing models are frequently developed for general consumer markets and do not sufficiently account for the specific features of the agro-industrial complex. Unlike conventional retail sectors, agro-industrial marketing is influenced by spatial dispersion of producers, seasonal production cycles, dependence on natural and climatic conditions, and the predominance of wholesale and business-to-business communication channels. These factors require more adaptive and context-sensitive models of marketing planning.

For Kazakhstan, this issue is especially relevant. The agro-industrial complex of Kazakhstan is characterized by large territorial scale, regional differences in infrastructure, uneven digitalization, and varying access of agricultural enterprises to modern marketing tools [1,2]. As a result, enterprises need decision-support models that can adapt marketing strategies to different budget levels, media channels, and target segments. A model that only maximizes one indicator cannot fully capture these practical requirements.

Recent studies [29–31] have highlighted that sustainable organizational performance depends on the effective integration of technological capabilities, innovation processes, and strategic decision-making rather than on isolated technology investments alone. The growing adoption of digital technologies and data-driven management approaches has increased the need for intelligent decision-support systems capable of optimizing complex business functions. In this context, AI-driven optimization frameworks offer significant potential for improving marketing resource allocation and enhancing competitiveness in the agro-industrial sector.

Previous studies have applied various optimization and machine learning techniques to marketing strategy analysis, resource allocation, and decision-support problems. However, many existing approaches either focus only on optimization performance or only on data-driven interpretation. In the context of agro-industrial marketing, practical decision-making requires both efficient optimization under conflicting objectives and interpretable strategic categorization of the obtained solutions. For this reason, the present study combines NSGA-II and K-means clustering. NSGA-II was selected because of its strong capability to generate diverse Pareto-optimal solutions for multi-objective problems, while K-means clustering was chosen due to its computational simplicity and ability to organize Pareto-optimal strategies into interpretable groups. The proposed hybridization therefore aims to provide both optimization efficiency and managerial interpretability within a unified decision-support framework.

Based on this literature review, several research gaps can be identified. First, there is a lack of studies that formulate marketing budget allocation in the agro-industrial complex as a multi-objective optimization problem involving effectiveness, audience coverage, and cost. Second, existing optimization-based studies often focus on generating optimal solutions but provide limited tools for interpreting these solutions from a managerial perspective. Third, the use of hybrid frameworks combining NSGA-II and machine learning remains insufficiently explored in the context of agro-industrial marketing. Fourth, there is a need for models adapted to the specific conditions of Kazakhstan's agro-industrial complex, where marketing decisions are shaped by regional, infrastructural, and budgetary constraints.

Therefore, this study addresses the identified gaps by proposing a hybrid NSGA-II and K-means-based framework for multi-objective marketing budget optimization in the agro-industrial complex of Kazakhstan. The proposed approach not only identifies Pareto-optimal allocations of marketing resources across digital media, television, radio, print media, and events, but also groups the obtained solutions into interpretable strategy clusters. This provides both computational optimization and practical decision support for agro-industrial enterprises operating under limited resources and uncertain market conditions.

3. Materials and Methods

3.1. General Framework of the Proposed Approach

This study proposes a hybrid decision-support framework for optimizing marketing budget allocation in the agro-industrial complex of Kazakhstan. The framework combines multi-objective evolutionary optimization with machine learning-based post-optimization analysis. The combination of NSGA-II and K-means clustering was selected because the marketing budget allocation problem involves both optimization complexity and managerial interpretability. NSGA-II is responsible for identifying Pareto-optimal solutions under conflicting objectives, including effectiveness, audience coverage, and campaign cost. However, the obtained Pareto front may contain numerous alternative solutions that are difficult to analyze directly from a managerial perspective. Therefore, K-means clustering is applied as a post-optimization analytical tool to organize the Pareto-optimal solutions

into interpretable strategy groups. This hybridization allows the framework to provide both computational optimization and practical decision-support functionality for agro-industrial enterprises operating under heterogeneous market and budget conditions. The main purpose of the proposed approach is to identify a set of efficient marketing strategies that simultaneously improve marketing effectiveness, increase audience coverage, and reduce campaign cost.

The methodological logic of the study consists of two consecutive stages. In the first stage, the Non-dominated Sorting Genetic Algorithm II is used to solve the multi-objective optimization problem and generate a Pareto-optimal set of marketing budget allocation strategies. In the second stage, K-means clustering is applied to the obtained Pareto-optimal solutions in order to classify them into interpretable groups. This makes it possible not only to obtain mathematically efficient solutions, but also to provide practical recommendations for agro-industrial enterprises with different budget levels and strategic priorities.

The proposed framework considers five major marketing channels: digital media, television, radio, print media, and events. These channels were selected because they reflect both modern digital communication tools and traditional promotion instruments that remain relevant for agricultural markets in Kazakhstan. Each marketing strategy is represented as a vector of budget shares allocated to these channels. The quality of each strategy is assessed using three criteria: marketing effectiveness, audience coverage, and campaign cost.

3.2. Problem Formulation

Let the set of marketing channels be denoted as Equation (1):

$$C = \{c_1, c_2, \dots, c_n\} \quad (1)$$

where n is the number of available marketing channels. In this study, $n = 5$, corresponding to digital media, television, radio, print media, and events.

A marketing strategy is represented by the budget allocation vector:

$$x = (x_1, x_2, \dots, x_n) \quad (2)$$

where x_i denotes the share of the total marketing budget allocated to the i -th channel. The value of x_i is constrained by minimum and maximum allowable budget shares for each channel, reflecting practical limitations of media planning and sector-specific requirements.

The general budget constraint is defined as:

$$\sum_{i=1}^n x_i \leq B \quad (3)$$

where B is the total available marketing budget. If the variables are normalized as budget shares, then the constraint can be written as:

$$\sum_{i=1}^n x_i = 1 \quad (4)$$

In addition, each channel is subject to lower and upper bounds:

$$x_i^{\min} \leq x_i \leq x_i^{\max}, \quad i = 1, 2, \dots, n \quad (5)$$

where $x_i^{\min}$ and $x_i^{\max}$ represent the minimum and maximum permissible shares of the marketing budget allocated to the i -th channel.

The optimization problem is formulated as a multi-objective problem because marketing managers need to consider several conflicting objectives simultaneously. In this study, three objective functions are used: marketing effectiveness, audience coverage, and campaign cost.

3.3. Objective Functions

The first objective is to maximize the overall marketing effectiveness of the campaign. Marketing effectiveness reflects the expected contribution of each communication channel to the achievement of marketing goals, such as increasing product visibility, strengthening customer engagement, and improving the probability of purchase or cooperation.

The total effectiveness of a marketing strategy is calculated as:

$$F_1(x) = \sum_{i=1}^n e_i x_i \quad (6)$$

where e_i is the effectiveness coefficient of the i -th marketing channel, and x_i is the corresponding budget share.

The second objective is to maximize audience coverage. Audience coverage reflects the potential reach of a marketing campaign across target groups, regions, and market segments. It is calculated as:

$$F_2(x) = \sum_{i=1}^n r_i x_i \quad (7)$$

where r_i is the audience reach coefficient of the i -th marketing channel.

The third objective is to minimize the total cost of implementing the marketing strategy. The cost function is defined as:

$$F_3(x) = \sum_{i=1}^n p_i x_i \quad (8)$$

where p_i is the cost coefficient of the i -th marketing channel.

Thus, the optimization problem can be expressed as follows:

$$\max F_1(x), \max F_2(x), \min F_3(x), \quad (9)$$

Subject to

$$\sum_{i=1}^n x_i = 1$$

$$x_i^{\min} \leq x_i \leq x_i^{\max}, \quad i = 1, 2, \dots, n \quad (10)$$

This formulation reflects the real decision-making conditions of agro-industrial enterprises, where increasing marketing effectiveness and audience coverage typically requires additional financial resources. Therefore, the objective is not to identify a single universal solution but to determine a set of Pareto-optimal strategies representing different trade-offs between performance and cost.

3.4. Pareto Optimality

A solution is considered Pareto-optimal if no other feasible solution can improve one objective without worsening at least one other objective. In the context of this study, a marketing strategy belongs to the Pareto-optimal set if it is impossible to increase effectiveness or audience coverage without increasing cost, or to reduce cost without decreasing effectiveness or coverage.

Let X denote the feasible solution space. A solution $x^* \in X$ is Pareto-optimal if there is no other solution $x \in X$ such that:

$$\begin{aligned}
 &F_j(x) \geq F_j(x^*) \text{ for all maximized objectives} \\
 \text{and} \\
 &F_j(x) \geq F_j(x^*) \text{ for at least one objective}
 \end{aligned}
 \tag{11}$$

while also satisfying the minimization condition for cost. The set of such non-dominated solutions forms the Pareto front. This front provides decision-makers with several alternative strategies, each corresponding to a specific balance between efficiency, reach, and cost.

3.5. NSGA-II Optimization Procedure

To solve the formulated multi-objective optimization problem, this study applies the NSGA-II algorithm. NSGA-II is well-suited for this type of problem because it can generate a diverse set of non-dominated solutions while maintaining a balanced representation of the Pareto front. The algorithm begins with the generation of an initial population of candidate marketing strategies. Each individual in the population represents a possible allocation of the marketing budget across the five selected channels. The fitness of each individual is evaluated according to the three objective functions: effectiveness, coverage, and cost.

At each generation, the population is sorted into non-dominated fronts. Solutions in the first front are not dominated by any other solution in the population. Solutions in the second front are dominated only by those in the first front, and so on. This ranking allows the algorithm to prioritize high-quality solutions while preserving multiple trade-off alternatives.

To maintain diversity among solutions, the crowding distance mechanism is used. This mechanism estimates how close a solution is to its neighboring solutions in the objective space. Solutions with larger crowding distances are preferred because they contribute to a more uniform distribution of the Pareto front.

The algorithm employs simulated binary crossover and polynomial mutation operators to generate new candidate solutions. The crossover operator combines two parent strategies to produce new budget allocation vectors, while the mutation operator introduces small random changes to budget shares. These operators enable the algorithm to thoroughly explore the solution space and avoid premature convergence.

The general procedure of NSGA-II in this study can be summarized as follows:

1. Generate an initial population of budget allocation strategies.
2. Evaluate each strategy using the objective functions for effectiveness, coverage, and cost.
3. Rank the population using non-dominated sorting.
4. Calculate the crowding distance for each solution.
5. Select parent solutions based on rank and crowding distance.
6. Generate offspring using crossover and mutation operators.
7. Combine parent and offspring populations.
8. Select the best solutions for the next generation.
9. Repeat the procedure until the stopping criterion is reached.
10. Extract the final Pareto-optimal set.

This procedure produces a set of alternative marketing strategies rather than a single solution. Such an outcome is particularly important for agro-industrial enterprises because marketing decisions depend on available budget, regional conditions, target segments, and managerial priorities.

In the implemented NSGA-II procedure, the optimization process used a population size of 100 individuals, a crossover probability of 0.9, and a mutation probability of 0.1. The optimization was executed for 200 generations, which was selected as the stopping

criterion based on convergence stability and preservation of Pareto-front diversity. These parameter values were selected to maintain a balance between computational efficiency and solution quality during the optimization process.

3.6. Machine Learning-Based Clustering of Pareto-Optimal Solutions

After the Pareto-optimal solutions are obtained, K-means clustering is applied to classify them into strategy groups. The purpose of clustering is to improve the interpretability of the optimization results and make them more useful for practical decision-making.

Each Pareto-optimal solution is described by a set of features, including the budget shares allocated to digital media, television, radio, print media, and events, as well as the resulting values of effectiveness, coverage, and cost. K-means clustering partitions the solutions into k clusters by minimizing the within-cluster distance between solutions and their corresponding cluster centroids.

Formally, K-means solves the following minimization problem:

$$\min \sum_{k=1}^K \sum_{x \in S_k} \|x - \mu_k\|^2 \quad (12)$$

where K is the number of clusters, S_k is the set of solutions assigned to the k -th cluster, and μ_k is the centroid of that cluster.

The number of clusters was set to three in order to provide practically interpretable categorization of the obtained Pareto-optimal marketing strategies. The selected clusters correspond to cost-efficient, balanced, and high-performance strategy groups. The choice of three clusters was guided by the observed distribution of optimization results and the need to maintain managerial interpretability of the obtained strategies. Increasing the number of clusters produced more fragmented groupings with limited practical distinction, while fewer clusters reduced the interpretability of strategic differences between solutions.

3.7. Data Description

The proposed hybrid NSGA-II and K-means framework was evaluated using a combination of real enterprise-level data, synthetic data, and a public Kaggle dataset on TV marketing to reflect agro-industrial marketing conditions in Kazakhstan. The real dataset comprised approximately 1200 marketing strategy records collected from 15 agro-industrial enterprises during the 2024–2025 period. These records included budget allocations across five marketing channels—digital media, television, radio, print media, and events—along with performance metrics such as effectiveness, audience coverage, cost, target segment, cluster assignment, and composite score. This dataset provides empirical grounding to evaluate the framework's practical applicability for real-world marketing decisions.

To augment the limited real dataset and explore a broader range of budget allocation scenarios, approximately 3500 synthetic records were generated. The synthetic data were created based on statistical distributions and realistic parameter ranges derived from the real dataset to preserve the relationships between budget allocations and performance metrics. Budget allocations for each marketing channel were sampled from distributions consistent with the observed minimum and maximum values, while maintaining proportional relationships between channels. Marketing effectiveness and audience coverage coefficients were generated using multivariate distributions that preserve the correlation structure observed in the real dataset. Implausible or extreme records were removed to ensure that the synthetic data accurately represent feasible marketing scenarios. While the synthetic dataset supports methodological validation and

scenario exploration, it cannot fully capture dynamic market behaviors or unobserved enterprise-specific patterns.

In addition, a public Kaggle dataset was incorporated to enhance the diversity of marketing scenarios and provide an openly accessible benchmark for reproducibility. This dataset complements the real and synthetic datasets but was not used as the primary basis for optimization analysis.

All datasets were preprocessed with normalization and feature standardization to ensure consistent scaling and improve the stability of NSGA-II optimization. This preprocessing ensures that the real, synthetic, and Kaggle datasets can be effectively integrated and analyzed within the proposed framework.

By combining real, synthetic, and public datasets, the framework allows evaluation from two complementary perspectives: synthetic data support methodological validation and scenario testing, while real enterprise-level and Kaggle datasets demonstrate practical relevance and reproducibility in agro-industrial marketing applications.

3.8. Evaluation Metrics

The quality of the obtained optimization results was evaluated using Pareto-front visualization, cluster analysis, correlation analysis, and the hypervolume indicator. Pareto-front visualization was used to examine the trade-off relationship between effectiveness, coverage, and cost. A three-dimensional Pareto front was constructed to represent the distribution of non-dominated solutions in the objective space.

The hypervolume indicator was used to assess the quality of the Pareto front. It measures the volume of the objective space dominated by the obtained Pareto-optimal solutions with respect to a predefined reference point. A larger hypervolume value indicates a better approximation of the Pareto front because it reflects both convergence toward optimal solutions and diversity across the objective space.

The hypervolume indicator can be expressed as:

$$HV = volume \left(\bigcup_{x \in P} [F_1(x), F_2(x), F_3(x)] \right) \quad (13)$$

where P is the Pareto-optimal solution set, and the volume is calculated relative to a reference point in the objective space.

In addition to hypervolume analysis, correlation analysis was conducted to examine the relationships between marketing channels and performance indicators. This made it possible to identify which channels were most strongly associated with effectiveness, coverage, and cost. Cluster-level analysis was then used to interpret the strategic meaning of the obtained solutions and to determine which combinations of channels were most appropriate for different budget conditions.

4. Results

4.1. General Overview of the Optimization Results

The proposed hybrid framework was evaluated through computational experiments aimed at identifying efficient marketing budget allocation strategies for agro-industrial enterprises. The optimization procedure generated a set of Pareto-optimal solutions representing alternative trade-offs between marketing effectiveness, audience coverage, and campaign cost. These solutions were further grouped using K-means clustering in order to provide an interpretable classification of marketing strategies.

The obtained results demonstrate that the effectiveness of marketing strategies in the agro-industrial complex depends not only on the total amount of budget allocated to promotional activities, but also on the structure of budget distribution among communication channels. In particular, the combination of digital media and television produced the strongest performance in terms of effectiveness and coverage, while radio and print media were more characteristic of cost-sensitive strategies. This confirms that marketing budget allocation in the agro-industrial complex should be considered as a multi-objective decision-making problem rather than as a single-criterion cost minimization task.

The optimization results are summarized in Table 1, which presents the average values of effectiveness, coverage, cost, and composite score for the identified clusters. The table also indicates the dominant marketing channels associated with each cluster.

Table 1. Results of modeling the effectiveness of different media channels for promoting agricultural products in the Kazakhstan market.

Cluster	Avg Efficiency	Avg Coverage	Avg Cost	Avg Composite Score	Key Channels
0	1.260	1.110	1.290	0.690	TV, Print, Radio
1	0.680	0.600	0.750	0.610	Radio, Print
2	1.560	1.390	1.730	0.660	Digital, TV

As shown in Table 1, Cluster 2 achieved the highest average efficiency and audience coverage, with values of 1.560 and 1.390, respectively. This cluster is mainly associated with the combined use of digital media and television. However, it also required the highest average cost, equal to 1.730. Therefore, Cluster 2 can be interpreted as a high-performance strategy group suitable for enterprises that prioritize market expansion, strong visibility, and broad audience reach.

Cluster 1 demonstrated the lowest average cost, equal to 0.750, but also had the lowest average efficiency and coverage values. This cluster is mainly associated with radio and print media. It can be interpreted as a cost-efficient strategy group suitable for agro-industrial enterprises with limited marketing budgets. Although such strategies do not provide the highest market impact, they remain practically relevant when the primary objective is to control expenditure.

Cluster 0 occupied an intermediate position between Cluster 1 and Cluster 2. It achieved relatively high values of efficiency and coverage while maintaining a moderate level of cost. The dominant channels in this cluster were television, print media, and radio. The highest average composite score was observed in Cluster 0, which indicates that this group provides the most balanced relationship between effectiveness, coverage, and cost. Therefore, Cluster 0 can be regarded as a balanced strategy group that may be suitable for enterprises seeking stable marketing performance without excessive expenditure.

4.2. Analysis of Enterprise-Level Optimization Results

A fragment of enterprise-level optimization results is presented in Table 2. The table includes budget allocation shares for five marketing channels—digital media, television, radio, print media, and events—and the corresponding values of efficiency, coverage, cost, segment, cluster, and composite score. These results make it possible to evaluate how different combinations of marketing channels affect the overall performance of promotional strategies in the agro-industrial complex.

Table 2. Enterprise-level optimization results.

Digital	TV	Radio	Print	Events	Efficiency	Coverage	Cost	Segment	Cluster	Score
0.726	0.235	0.679	0.194	0.160	0.330	1.532	1.928	0	2	0.647
0.106	0.117	0.102	0.172	0.133	0.480	0.426	0.535	0	1	0.582
0.106	0.100	0.101	0.172	0.133	0.480	0.422	0.521	0	1	0.594
0.102	0.104	0.138	0.275	0.153	0.590	0.519	0.638	0	1	0.615
0.133	0.117	0.100	0.172	0.130	0.500	0.444	0.562	0	1	0.582
0.108	0.580	0.112	0.285	0.106	0.940	0.826	0.962	0	1	0.675
0.104	0.416	0.1794	0.294	0.137	0.870	0.774	0.928	0	1	0.653
0.726	0.236	0.687	0.143	0.160	1.682	1.512	1.905	0	2	0.645
0.102	0.572	0.138	0.275	0.153	0.980	0.862	1.013	0	0	0.672
0.699	0.220	0.666	0.157	0.160	1.636	1.471	1.852	0	2	0.645
0.378	0.898	0.350	0.169	0.157	1.574	1.389	1.729	0	2	0.658
0.276	0.886	0.359	0.234	0.161	1.539	1.365	1.658	0	2	0.670
0.146	0.299	0.101	0.298	0.107	0.735	0.644	0.778	0	1	0.638
0.100	0.8797	0.138	0.285	0.136	1.231	1.084	1.246	0	0	0.698
0.138	0.813	0.175	0.291	0.164	1.262	1.113	1.302	0	0	0.688
0.221	0.896	0.331	0.184	0.189	1.470	1.304	1.573	0	2	0.673
0.276	0.897	0.353	0.182	0.136	1.490	1.323	1.607	0	2	0.669
0.133	0.3718	0.105	0.272	0.107	0.771	0.677	0.809	0	1	0.647
0.416	0.894	0.334	0.168	0.185	1.622	1.439	1.775	0	2	0.662
0.392	0.833	0.312	0.168	0.157	1.513	1.342	1.655	0	2	0.660
0.228	0.8981	0.350	0.168	0.135	1.438	1.278	1.543	0	2	0.670
0.416	0.897	0.294	0.168	0.185	1.596	1.414	1.739	0	2	0.664
0.108	0.861	0.112	0.271	0.106	1.170	1.030	1.179	0	0	0.698
0.148	0.888	0.168	0.298	0.162	1.331	1.173	1.367	0	0	0.693
0.109	0.881	0.252	0.296	0.102	1.306	1.154	1.348	0	0	0.690
0.126	0.893	0.107	0.120	0.109	1.113	0.983	1.132	1	0	0.691
0.133	0.656	0.250	0.173	0.105	1.057	0.938	1.122	1	0	0.662
0.102	0.8413	0.138	0.275	0.153	1.208	1.064	1.228	1	0	0.695
0.133	0.897	0.186	0.183	0.181	1.281	1.132	1.325	1	0	0.687
0.699	0.220	0.666	0.119	0.160	1.613	1.452	1.829	1	2	0.643
0.112	0.880	0.107	0.120	0.106	1.026	0.893	1.102	1	0	0.649
0.148	0.862	0.250	0.298	0.179	1.385	1.223	1.444	1	0	0.685
0.106	0.886	0.103	0.285	0.104	1.189	1.046	1.193	1	0	0.702
0.122	0.893	0.109	0.123	0.136	1.135	1.002	1.156	1	0	0.691
0.182	0.211	0.101	0.271	0.106	0.671	0.589	0.729	1	1	0.618
0.104	0.131	0.179	0.294	0.102	0.618	0.541	0.667	1	1	0.614
0.136	0.312	0.246	0.197	0.181	0.854	0.750	0.927	1	1	0.634
0.104	0.418	0.320	0.294	0.138	0.986	0.874	1.070	1	0	0.645
0.133	0.645	0.250	0.173	0.110	1.051	0.932	1.117	1	0	0.661

Table 2. *Cont.*

Digital	TV	Radio	Print	Events	Efficiency	Coverage	Cost	Segment	Cluster	Score
0.184	0.843	0.328	0.196	0.178	1.390	1.233	1.484	1	2	0.672
0.109	0.416	0.125	0.282	0.137	0.816	0.709	0.872	1	1	0.638
0.226	0.840	0.252	0.186	0.153	1.339	1.186	1.422	1	0	0.673
0.235	0.8795	0.238	0.269	0.162	1.431	1.265	1.509	1	2	0.680
0.105	0.231	0.138	0.281	0.160	0.705	0.612	0.753	1	1	0.628
0.185	0.211	0.101	0.271	0.136	0.706	0.614	0.760	1	1	0.624
0.103	0.416	0.125	0.282	0.160	0.848	0.745	0.886	1	1	0.656
0.423	0.88	0.102	0.125	0.106	1.352	1.193	1.443	1	0	0.669
0.134	0.397	0.100	0.296	0.143	0.834	0.732	0.873	1	1	0.654
0.100	0.211	0.138	0.271	0.106	0.630	0.548	0.676	1	1	0.617
0.123	0.371	0.106	0.122	0.110	0.668	0.590	0.712	1	1	0.629

The enterprise-level results confirm the patterns identified in the cluster-level analysis. Strategies with higher shares of digital media and television generally produced higher values of efficiency and audience coverage. For example, solutions assigned to Cluster 2 demonstrated efficiency values reaching approximately 1.61–1.68 and coverage values above 1.45 in several cases. These results indicate that digital media and television can play a central role in increasing the visibility of agricultural products and expanding communication with target audiences.

At the same time, the results also show that high-performance strategies are associated with higher implementation costs. This is consistent with the logic of multi-objective optimization: increasing marketing effectiveness and coverage usually requires greater financial investment. Therefore, the practical value of the Pareto-optimal solution set lies in its ability to provide several alternatives rather than a single universal strategy.

Cluster 1 included strategies with lower cost values, often below 1.0. These strategies relied more strongly on radio and print channels and were characterized by moderate effectiveness and coverage. Such configurations may be useful for smaller agro-industrial enterprises, regional producers, or enterprises operating under strict budget limitations. Although their overall marketing impact is lower than that of digital- and television-oriented strategies, they provide a feasible option for maintaining market communication at reduced cost.

The comparison of Segment 0 and Segment 1 also shows that the effectiveness of marketing strategies differs across target groups. Segment 0 generally included higher-score solutions, especially in clusters with stronger digital and television components. Segment 1 contained more cost-sensitive solutions, with several strategies assigned to Cluster 1. This suggests that segment-specific conditions should be considered when selecting marketing strategies. A budget allocation model that performs well for one market segment may not necessarily be optimal for another.

4.3. Three-Dimensional Pareto Front Analysis

Figure 1 presents the three-dimensional Pareto front generated by the proposed hybrid optimization method. The three axes represent marketing effectiveness, audience coverage, and campaign cost, while the color scale reflects the composite score of the corresponding solutions.

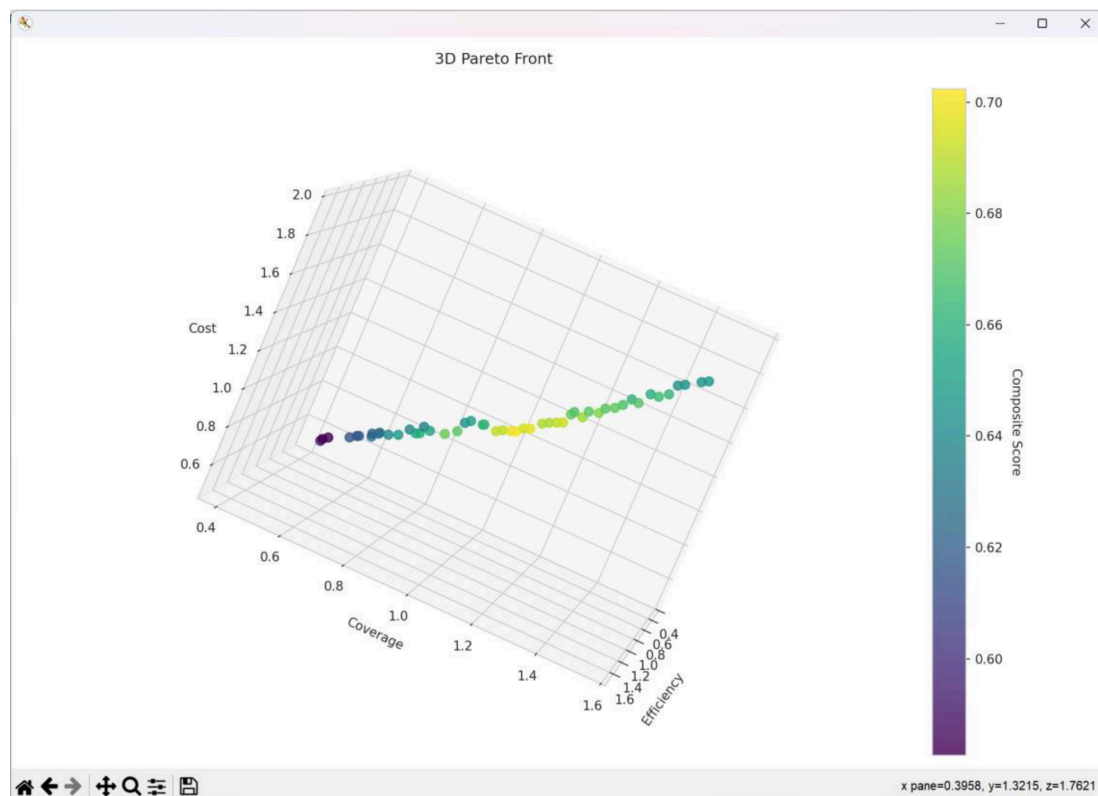


Figure 1. Pareto front in 3D format generated by the proposed hybrid method.

The distribution of points along the Pareto front confirms the existence of clear trade-offs among the three optimization criteria. Solutions with higher effectiveness and broader audience coverage are generally associated with higher cost values. This pattern reflects the real structure of marketing decision-making in the agro-industrial complex, where stronger promotional impact usually requires greater investment in high-reach communication channels.

The Pareto front also demonstrates the nonlinear nature of the relationship between budget allocation and marketing performance. A proportional increase in cost does not always lead to a proportional increase in effectiveness or coverage. This indicates that inefficient budget allocation may result in unnecessary expenditure without a corresponding improvement in marketing outcomes. Therefore, the use of multi-objective optimization is justified because it helps identify solutions where the balance between cost and performance is more favorable.

The solutions with the highest composite score are located in regions where effectiveness, coverage, and cost are relatively well balanced. These solutions are particularly important for practical decision-making because they represent marketing strategies that do not simply maximize one criterion, but provide an acceptable compromise among all three objectives. For agro-industrial enterprises, such strategies can serve as recommended configurations for planning promotional campaigns under realistic budget constraints.

4.4. Two-Dimensional Pareto Frontier and Cluster Interpretation

Figure 2 shows the two-dimensional Pareto frontier reflecting the trade-off between marketing effectiveness and audience coverage. The size of the markers corresponds to the cost of implementing the strategy, while the color classification represents the identified clusters.

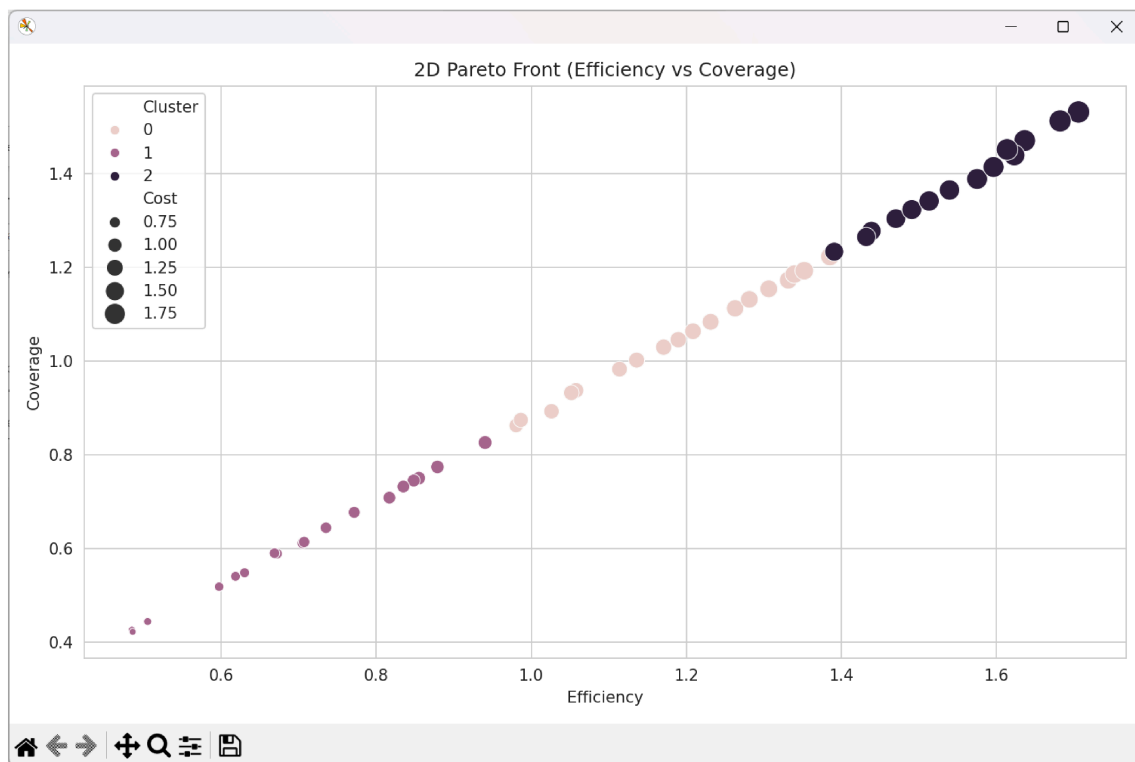


Figure 2. Two-dimensional Pareto frontier reflecting the trade-off between marketing effectiveness and audience coverage.

The visualization shows that the Pareto-optimal solutions are not concentrated in a single region, but are distributed across different areas of the objective space. This confirms the presence of several possible strategic alternatives. Some solutions provide relatively high effectiveness with moderate coverage, while others achieve broader audience reach at higher cost.

The cluster structure provides additional interpretation of the Pareto frontier. Cluster 0 represents balanced strategies with relatively strong effectiveness and moderate-to-high coverage. These solutions are suitable for enterprises that aim to achieve stable performance while avoiding excessive cost. Cluster 1 contains more cost-sensitive strategies. These solutions are characterized by lower implementation cost and moderate performance indicators. They may be appropriate for enterprises with limited budgets or for regional campaigns where the objective is to maintain basic market presence. Cluster 2 includes high-performance strategies, usually associated with stronger use of digital media and television. These solutions provide the highest levels of effectiveness and coverage, but they require larger financial resources.

The marker size distribution also confirms that the best-performing solutions are often more expensive. However, not all high-cost solutions are equally efficient. This further supports the need for Pareto-based optimization, since it allows decision-makers to avoid strategies that are costly but do not provide sufficient improvement in effectiveness or coverage.

4.5. Correlation Analysis of Marketing Channels and Performance Indicators

Figure 3 presents the correlation matrix between marketing channels and the main performance indicators. The correlation analysis was used to identify the relationships among digital media, television, radio, print media, events, effectiveness, coverage, and cost.

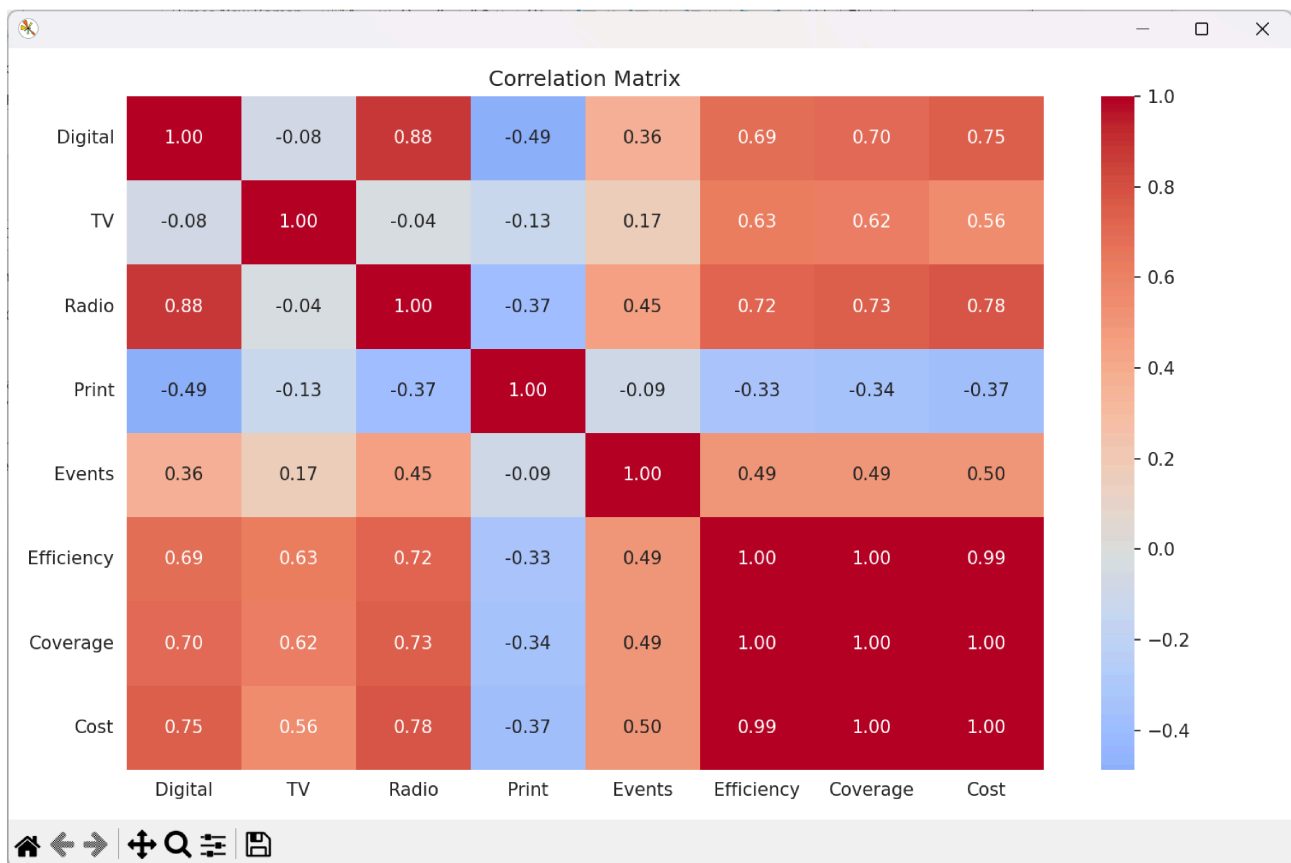


Figure 3. Correlation matrix of marketing channels and performance indicators.

The results show a strong positive correlation between digital media and radio, with a correlation coefficient of 0.88. This may indicate that these channels can complement each other in integrated promotional strategies. Digital channels also demonstrated moderate positive relationships with effectiveness, coverage, and cost. This means that increasing the share of digital media is generally associated with improved marketing outcomes, but also with higher campaign expenditure.

Television showed moderate positive correlations with effectiveness and coverage. This result confirms the role of television as a high-reach communication channel, especially for broad promotional campaigns. However, television also tends to increase the overall cost of the campaign, which means that its use should be carefully balanced with other channels.

Radio demonstrated significant positive relationships with effectiveness and coverage. This suggests that radio remains a relevant marketing channel for agro-industrial enterprises, particularly in regional markets where traditional media continue to play an important role. In combination with digital channels, radio may support broader audience engagement and strengthen communication with geographically dispersed consumers.

Print media showed negative correlations with several indicators, particularly with digital media and radio. This result may reflect the declining relative effectiveness of print-based promotion compared with more flexible and interactive communication channels. Nevertheless, print media may still be useful in specific local contexts, especially where digital access is limited or where traditional communication formats remain trusted by the target audience.

Events showed moderate positive correlations with several indicators. This suggests that exhibitions, presentations, and regional events may contribute to marketing effectiveness, especially when direct interaction with customers, distributors, or business partners is required. However, their role appears to be complementary rather than dominant.

4.6. Comparative Analysis by Market Segments

Figure 4 presents a comparative analysis of key marketing indicators across different segments. The visualization includes the distribution of effectiveness, coverage, and cost values, making it possible to assess intersegment differences in marketing performance.

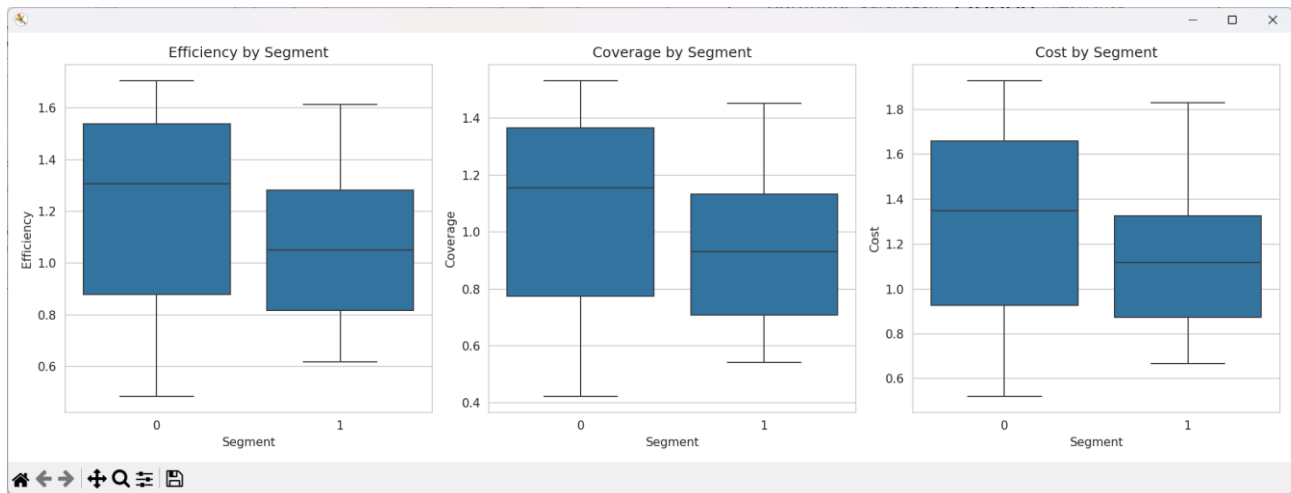


Figure 4. Comparative analysis of key indicators of marketing strategies by segments.

The results indicate that marketing strategies do not perform uniformly across all segments. Differences in median values and interquartile ranges suggest that segment affiliation influences the effectiveness of budget allocation. This finding is important because agro-industrial markets in Kazakhstan are characterized by regional heterogeneity, differences in purchasing behavior, and varying access to communication channels.

In some segments, higher effectiveness and coverage can be achieved through stronger investment in digital media and television. In other segments, more traditional channels such as radio, print media, and events may remain relevant. Therefore, the selection of a marketing strategy should be segment-specific rather than universal.

The comparative analysis also confirms that campaign cost varies considerably between segments. This means that enterprises should not only focus on maximizing performance indicators, but also consider the financial feasibility of each strategy. The proposed hybrid framework supports this type of decision-making by providing a set of alternative solutions adapted to different segment conditions.

4.7. Budget-Level Scenario Analysis

Figure 5 illustrates the optimal distribution of the marketing budget across different funding levels. The analysis considers low, medium, and high budget scenarios and shows how the share of each communication channel changes depending on the available financial resources.

The results show that budget size has a direct influence on the structure of marketing investment. Under low-budget conditions, the model tends to allocate a larger share of resources to relatively cost-efficient channels, such as radio and print media. This allows enterprises to maintain promotional activity while controlling expenditure.

Under medium-budget conditions, the allocation becomes more balanced. The model distributes resources among traditional and digital channels, allowing enterprises to improve coverage and effectiveness without a sharp increase in cost. This scenario is particularly relevant for enterprises that aim to expand their market presence gradually.

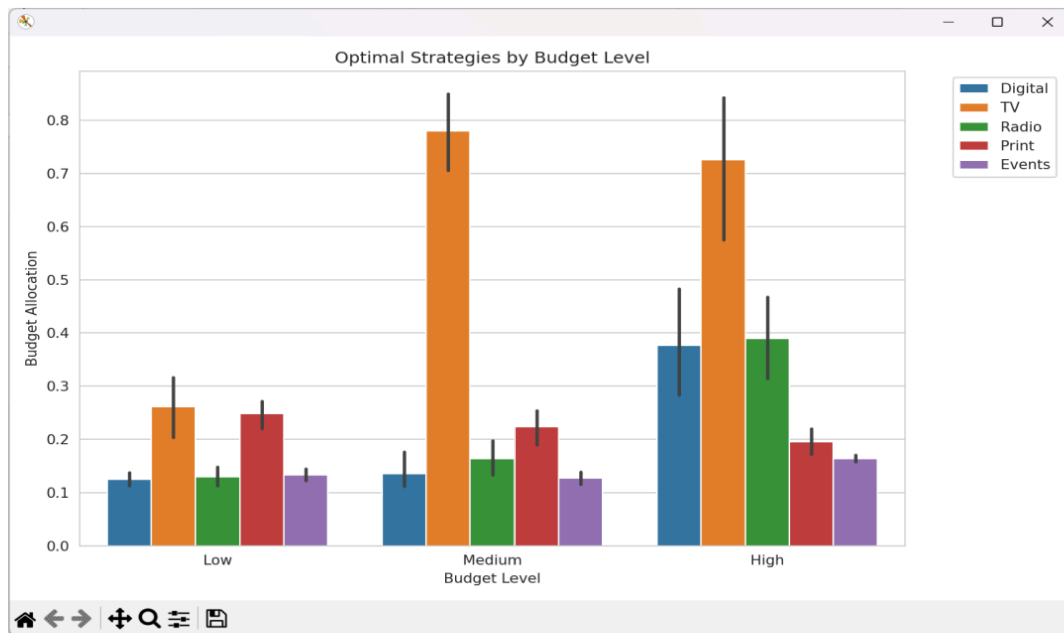


Figure 5. Analysis of the optimal distribution of the marketing budget by funding levels.

Under high-budget conditions, the share of digital media and television increases. This reflects the stronger performance potential of these channels in terms of audience reach and marketing effectiveness. However, the increase in cost also becomes more pronounced. Therefore, high-budget strategies are most appropriate for enterprises seeking active market expansion, brand strengthening, or promotion across multiple regions.

Overall, the budget-level analysis confirms that there is no single optimal allocation structure for all enterprises. The most appropriate strategy depends on available resources, target segments, and expected marketing outcomes.

4.8. Comparative Distribution of the Best Strategies

Figure 6 presents the comparative distribution of the marketing budget in the three most effective strategies identified during the optimization process.

The comparison of the three best strategies reveals several important patterns. First, all high-performing strategies rely on a combination of multiple channels rather than on a single dominant channel. This confirms the importance of integrated marketing communication in the agro-industrial complex. Second, digital media and television play a central role in achieving high effectiveness and broad coverage. Third, radio, print media, and events serve as complementary channels that can improve communication stability and adapt the strategy to specific regional or segment conditions.

The differences among the three best strategies indicate that similar performance levels can be achieved through different budget allocation structures. This is one of the main advantages of the Pareto-based approach: it provides decision-makers with flexibility. Instead of prescribing one fixed solution, the model offers several efficient alternatives that can be selected according to managerial priorities and resource availability.

Findings based on synthetic data are intended to validate the methodology and explore a wide range of marketing budget allocation scenarios, whereas observations from the real enterprise-level dataset provide practical insights into actual marketing performance in Kazakhstan.

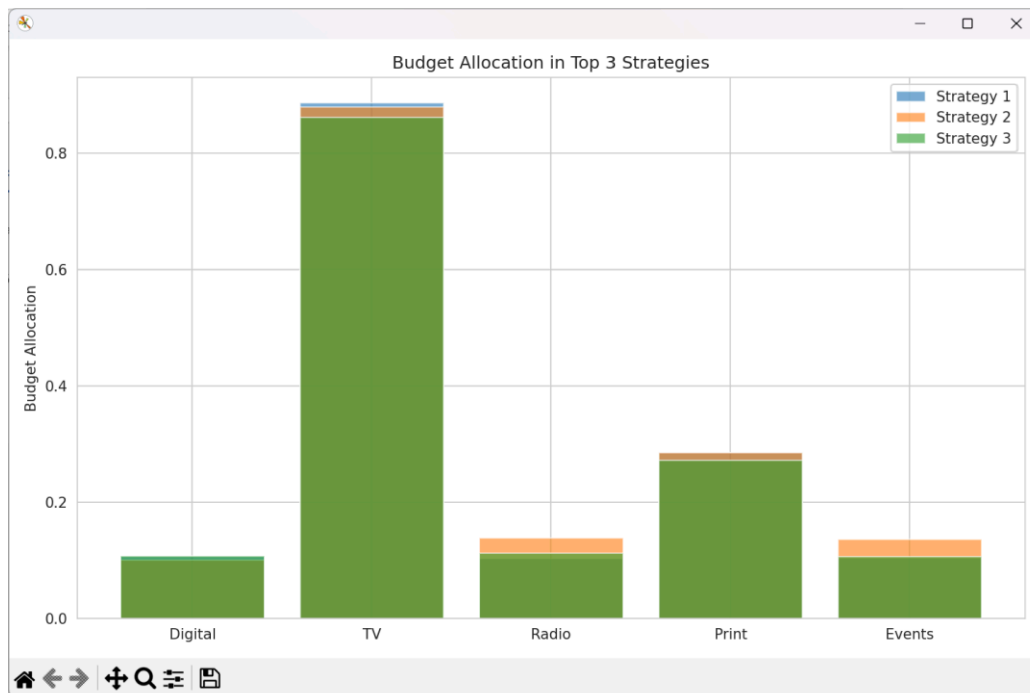


Figure 6. Comparative distribution of the marketing budget in the three most effective strategies for the agro-industrial complex.

4.9. Summary of Key Findings

The results of the computational experiments confirm the effectiveness of the proposed hybrid NSGA-II and machine learning framework for marketing budget optimization in the agro-industrial complex. The main findings can be summarized as follows.

First, the optimization results demonstrate that digital media and television provide the highest contribution to marketing effectiveness and audience coverage. Strategies based on these channels achieved the strongest performance indicators, although they were also associated with higher costs.

Second, radio and print media remain relevant for cost-sensitive strategies. They are particularly useful for enterprises with limited budgets or for regional market segments where traditional communication channels continue to be important.

Third, the Pareto-front analysis confirmed the existence of trade-offs between effectiveness, coverage, and cost. This means that marketing budget allocation in the agro-industrial complex cannot be reduced to a single-objective optimization problem.

Fourth, K-means clustering made it possible to transform the Pareto-optimal solution set into interpretable groups of strategies. This improves the practical applicability of the model because managers can select strategies according to budget level, target segment, and desired marketing outcome.

Fifth, the correlation and segment-level analyses showed that the effectiveness of marketing channels depends on the interaction between channel structure, segment characteristics, and budget constraints. Therefore, adaptive and data-driven marketing planning is essential for agro-industrial enterprises operating in heterogeneous market conditions.

Overall, the obtained results confirm that the proposed hybrid framework can serve as a practical decision-support tool for planning marketing campaigns in the agro-industrial complex of Kazakhstan. It enables enterprises to evaluate alternative budget allocation strategies, identify efficient channel combinations, and select the most appropriate solution under conditions of limited resources and market uncertainty.

5. Discussion

The results of this study confirm that marketing budget allocation in the agro-industrial sector should be approached as a multi-objective decision-making problem rather than a simple cost distribution task. Agro-industrial enterprises in Kazakhstan operate under different financial, regional, and infrastructural conditions, making it difficult to rely on a single marketing strategy for all situations. Therefore, marketing decisions must balance several competing objectives, including effectiveness, audience coverage, and campaign cost.

The proposed hybrid framework combines NSGA-II optimization with K-means clustering to address these challenges. NSGA-II generates multiple Pareto-optimal solutions representing different trade-offs between cost, effectiveness, and audience reach. Instead of forcing a single optimal solution, the framework allows enterprises to choose strategies according to their available budget, operational priorities, and market conditions.

The results indicate that strategies combining digital media and television generally achieve the highest marketing effectiveness and audience coverage. These strategies were mainly grouped within the high-performance cluster, although they were also associated with higher implementation costs. This suggests that digital media and television are particularly suitable for enterprises aiming to increase brand visibility and expand into broader regional or national markets.

At the same time, traditional marketing channels such as radio and print media remain relevant for cost-sensitive enterprises. Although their effectiveness was lower compared with digital and television channels, these strategies required significantly lower investment. This finding is important for smaller agricultural enterprises and regional producers that operate with limited marketing resources.

One of the key practical advantages of the proposed framework is the clustering-based interpretation of Pareto-optimal solutions. Without clustering, the Pareto front may contain many technically efficient solutions that are difficult for managers to interpret directly. K-means clustering simplifies this process by organizing similar solutions into understandable strategy groups, including cost-efficient, balanced, and high-performance categories. This improves the practical usability of the optimization results and supports easier managerial decision-making.

The correlation analysis also highlights the importance of integrated marketing planning. The positive relationship between digital media and radio suggests that these channels may complement each other in certain promotional strategies. Digital media provide targeted communication and broader online visibility, while radio may improve regional awareness in areas where traditional media consumption remains important.

From a methodological perspective, the study demonstrates the usefulness of combining multi-objective optimization with machine learning-based interpretation techniques. Previous marketing budget allocation studies often focused only on optimization performance or relied mainly on expert judgment. In contrast, the proposed framework simultaneously addresses optimization efficiency and practical interpretability, making it more suitable for complex agro-industrial marketing environments.

The use of NSGA-II is justified because the proposed problem contains only three conflicting objectives. Compared with many-objective algorithms such as NSGA-III, NSGA-II provides sufficient Pareto diversity and stable convergence while maintaining lower computational complexity. In addition, K-means clustering was selected because it offers simple and computationally efficient grouping of optimization results, making the framework more practical for real-world decision-support applications.

Conclusions drawn from synthetic simulations are presented cautiously to indicate their methodological purpose, while those based on real data reflect the empirical applicability of the proposed framework.

The findings also have practical implications for agro-industrial enterprises in Kazakhstan. Enterprises with limited budgets may benefit from cost-efficient strategies relying more on radio and print media, while enterprises with larger budgets may prioritize digital media and television to maximize audience reach and marketing effectiveness. Therefore, the framework supports flexible marketing planning according to enterprise size, budget level, and market objectives.

The proposed marketing strategy groups provide actionable guidance for agro-industrial enterprises of different sizes and operational conditions. Cost-efficient strategies are most suitable for small or budget-constrained enterprises that aim to maintain essential audience coverage while minimizing marketing expenditures. Balanced strategies are appropriate for medium-sized enterprises seeking a trade-off between marketing effectiveness and cost efficiency, enabling moderate investment in multiple channels to achieve overall performance. High-performance strategies are intended for large enterprises with higher budgets and greater digital readiness, focusing on maximizing audience reach, brand visibility, and market penetration. Additionally, the practical application of each strategy may vary according to regional market accessibility, target customer segments, and product types, allowing managers to select marketing approaches that best align with their operational context, strategic objectives, and resource availability. By differentiating strategies in this way, the framework supports data-driven, adaptive decision-making and enables enterprises to plan marketing campaigns effectively under diverse budgetary and infrastructural conditions.

Several limitations of the proposed framework should be acknowledged. First, a portion of the analysis relies on synthetically generated data due to limited availability of large-scale enterprise-level marketing datasets. Although the synthetic data were generated using realistic parameter ranges and statistical properties, additional validation using larger real-world datasets is necessary to fully confirm the framework's practical applicability. Second, the current framework considers a limited number of marketing channels and static performance indicators, whereas real marketing environments are dynamic and influenced by seasonality, economic fluctuations, regional heterogeneity, and changing consumer behavior. Third, variations in media effectiveness over time are not explicitly modeled, which may affect the performance of the identified marketing strategies in practice.

Furthermore, the objective functions in this study are formulated as linear weighted combinations of marketing effectiveness, audience coverage, and campaign cost. While this linear assumption simplifies computation and ensures tractability for multi-objective optimization, it does not fully capture diminishing marginal returns or saturation effects inherent in real-world marketing channels. The linear model provides a practical approximation under limited data availability and allows the framework to generate actionable strategy groups for cost-efficient, balanced, and high-performance approaches.

Future studies may extend the framework by incorporating additional marketing channels, dynamic optimization models, and alternative clustering techniques such as hierarchical clustering or Gaussian mixture models. Integrating uncertainty-aware optimization and predictive machine learning approaches can further improve adaptability, allowing the framework to better support real-time, data-driven marketing decision-making in complex agro-industrial environments. Future research may explore the incorporation of nonlinear marketing response models, such as S-shaped Logistic or Vidale–Wolfe models, which can more accurately reflect channel-specific saturation and improve the precision of budget allocation outcomes. In addition, the framework's recommendations could be qualitatively

or semi-quantitatively compared with historical marketing campaigns from collaborating enterprises, providing practical validation to ensure that the proposed strategies are realistic, implementable, and aligned with observed managerial practices.

Overall, the proposed hybrid NSGA-II and K-means framework provides a practical and interpretable solution for multi-objective marketing budget optimization in Kazakhstan's agro-industrial sector. The study demonstrates that combining optimization with clustering-based interpretation can improve both decision quality and managerial usability, supporting more data-driven and adaptive marketing planning in the agro-industrial complex.

6. Conclusions

This study developed a hybrid NSGA-II and K-means framework for marketing budget allocation in Kazakhstan's agro-industrial sector, addressing the conflicting objectives of marketing effectiveness, audience coverage, and campaign cost. The framework was evaluated using both real enterprise-level data and synthetic data to ensure methodological validation and practical applicability.

The findings from real enterprise-level data provide empirical insights into practical marketing strategy performance, demonstrating the framework's relevance for decision-making in actual agro-industrial enterprises. In contrast, results obtained from synthetic data illustrate the framework's robustness across a wider range of scenarios, supporting methodological validation and exploration of diverse budget allocation strategies. By clearly distinguishing between these sources, conclusions are expressed cautiously, avoiding overgeneralization from simulation-based results to real-world market conditions.

The integration of NSGA-II with K-means clustering improved both optimization efficiency and interpretability, allowing managers to select strategies according to budget, regional conditions, and marketing priorities. Cost-efficient strategies are suitable for budget-limited enterprises, balanced strategies provide a compromise between cost and performance, and high-performance strategies maximize audience reach and marketing effectiveness.

Despite these contributions, the study has limitations. Part of the analysis relies on synthetic data, and only five marketing channels were considered. Future research should incorporate larger real-world datasets, additional digital marketing channels [32–34], and dynamic optimization models to further enhance practical applicability. Consideration of market uncertainty, seasonality, and regional heterogeneity could also improve the robustness of the proposed framework.

Overall, the proposed hybrid framework offers a practical, interpretable, and data-driven approach to marketing budget optimization, combining multi-objective optimization with clustering-based interpretation to support adaptive and informed decision-making in the agro-industrial sector.

Author Contributions: Conceptualization, Z.K., R.U. and Z.A.; methodology, A.K. (Aizhan Kassymova); software, A.K. (Alpamis Kutlimuratov); validation, A.A., P.A. and Y.-I.C.; formal analysis, A.K. (Aizhan Kassymova) and R.U.; investigation, Z.K. and Z.A.; resources, Z.K. and A.K. (Aizhan Kassymova); data curation, P.A., A.A. and A.K. (Alpamis Kutlimuratov); writing—original draft preparation, Z.K., R.U. and Z.A.; writing—review and editing, A.K. (Alpamis Kutlimuratov) and A.A.; visualization, R.U. and A.K. (Alpamis Kutlimuratov); supervision, P.A. and A.K. (Alpamis Kutlimuratov); project administration, Y.-I.C. and A.A.; funding acquisition, Y.-I.C. and Z.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the Ministry of Trade, Industry and Energy and implemented by the Korea Institute for Advancement of Technology. The projects include Development of an Inter-

national Standardization and Sustainability Integration Framework for AI Industry Internalization and Global Competitiveness Enhancement (RS-2025-07372968).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The dataset is publicly available at <https://www.kaggle.com/datasets/samarthpujari/tv-marketing>, accessed on 10 July 2026.

Acknowledgments: The authors would like to thank the editor and anonymous referees for their constructive comments in improving the contents and presentation of this paper.

Conflicts of Interest: The authors declare no conflicts of interest.

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