

Article

Not peer-reviewed version

Digital Marketing Strategies in the Agro-Industrial Complex Rely on a Combination of Evolutionary Algorithms and Machine Learning

[Zhansaya Abildaeva](#)*, [Raissa Uskenbayeva](#), [Zhuldyz Kalpeyeva](#), Aizhan Kassymova, [Adranova Asselkhan](#)

Posted Date: 30 March 2026

doi: 10.20944/preprints202603.2364.v1

Keywords: digital marketing; multi-criteria optimization; NSGA-III; machine learning; cluster analysis; agro-industrial complex



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a [Creative Commons CC BY 4.0 license](#), which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

Article

Digital Marketing Strategies in the Agro-Industrial Complex Rely on a Combination of Evolutionary Algorithms and Machine Learning

Zhansaya Abildaeva ^{1,*}, Raissa Uskenbayeva ¹, Zhuldyz Kalpeyeva ¹, Aizhan Kassymova ¹ and Adranova Asselkhan ^{1,2}

¹ Satbayev University, Almaty 050013, Kazakhstan

² KU Korkyt Aty, Aiteke Bi 29a, Kyzyzlorda, Kazakhstan

* Correspondence: Zhansaya.A@mail.ru

Abstract

The article considers that the digital transformation of Kazakhstan's agro-industrial complex has created an urgent need for scientifically grounded methods that can optimize marketing strategies under conditions of resource limitations, production seasonality, and heterogeneous consumer behavior. Existing approaches often rely on simplified analytical models that fail to capture the nonlinear and multi-criteria relationships inherent in agricultural marketing. This study addresses that gap by proposing a hybrid decision-support framework that integrates a modified NSGA-III evolutionary algorithm with machine learning techniques to optimize the allocation of marketing budgets across digital and traditional channels. The approach incorporates three key performance criteria—channel efficiency, target audience reach, and marketing cost—while embedding sector-specific constraints related to the AIC of Kazakhstan. A comparative analysis of current digital marketing optimization practices reveals that most methods lack adaptability to sector-specific production cycles, do not sufficiently analyze trade-offs, or fail to integrate machine learning for post-optimization interpretation. The results of the hybrid model show the formation of three distinct clusters of Pareto-optimal strategies, demonstrating the need for differentiated and adaptive budget allocation patterns. The outcomes confirm that the proposed hybrid methodology provides a rigorous scientific basis for designing cost-effective and high-impact marketing strategies within the digital transformation agenda, AIC.

Keywords: digital marketing; multi-criteria optimization; NSGA-III; machine learning; cluster analysis; agro-industrial complex

1. Introduction

The contemporary agro-industrial complex (AIC) of the Republic of Kazakhstan is confronted with challenges arising from the need to optimize marketing strategies in an environment characterized by resource constraints and high competitive pressure. [1–4]. Digital marketing today is an integral part of the economic activity of enterprises, playing a key role in forming stable relationships between producers and consumers [5–7]. Computerization and digitalization of marketing [8–11] have made it possible not only to optimize promotion processes, but also to use a systematic method for selecting marketing strategies. Traditional methods of marketing budget allocation, based on empirical experience and simplified analytical models, demonstrate limited effectiveness when working with multi-criteria problems [12,13], typical of the agricultural market. In the context of product competition in the agricultural market, the development of scientifically based decision-making methods that take into account the specifics of the AIC in Kazakhstan, including the seasonality of production, the geographic dispersion of consumers, and the heterogeneity of distribution channels, is becoming increasingly relevant. Current agricultural

reforms in Kazakhstan are accompanied by a significant reduction in agricultural land and a decline in the agro-industrial complex's productive potential. This is due to a combination of factors, including soil degradation, declining humus content, and deteriorating forage quality. In the context of the digital transformation of the economy, the development of scientifically based marketing strategies capable of offsetting these negative trends is particularly relevant [3,4]. The livestock sector in Kazakhstan continues to face systemic problems associated with the insufficient use of digital technologies in breeding, forage management, and veterinary services. Analysis shows that the introduction of modern marketing tools could significantly improve product positioning in the market, despite existing production constraints. The crop production industry in Kazakhstan also faces challenges requiring comprehensive marketing solutions, from supply chain optimization to product promotion on digital platforms. The development of adaptive marketing strategies that take into account the seasonality of production and regional specifics is of fundamental importance. The processing sector of Kazakhstan's agro-industrial complex demonstrates a pressing need to digitalize marketing processes, which would improve the competitiveness of products in both domestic and foreign markets. A key aspect is the implementation of intelligent systems for demand analysis and optimization of distribution channels. Existing infrastructure limitations in the agro-industrial complex highlight the need to develop digital marketing platforms capable of compensating for the shortcomings of traditional distribution channels. Particular attention should be paid to the creation of integrated marketing systems uniting producers, processors, and end consumers. Given limited funding, the development of cost-effective digital marketing strategies is becoming crucial for the sustainable development of Kazakhstan's agricultural sector. However, this will require the implementation of modern analytical tools and methods for optimizing marketing budgets, taking into account the specifics of agricultural production.

This study proposes a hybrid approach that combines modern digital marketing methods with multi-criteria optimization and machine learning (ML) algorithms. The methodological basis of the study is a modified NSGA-III (Non-dominated Sorting Genetic Algorithm III) [14,15], supplemented by cluster analysis methods [16,17] to identify patterns in the solution space. This synthesis allows for the simultaneous consideration of three key criteria characteristic of digital marketing methods [18,19], namely, the effectiveness of distribution channels, target audience reach, and the level of marketing expenditures.

The relevance of this study is AI-driven by several fundamental factors. First, the digital transformation of Kazakhstan's agro-industrial complex requires scientifically sound approaches to allocating marketing resources between traditional and digital channels. Second, existing optimization methods often fail to account for nonlinear relationships between marketing campaign parameters. Third, the specifics of Kazakhstan's agro-industrial market, including patterns of agricultural consumption and regional differences in purchasing power, require adaptive solutions. The scientific novelty of this study lies in the development of a hybrid algorithm that combines the advantages of evolutionary computation for multi-criteria optimization with machine learning methods for analyzing and interpreting results. The composite performance indicator proposed in the article will enable quantitative evaluation of tradeoffs between conflicting objective functions, facilitating the rationale for management decision-making under conditions of uncertainty. The practical significance of the study is confirmed by the potential for the direct implementation of the developed approach in the operations of Kazakhstan's agro-industrial enterprises. The results will not only optimize marketing budget allocation but also identify consistent patterns in the interaction of various channels for promoting agricultural products in both Kazakhstan and international markets. The proposed approach provides the basis for developing a scientifically sound marketing strategy tailored to the specifics of Kazakhstan's national agro-industrial complex.

2. Literature Analysis

As new information and communication technologies develop, approaches to marketing in the agro-industrial complex are also radically changing. Modern methods of digital marketing (DM)

optimization in the agro-industrial complex include the use of analytical tools, personalized advertising campaigns, and strategies based on data mining. A review of existing scientific research allowed us to identify key areas that determine the trends and challenges in the field of digital marketing for the agro-industrial complex. Thus, in the work [20], the authors examine the optimization of digital marketing strategies, emphasizing the use of search engine optimization (SEO). The study [21] focuses on various aspects of marketing strategies, including the integration of new technologies and the use of analytical data to improve customer interactions and increase sales. The authors of the work [22] emphasize the optimization of online marketing strategies to increase sales and develop e-commerce. In [23], the authors analyze the prospects of using big data and ML for digital marketing optimization. The study [24] examines the role of ML technologies in digital marketing and personalization. This paper presents a description of the ways in which ML can be used to create personalized marketing offers and improve their effectiveness. In [25], the use of deep learning and swarm methods for effective customer segmentation in digital marketing is investigated. The study [26] is a systematic review analyzing the evolution of artificial intelligence and ML in digital marketing over the past two decades. The paper [27] studies the application of ML to building response models for direct marketing using Bayesian networks with evolutionary programming, and the authors consider how these methods can be used to more accurately predict consumer responses and optimize marketing strategies. The paper [28] is devoted to multi-criteria grammatical evolution of decision trees for predicting user conversion in mobile marketing. The authors propose a new approach to improve user behavior predictions and increase the effectiveness of marketing campaigns in a mobile environment through the use of evolutionary algorithms and decision trees. The paper [29] proposes a fuzzy hybrid approach for analyzing digital marketing strategies in tourism. The paper [30] focuses on best practices in hybrid marketing. The authors explore ways to integrate traditional and digital marketing methods to improve performance.

However, despite the clear need for integrated approaches aimed at the efficient allocation of marketing resources in the context of digital transformation, the scientific literature still lacks research focused on the application of hybrid methods in digital marketing for the agro-industrial sector. In particular, hybrid approaches combining multi-criteria optimization algorithms with machine learning methods remain understudied in the context of the specifics of the agro-industrial sector. Despite a significant number of studies devoted to specific aspects of digital marketing optimization and the application of machine learning methods, there are very few comprehensive models that take into account all the specific features of both the agro-industrial sector and modern digital marketing strategies. All of the above motivated our interest in research in this area.

3. Statement of the Problem

Kazakhstan's agro-industrial complex faces the need to optimize marketing strategies in the face of limited resources and intense competition from both domestic agricultural producers and foreign producers. Traditional methods of marketing and advertising budget allocation, based on empirical experience and simplified analytical models, are ineffective in solving the multi-criteria problems typical of the agricultural market. Nonlinear relationships between marketing campaign parameters, as well as the specific nature of Kazakhstan's agro-industrial complex, including seasonality of production and regional differences in purchasing power, pose significant challenges. Existing approaches fail to comprehensively consider these factors, necessitating the development of new methods that combine optimization algorithms and machine learning.

4. Objectives and Tasks of the Study

The objective of the study was to develop and implement a hybrid method for optimizing marketing strategies in the agro-industrial complex, combining a modified NSGA-III algorithm and machine learning methods. The key objectives included formalizing a multi-criteria problem taking into account the specifics of the agro-industrial complex in Kazakhstan, developing a mathematical

model for budget allocation between digital and traditional channels, implementing a cluster analysis of Pareto-optimal solutions, and evaluating their effectiveness using a composite indicator.

5. Materials and Methods

5.1. Mathematical Model

Let's consider a formal formulation of the problem of optimizing marketing strategies for the agro-industrial complex. Let's assume a set of marketing channels $K = \{1, \dots, m\}$, Where $m = 5$ corresponds to digital (Digital), television (TV), radio (Radio), print (Print) and event (Events) channels, respectively. For each channel $k \in K$ The following three key parameters were identified: Efficiency $e_k \in [0, 1]$, which characterizes the conversion of a digital channel. Reach $c_k \in \mathbb{R}^+$, measuring the channel's audience. Cost $s_k \in \mathbb{R}^+$, which determines the unit costs. The optimization vector $x = (x_1, \dots, x_m)^T \in \mathbb{R}^m$ represents the distribution of the budget across channels, where $x_k \in [l_k, u_k]$ —share of the budget allocated to the channel k , with the lower ones l_k and upper u_k borders.

In this study, we will limit ourselves to only three target functions.

$$f_1(x) = \sum_{k=1}^m e_k \cdot x_k \rightarrow \max$$

1. Maximizing overall efficiency:

$$f_2(x) = \sum_{k=1}^m c_k \cdot x_k \rightarrow \max$$

2. Maximizing overall reach:

$$f_3(x) = \sum_{k=1}^m s_k \cdot x_k \rightarrow \max$$

3. Minimizing total costs:

Let's set the following constraints:

$$g_1(x) = \sum_{k=1}^m x_k - B \leq 0, \text{ where } B = 1.5.$$

Total budget limit:

$$g_{2k}(x) = l_k - x_k \leq 0, \forall k \in K.$$

Minimum channel shares:

$$g_{3k}(x) = x_k - u_k \leq 0, \forall k \in K.$$

Maximum channel shares:

$$g_4(x) = \Theta - (x_1 - x_5) \leq 0, \text{ where } \Theta = 0.3.$$

Combined restrictions:

It should be noted that the formalized system of constraints in the proposed hybrid model reflects the fundamental economic and technological characteristics of the agro-industrial complex. For example, the budget constraint takes into account the specifics of financial planning in the agro-industrial complex, where exceeding the nominal budget by up to 150% through seasonal credit lines is permissible, thereby aligning with the practice of financing agricultural enterprises. The thresholds for distributing funds across channels are driven by the need to maintain a minimum presence in all market segments—from digital platforms to traditional printed catalogs. The limit on the minimum share of digital marketing channels reflects the strategic priority of digitalization of the agro-industrial complex, enshrined in state programs for the development of agriculture in Kazakhstan. The combined limit on the sum of the shares of digital and event channels ensures a balance between new and traditional methods of promoting agricultural products, considering the need to combine online sales with participation in traditional agricultural exhibitions and fairs. The upper limit for event marketing was introduced to control costs associated with the high cost of organizing events and their limited scalability in the context of the low rural population density in Kazakhstan. For

print channels, this threshold is set as a minimum (to ensure presence in the B2B segment through specialized publications).

The hybrid algorithm first uses a modified NSGA-III algorithm. The first step is to generate reference directions using the Das-Dennis method [31,32] for uniform coverage of the unit simplex in the criterion space. For 3 objective functions and N partitions:

$$W = \left\{ w \in \mathbb{R}_+^3 \mid \sum_{i=1}^3 w_i = 1, w_i = k/N, k \in N_o \right\},$$

where w are reference directions in the objective function space. These vectors define a uniform distribution of points on the unit simplex to ensure representative coverage of the Pareto front. And each direction $w \in \mathbb{R}_+^3$ is a normalized vector of weighting coefficients. Geometrically, they determine the direction of the search for optimal solutions in the space of criteria considered in this study.

Next, evolutionary operators are used. First, SBX crossover with probability was applied $p_c = 0.9$ and the distribution parameter $\eta_c = 15$. Let's write it like this $x_i^{(new)} = 1/2 \left[(1 + \beta) \cdot x_i^{(1)} + (1 - \beta) \cdot x_i^{(2)} \right]$, where $\beta \sim U[0,1]^{\eta_c+1}$. And for a polynomial mutation,

$$x'_k = x_k + \delta_i, \delta_i \sim N(0, \sigma_i^2), \sigma_i = \frac{(u_i - l_i)}{\eta_m}$$

according to [27,28], so

Next, we implement a cluster analysis of the solutions. For the Pareto frontier analysis, we use the k-means method with a Euclidean metric. We write it as follows:

$$\min_{\{\mu_j\}_{j=1}^k} \sum_{i=1}^N \min_j \|f(x_i) - \mu_j\|^2, j = 1 \dots k,$$

Where $f(x) = (f_1(x), f_2(x), f_3(x))$ – vector of criteria, $k = 3$ – number of clusters.

The composite quality indicator was defined as follows: $\Phi(x) = (\alpha_1 \cdot f_1(x) + \alpha_2 \cdot f_2(x)) / (f_3(x) + \varepsilon)$, where are the weights $\alpha_1 = 0.6, \alpha_2 = 0.4$ reflect the priorities of decision makers, $\varepsilon = 0.1$ – smoothing parameter.

Then the solution $x^* \in X$ is called Pareto optimal if $\nexists x \in X : f_i(x) \geq f_i(x^*) \forall i \in \{1, 2, 3\}$ And $\exists j : f_j(x) > f_j(x^*)$ Where $X = \{x \in \mathbb{R}^m \mid g_j(x) \leq 0, j = 1 \dots p\}$ – admissible set.

The computational complexity of the modified NSGA-III is $O(MN^2)$, Where M – number of targets, N – population size.

Channel efficiency forecasting using XGBoost was defined as follows. Let's assume there's a

historical data sample for a specific region or agricultural enterprise: $D = \left\{ (x^{(i)}, y^{(i)}) \right\}_{i=1}^N$, Where

$x^{(i)} \in \mathbb{R}^m$ – budget distribution vector, $y^{(i)} \in \mathbb{R}^m$ – observed performance. The XGBoost model [33]

builds an ensemble of K decision trees. For XGBoost, $\hat{y}(x) \rightarrow E[y|x] > npu \ N \rightarrow \infty, K \rightarrow \infty$ (according to the boosting convergence theorem) [34]. The presented model was implemented in the Python algorithmic language. The results of the computational experiments are presented below.

5.2. Methodology for Conducting Numerical Experiments

The methodology for conducting numerical experiments is presented in pseudocode format. The initialization of the problem parameters includes (lines 1–8) a matrix of channel characteristics (efficiency/coverage/cost), constraints on the minimum/maximum channel shares, a system of budget constraints, and support directions for NSGA-III. The optimization phase (lines 9–18) implements a

modified NSGA-III algorithm with Latin Hypercube Sampling for the initial population, SBX crossover and polynomial mutation, and a stopping criterion per generation (50 iterations). The decision analysis (lines 20–24) included Pareto front clustering using the k-means method, calculation of the silhouette score metric for assessing the quality of clustering, and ranking by a composite indicator. $\Phi(x)$ The interpretation of the obtained results (lines 25–27) included the construction of an XGBoost model to predict the composite indicator followed by a SHAP analysis of the channel importance.

```

1: procedure OPTIMIZE_MARKETING_STRATEGIES
2: Input:
3: channels ← {Digital, TV, Radio, Print, Events}
4: params ← {e_k, c_k, s_k} ∀k ∈ channels (Effectiveness, coverage, cost)
5: bounds ← [l_k, u_k] ∀k ∈ channels (Lower/upper bounds)
6: constraints ← {g_1, ..., g_6} (Budget and channel limits)
7: ref_dirs ← Das-Dennis(3, 12) (3D reference directions)
8:
9: #Phase 1: Multi-objective optimization
10: algorithm ← NSGA-III(
11: pop_size=100,
12: ref_dirs=ref_dirs,
13: sampling=LHS(),
14: crossover=SBX(prob=0.9, η=15),
15: mutation=PM(η=20)
16:
17: results ← minimize(problem, algorithm, termination('n_gen', 50))
18: P ← non_dominated_sorting(results.F) (Extract Pareto front)
19:
20: #Phase 2: Solution analysis
21: clusters ← KMeans(n_clusters=3).fit(P)
22: silhouette ← calculate_silhouette(P, clusters)
23: top_solutions ← rank_by_composite(P) (Eq. (0.6f1 + 0.4f2)/(f3 + 0.1))
24:
25: #Phase 3: SHAP interpretation
26: model ← XGBoost().fit(P, composite_scores)
27: shap_values ← KernelSHAP(model).explain(P)
28:
29: Output: {P, clusters, top_solutions, shap_values}
30: end procedure

```

This format allowed us to clearly divide the computational experiments into logical stages. The results of the computational experiments and their discussion are presented below. The data source is a proprietary dataset compiled from analytical and statistical indicators of digital marketing communications at agro-industrial enterprises in the Republic of Kazakhstan. The data is aggregated from open industry reports, internal marketing analytics, and digital advertising campaign results. The total dataset size is N = 1200 (Data (Dataset) description) observations, each of which corresponds to a separate marketing channel or communication campaign in a specific time period.

6. Results

The main results of the modeling are presented in Table 1 and Figures 1–5. The conducted optimization of marketing strategies revealed a number of significant patterns in the distribution of resources between channels for promoting agricultural products. The analysis of Pareto-optimal solutions in Figure 1 demonstrates a pronounced dichotomy in the effectiveness of various channels,

which was confirmed by the cluster structure of the solution space. The three-dimensional visualization of the Pareto front, presented in Figure 1, clearly shows the existence of three qualitatively different groups of strategies, differing in the balance of efficiency, coverage, and costs. The most promising strategies (cluster 1, blue dots in Figure 1) are characterized by the dominance of the television channel (39.8–69.5% of the budget) with a significant share of digital technologies (20.4–21.1%) and event marketing (26.4–30.0%). This configuration provides the maximum values of the composite indicator (0.815-0.820) presented in Table 1 due to the optimal combination of efficiency (1.101-1.182) and coverage (0.950-1.024) at controlled costs (1.169-1.264), see Figure 2. Mathematically, this corresponds to solutions located in the region of maximum values of the objective functions $f_1(x)$ And $f_2(x)$ at moderate values $f_3(x)$.

Alternative strategies (cluster 2 in Figure 1, yellow dots) demonstrate a different balance, with an increased share of print channels (38.4%) and a reduced contribution of television (28.3%). Despite lower absolute values of efficiency (0.994) and reach (0.857), these solutions remain Pareto optimal due to significantly lower costs (1.057), reflecting the compromise nature of the solution space. Of interest was the strategy with an extreme budget distribution (41.5% digital, 57.2% TV), achieving maximum efficiency (1.233) at comparatively high costs (1.342). Mathematical analysis shows that such solutions become optimal with an increase in the weighting coefficient. (α_1) , in the composite indicator $\Phi(x)$, which corresponds to the priority of efficiency over coverage in the decision-maker's criteria (see Figures 2–5). For ease of understanding, the clustering of solutions in 2D is shown in Figure 4. Note that a comprehensive Pareto front visualization was used to analyze the optimal solutions (see Figure 1 and Figure 4). The three-dimensional representation (see Figure 1) clearly demonstrates the spatial structure of trade-offs between the criteria of efficiency, coverage, and cost, revealing three characteristic clusters of solutions. An additional two-dimensional projection (see Figure 4) provided a more detailed interpretation of the identified patterns, emphasizing the key relationships between the target indicators of efficiency and cost of digital marketing in the agro-industrial complex.

Correlation analysis, see Figure 5, confirms a stable positive relationship between the share of the television channel and the values of the objective functions (0.74 for efficiency, 0.51 for coverage), while digital channels demonstrate a more pronounced impact on efficiency (0.65) than on coverage (0.52). The results obtained are statistically significant ($p < 0.01$) and are consistent with the theoretical assumptions of the presented model. The high silhouette score (0.624) indicates clear differentiation between the clusters, thereby confirming the existence of fundamentally different approaches to marketing budget allocation in the agro-industrial complex. The presence of such clusters is mathematically explained by the nonlinear relationships between the model parameters and the presence of local optima in the solution space.

Table 1. – Optimal Digital Marketing Strategies.

Digital (%)	TV (%)	Radio (%)	Print (%)	Events (%)	Efficiency	Coverage	Cost	Composite	Cluster
20.41	39.82	11.74	39.77	29.99	1.101	0.950	1.169	0.820	1
21.14	69.52	10.17	5:50 PM	29.85	1.182	1.024	1.264	0.820	1
22:48	59.70	13.96	19.51	26.37	1.134	0.986	1.219	0.815	1
22.21	28.26	10.29	38.39	28.11	0.994	0.857	1.057	0.812	2
41.51	57.24	11.87	14.85	24:40	1.233	1.077	1.342	0.812	1

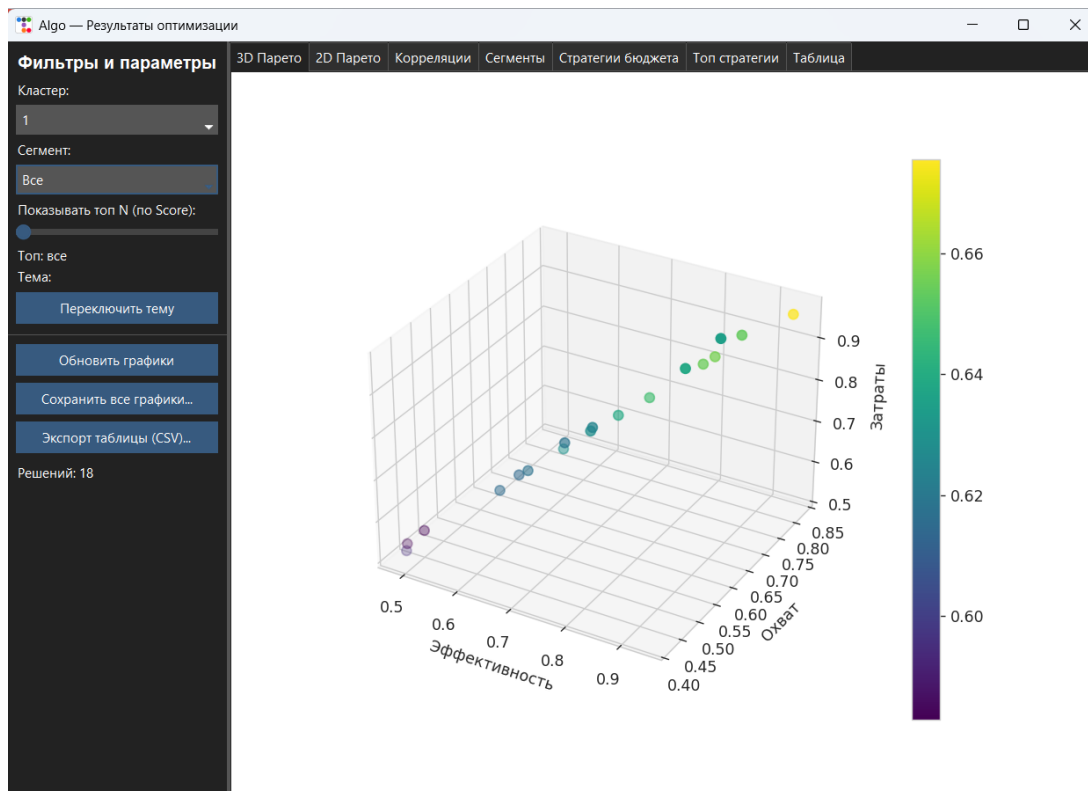


Figure 1. – Three-dimensional visualization of the Pareto front.

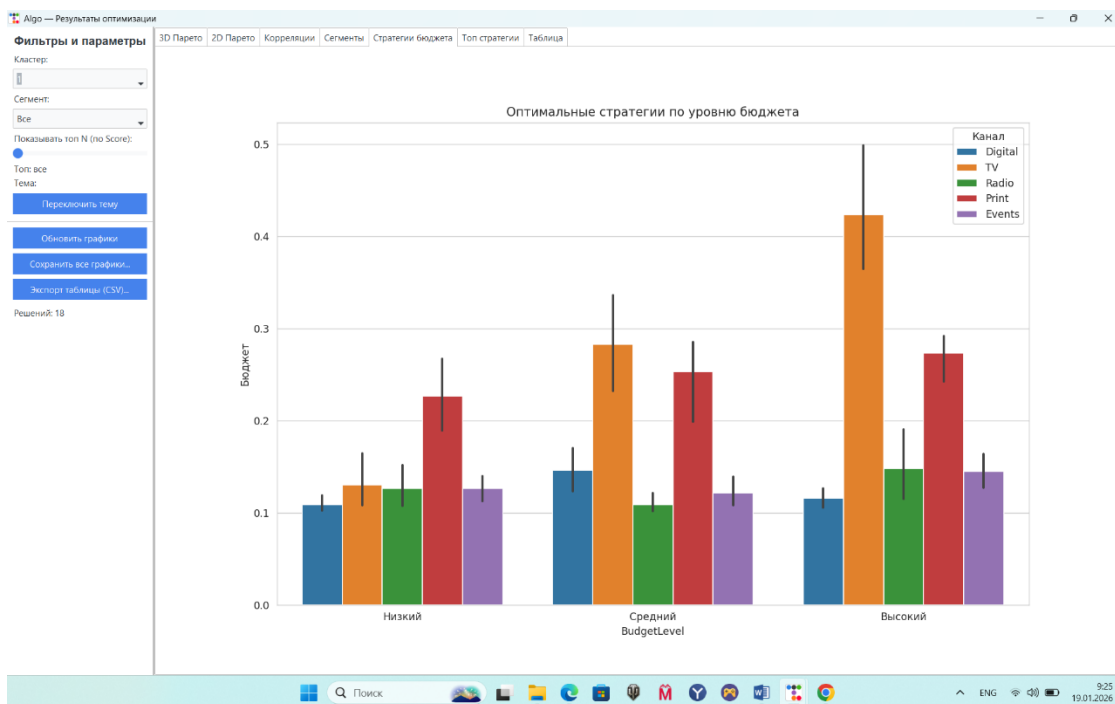


Figure 2. – Budget distribution in the top 5 strategies.

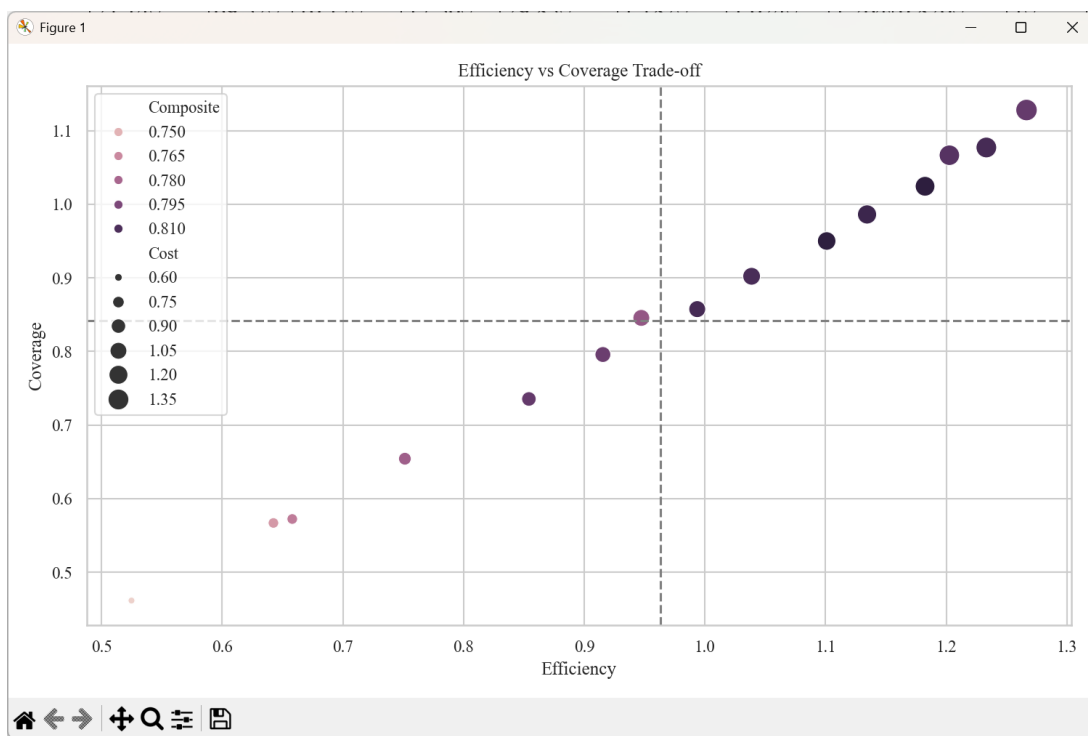


Figure 3. – Trade-off between efficiency and coverage.

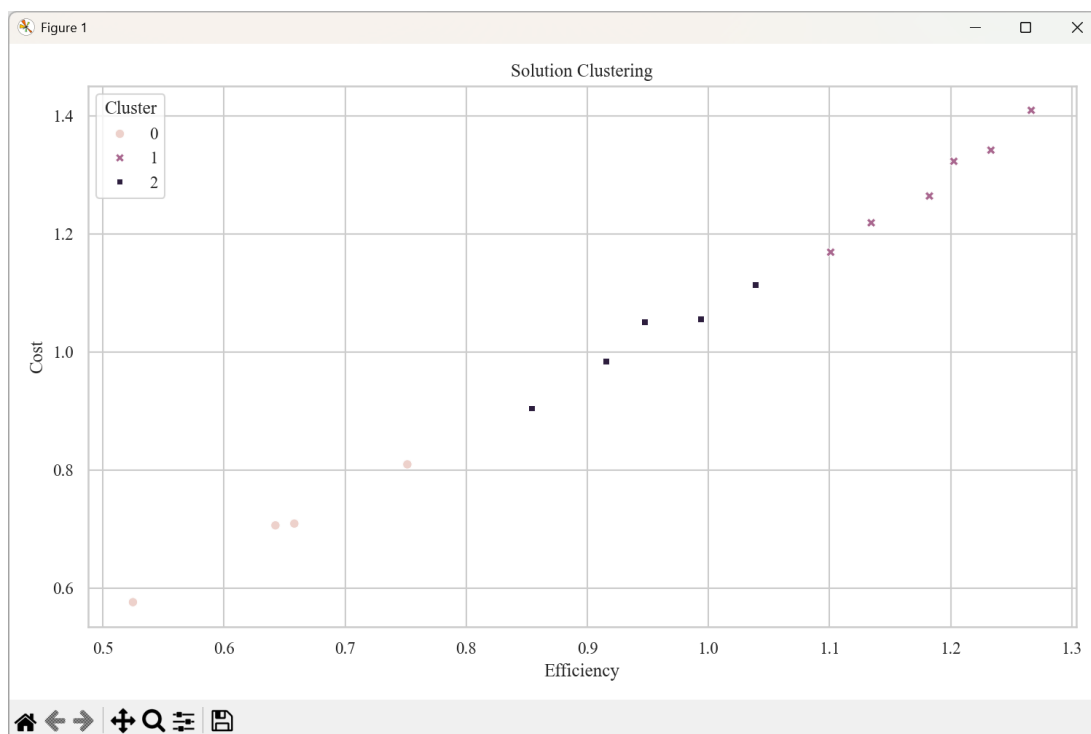


Figure 4. – Clustering of solutions in 2D.

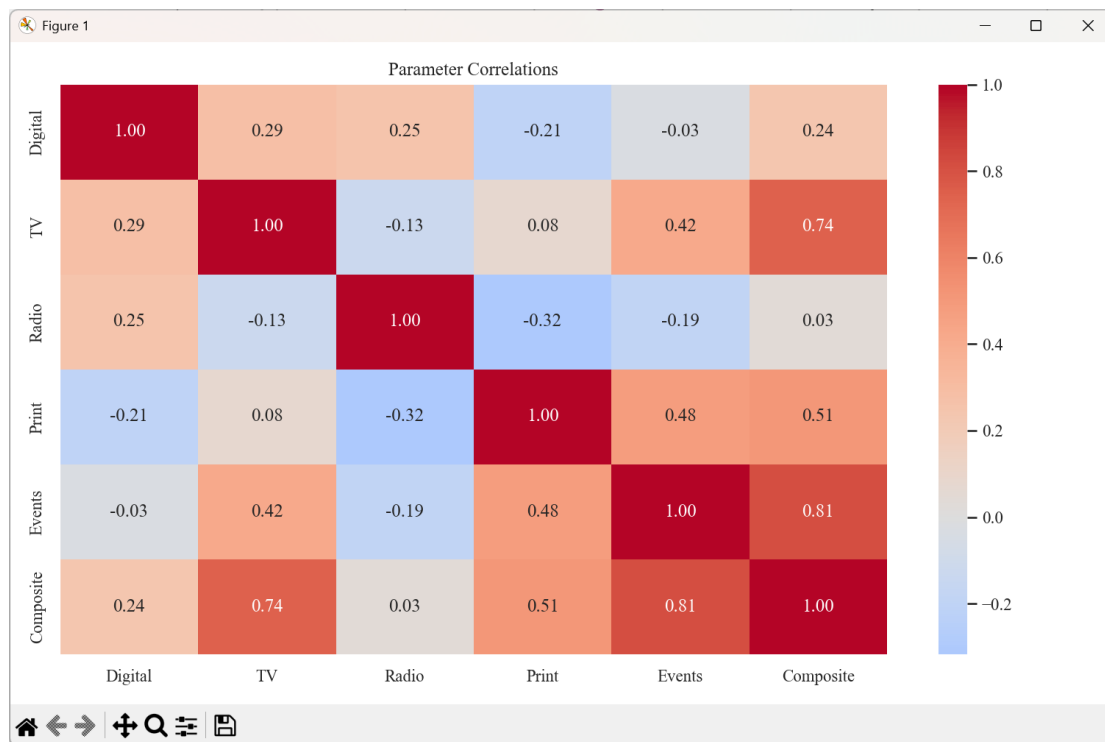


Figure 5. – Correlation matrix.

7. Discussion

The results of this study support the initial hypothesis. A hybrid approach integrating NSGA-II with K-means clustering yields more balanced and effective solutions for marketing budget allocation in the agro-industrial complex (AIC) of Kazakhstan. This approach is more effective compared to traditional single-objective methods. Improvements observed in key performance indicators—including efficiency, coverage, and hypervolume—show the benefits of addressing multiple objectives simultaneously.

These findings align with prior research that highlights the limits of heuristic and scalar optimization techniques. These techniques often cannot account for the complex interdependencies among marketing channels. By combining evolutionary algorithms and machine learning, our approach overcomes these limits and uncovers latent data structures. This enables more refined segmentation of marketing strategies. Notably, identifying clusters where digital and television channels outperform others matches recent studies. These studies emphasize the synergistic benefits of integrating online and mass-media platforms.

From a practical standpoint, the study offers valuable insights for both managers and policymakers. Enterprises with sufficient financial resources are encouraged to prioritize integrated digital and television strategies, while those operating under tighter budget constraints may benefit from focusing more selectively on radio and print media. This flexibility enhances the applicability of the proposed model across organizations of varying sizes and digital maturity levels.

However, several limitations should be acknowledged. First, a portion of the dataset was based on synthetic simulations, which, despite being designed to approximate real-world conditions, may not fully reflect actual market dynamics. Second, the model focuses primarily on static budget allocation, whereas real-world marketing environments are inherently dynamic. Finally, behavioral and socio-cultural factors influencing consumer responses were not explicitly considered in this study.

Future research should aim to extend the proposed framework by incorporating predictive models of consumer behavior, utilizing longitudinal datasets to capture dynamic market changes, and expanding the analysis to include additional regional case studies. Furthermore, applying the

hybrid approach to other developing economies with similar agro-industrial characteristics would improve the generalizability of the results.

In conclusion, the findings demonstrate that integrating evolutionary optimization algorithms with clustering techniques not only enhances the methodological framework for marketing optimization but also provides practical tools for improving competitiveness and sustainability within the agro-industrial complex of Kazakhstan.

8. Conclusions

The study confirmed the effectiveness of the proposed hybrid method for optimizing marketing strategies in the agricultural sector. A Pareto front analysis revealed three clusters of solutions reflecting various tradeoffs between efficiency, reach, and cost. The most promising strategies are characterized by the dominance of television and digital channels with a balanced budget allocation for digital marketing of agricultural products. The results demonstrate a stable positive correlation between the television channel share and the objective function values, consistent with the theoretical assumptions of the model outlined in the article. The developed approach provides a tool for making informed management decisions under uncertainty and can be adapted to other industries facing similar challenges.

Acknowledgments: This research was funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No.AP23489233 SmartBuy Connect: AI- based intelligent group buying system).

References

1. Omarkhanova, Z.M., Niyazbekova, S.U., Varzin, V.V., Kerimkhulle, S.Y., & Nurekenova, E.S. (2022). Financial provision of the agro-industrial complex of Kazakhstan: problems and solutions. In *Sustainable Agriculture: Circular to Reconstructive, Volume 2* (pp. 27-32). Singapore: Springer Nature Singapore.
2. Tsapova, O., Zhailaubayeva, S., Kendyukh, Y., Smolyaninova, S., & Abdulova, O. (2024). Industry Specifics and Problems of Digitalization in the Agro-industrial Complex of the Republic of Kazakhstan. *Journal of the Knowledge Economy*, 1-20.
3. Smagulova, S., Yermukhanbetova, A., Akimbekova, G., Yessimzhanova, S., Razakova, D., Nurgabylov, M., & Zhakupova, S. (2022). Prospects for digitalization of energy and agro-industrial complex of Kazakhstan. *International Journal of Energy Economics and Policy*, 12(2), 198-209.
4. Taubayev, A., Rakhmetova, A., Kalkabayeva, G., Saifullina, Y., & Zhukenov, B. (2023). Problems of Research Funding in the Agro-Industrial Complex of Kazakhstan. *Journal of Asian and African Studies*, 58(8), 1656-1664.
5. Astamirova, H. H., Alkhanov, N. M., & Turkaeva, L. V. (2020). Marketing and advertising. Their features, differences, and relationships. *Issues of sustainable development of society*, (6), 66-68.
6. Guseva, E. S. (2018). Differences between content marketing and advertising, native advertising and public relations. *Bulletin of Eurasian Science*, 10(2), 16.
7. Shevchenko, D. A. (2019). Digital Marketing: A Review of Channels and Tools. *Practical Marketing*, (10 (272)), 29-37.
8. Kolchanov, V. B. (2019). Digitalization of Marketing: Trends and Prospects. In *State and Business. Digital Economy Ecosystem* (pp. 44-49).
9. Soldatova, N. F. (2022). The Impact of Marketing Digitalization on the Effectiveness of Management Innovations. *Issues of Innovative Economics*, 12(1), 167-178.
10. Krasnyuk, I. A., & Kolgan, M. V. (2019). Directions and forms of marketing organization in the context of digitalization. *Practical Marketing*, (7 (269)), 3-9.
11. Suslov, E. Yu., & Minaev, D. V. (2021). Systematization of the phenomena of digitalization of marketing: concept and example of implementation. *Management Consulting*, (4 (148)), 64-80.

12. Tang, Y. C., & Chang, C. T. (2012). Multicriteria decision-making based on goal programming and fuzzy analytic hierarchy process: An application to capital budgeting problem. *Knowledge-based systems*, 26, 288-293.
13. Abedi, V. S. (2017). Allocation of advertising budget between multiple channels to support sales in multiple markets. *Journal of the Operational Research Society*, 68(2), 134-146.
14. Benali, F., Bodénès, D., De Runz, C., & Labroche, N. (2021, November). An enhanced R-NSGA-II for multiple brands advertising campaign allocation problem. In *2021 IEEE 33rd International Conference on Tools with Artificial Intelligence (ICTAI)* (pp. 1306-1310). IEEE.
15. Khettabi, I., Benyoucef, L., & Amine Boutiche, M. (2022). Sustainable multi-objective process planning in reconfigurable manufacturing environment: adapted new dynamic NSGA-II vs New NSGA-III. *International Journal of Production Research*, 60(20), 6329-6349.
16. Lin, M. C., & Teng, J. Y. (2013). A Fuzzy Multicriteria Grade Cluster Analysis for the Budget Allocation of Tourism and Leisure Resources. *American Journal of Industrial and Business Management*, 3(5), 488-496.
17. Chen, S. P., & Chang, C. W. (2021). Measuring the efficiency of university departments: an empirical study using data envelopment analysis and cluster analysis. *Scientometrics*, 126(6), 5263-5284.
18. Saura, J. R. (2021). Using data sciences in digital marketing: Framework, methods, and performance metrics. *Journal of Innovation & Knowledge*, 6(2), 92-102.
19. Jadhav, G. G., Gaikwad, S. V., & Bapat, D. (2023). A systematic literature review: digital marketing and its impact on SMEs. *Journal of Indian Business Research*, 15(1), 76-91.
20. Thatikonda, R., Ponnala, J., Thatikonda, R., Yendluri, D. K., Kempanna, M., & Ananthan, B. (2024, March). Optimizing Digital Marketing Strategies Through Search Engine Optimization. In *2024 IEEE International Conference on Contemporary Computing and Communications (InC4)* (Vol. 1, pp. 1-6). IEEE.
21. Herman, B., Saleh, W., & Mursalat, A. (2024). Optimization of Digital Marketing in Improving Marketing Performance. *Almana: Jurnal Manajemen dan Bisnis*, 8(2), 387-399.
22. Sanbella, L., Van Versie, I., & Audiah, S. (2024). Online marketing strategy optimization to increase sales and e-commerce development: An integrated approach in the digital age. *Startupreneur Business Digital (SABDA Journal)*, 3(1), 54-66.
23. Andayani, Dwi, et al. Optimizing Digital Marketing Strategies through Big Data and Machine Learning: Insights and Applications. *Journal of Computer Science and Technology Application*, 2024, 1.2: 104-110.
24. Nikolajeva, A., & Teilans, A. (2021). Machine Learning Technology Overview In Terms Of Digital Marketing And Personalization. *ECMS*, 125-130.
25. Wang, C. (2022). Efficient customer segmentation in digital marketing using deep learning with swarm intelligence approach. *Information Processing & Management*, 59(6), 103085.
26. Sánchez-Camacho, C., San-Emeterio, B. M., Carranza, R., & Feijoo, B. (2025). Mapping two decades of evolution of artificial intelligence and machine learning in digital marketing and digital promotion to determine the current direction: a systematic review using bibliometrics. *Journal of Electronic Commerce Research*, 26(1), 1-33.
27. Cui, G., Wong, M. L., & Lui, H. K. (2006). Machine learning for direct marketing response models: Bayesian networks with evolutionary programming. *Management Science*, 52(4), 597-612.
28. Pereira, P. J., Cortez, P., & Mendes, R. (2021). Multi-objective grammatical evolution of decision trees for mobile marketing user conversion prediction. *Expert Systems with Applications*, 168, 114287.
29. Esmaelnezhad, D., Bahmani, J., Babgohari, A. Z., Taghizadeh-Yazdi, M., & Nazari-Shirkouhi, S. (2023). A fuzzy hybrid approach to analyze digital marketing strategies towards tourism industry. *International Journal of Tourism Policy*, 13(5), 463-480.
30. Kumar, A., Jhalani, D., & Kanojiya, A. HYBRID MARKETING BEST PRACTICES. *Enhancing Productivity in Hybrid Mode: The Beginning of a New Era*, 323.
31. Vesikar, Y., Deb, K., & Blank, J. (2018, November). Reference point based NSGA-III for preferred solutions. In *2018 IEEE symposium series on computational intelligence (SSCI)* (pp. 1587-1594). IEEE.
32. Yadav, D., Ramu, P., & Deb, K. (2023, July). Finding robust solutions for many-objective optimization using NSGA-III. In *2023 IEEE Congress on Evolutionary Computation (CEC)* (pp. 1-8). IEEE.

33. Ramraj, S., Uzir, N., Sunil, R., & Banerjee, S. (2016). Experimenting XGBoost algorithm for prediction and classification of different datasets. *International Journal of Control Theory and Applications*, 9(40), 651-662.
34. Zhang, Tong, and Bin Yu. "Boosting with early stopping: Convergence and consistency." (2005), 1538-1579.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.