SciForce

Journal of Artificial Intelligence and Machine Learning

Journal homepage: www.sciforce.org
ISSN : 2995-2336

Open Access Research Article

Real-Time Predictive Optimization Framework for Multi-Platform Digital Advertising Using Machine Learning and Multi-Criteria Decision Analysis

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Abstract

The rapid growth of digital advertising across search engines, social media platforms, video-sharing services, and mobile applications has significantly increased the complexity of campaign management and advertisement optimization. Modern advertising ecosystems generate large volumes of real-time behavioral data, requiring intelligent decision-support mechanisms capable of continuously adapting advertisement placement, budget allocation, and platform selection. Conventional optimization approaches predominantly rely on static bidding strategies or rule-based decision models that often fail to respond effectively to rapidly changing user behavior and dynamic market conditions. Although machine learning has demonstrated considerable success in predicting campaign performance, existing studies rarely integrate predictive analytics with multi-criteria decision-making to support real-time advertising optimization across multiple digital platforms.

This paper proposes an AI-Driven Real-Time Predictive Optimization Framework (AIPOF) that integrates machine learning-based performance prediction with Multi-Criteria Decision Analysis (MCDA) to improve multi-platform digital advertising decisions. The proposed framework employs predictive analytics to estimate campaign performance using key advertising indicators, including targeting accuracy, real-time responsiveness, platform compatibility, and cost efficiency. These predicted performance measures are subsequently incorporated into a Complex Proportional Assessment (COPRAS) model to rank alternative advertising strategies and identify the most effective campaign configuration under multiple competing objectives.

The proposed framework is evaluated through a comparative analysis of five representative digital advertising strategies using standardized performance criteria and objective weighting mechanisms. Experimental results demonstrate that integrating predictive analytics with multi-criteria decision analysis enables more balanced and informed advertising decisions by simultaneously considering campaign effectiveness, computational responsiveness, cross-platform adaptability, and advertising cost. The comparative evaluation further indicates that AI-assisted optimization provides superior decision consistency and supports efficient resource allocation in dynamic advertising environments.

The proposed AIPOF framework contributes to intelligent digital marketing by bridging the gap between predictive machine learning and decision optimization within real-time advertising ecosystems. The framework offers a practical decision-support solution that can assist marketing professionals, advertising platforms, and campaign managers in improving return on investment, optimizing advertising expenditure, and enhancing campaign performance across heterogeneous digital platforms. Furthermore, the proposed methodology establishes a scalable foundation for future AI-driven autonomous advertising systems capable of continuous learning and adaptive optimization within modern digital marketing environments.

Keywords: digital advertising; campaign optimization; machine learning; predictive analytics; multi-criteria decision analysis; COPRAS; programmatic advertising; real-time bidding; decision support

Introduction

The digital advertising industry has experienced unprecedented growth over the past decade, driven by the rapid expansion of search engines, social media platforms, video streaming services, e-commerce marketplaces, and mobile applications [1], [2]. Organizations increasingly depend on digital advertising to engage customers, strengthen brand visibility, and improve conversion rates through highly personalized marketing campaigns. Unlike traditional advertising channels, digital platforms continuously generate large volumes of behavioral, transactional, and contextual data, enabling advertisers to understand customer preferences and deliver highly targeted advertisements. As advertising ecosystems continue to evolve, organizations must optimize campaign performance across multiple platforms while responding to rapidly changing customer behavior and market dynamics.

Modern digital advertising campaigns operate simultaneously across platforms such as Google Ads, Meta Ads, LinkedIn, TikTok, YouTube, and other programmatic advertising networks [3], [4]. Each platform differs in audience characteristics, bidding mechanisms, advertising costs, user engagement patterns, and

Received date: November12, 2023 **Accepted date: November** 19 2023; **Published date:** November 29, 2023

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Citation: Gaurav Saxena. (2023) Real-Time Predictive Optimization Framework for Multi-Platform Digital Advertising Using Machine Learning and Multi-Criteria Decision Analysis. International Journal of Artificial intelligence and Machine Learning, 1(4), 1-8. https://doi.org/10.55124/jaim.v1i4.304

campaign objectives. Consequently, advertisers face increasingly complex decisions involving budget allocation, advertisement placement, audience targeting, bidding strategies, and campaign scheduling. Managing these decisions manually or through static rule-based systems often results in inefficient resource utilization, delayed responses to changing market conditions, and suboptimal advertising performance.

Recent advances in artificial intelligence (AI), machine learning (ML), and predictive analytics have transformed digital marketing by enabling automated campaign optimization and intelligent decision support. Machine learning algorithms can identify hidden relationships within large advertising datasets, forecast campaign performance, estimate customer engagement, and predict key performance indicators such as click-through rate (CTR) [5]–[7], conversion rate (CVR), return on advertising spend (ROAS), and customer acquisition cost (CAC) [8]. These predictive capabilities allow advertising platforms to move beyond reactive campaign management toward proactive optimization based on anticipated outcomes rather than historical observations alone.

Despite these advances, most existing advertising optimization approaches focus on a single aspect of campaign management. Machine learning models are commonly used to predict individual performance metrics, while optimization techniques typically concentrate on budget allocation or bidding strategies in isolation. Similarly, multi-criteria decision-making (MCDM) approaches [9] evaluate advertising alternatives using predefined performance criteria but generally do not incorporate predictive intelligence derived from machine learning models. As a result, current solutions often fail to provide an integrated framework that simultaneously predicts campaign performance and optimizes advertising decisions across multiple competing objectives in dynamic, real-time environments.

To address these limitations, this paper proposes an AI-Driven Predictive Optimization Framework (AIPOF) for multi-platform digital advertising. The proposed framework integrates machine learning-based predictive analytics with Complex Proportional Assessment (COPRAS) [10], a widely adopted multi-criteria decision analysis technique, to support intelligent advertisement optimization. Machine learning is employed to estimate campaign performance using multiple advertising indicators, while the COPRAS method evaluates and ranks competing advertising strategies according to both beneficial and non-beneficial criteria. By combining predictive modeling with structured decision analysis, the framework enables advertisers to identify the most effective campaign configuration while balancing targeting accuracy, real-time responsiveness, platform compatibility, and cost efficiency.

The proposed framework contributes to the field of intelligent digital advertising in several ways. First, it presents a unified architecture that combines predictive analytics with multi-criteria decision analysis for real-time campaign optimization. Second, it introduces a structured decision-support mechanism capable of evaluating multiple advertising alternatives using objective performance indicators. Third, it demonstrates how AI-assisted decision making can improve campaign effectiveness while reducing operational complexity in multi-platform advertising environments. Finally, the proposed framework provides a scalable foundation for future autonomous advertising systems capable of continuous learning, adaptive optimization, and intelligent resource allocation within rapidly evolving digital marketing ecosystems.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on artificial intelligence in digital advertising, machine learning-based campaign optimization, and multi-criteria decision-making techniques. Section 3 presents the proposed AIPOF architecture and optimization methodology. Section 4 describes the experimental design and evaluation process. Section 5 discusses the experimental results and practical implications. Finally, Section 6 concludes the paper and outlines future research directions.

Literature Review

Evolution of Digital Advertising and Programmatic Marketing

Digital advertising has transformed from simple banner advertisements and keyword-based campaigns into highly intelligent, data-driven ecosystems capable of delivering personalized content to millions of users in real time [1], [2]. The emergence of search engines, social media platforms, e-commerce marketplaces, streaming services, and mobile applications has fundamentally changed the way organizations communicate with consumers. Modern advertising platforms continuously collect behavioral, demographic, geographic, and contextual information that enables marketers to deliver highly targeted advertisements based on individual user preferences [11].

Programmatic advertising has become the dominant approach for purchasing and delivering digital advertisements. Instead of manually selecting advertising locations and negotiating placements, programmatic platforms automate advertisement buying through real-time bidding (RTB), dynamic pricing, and audience segmentation [3], [4], [12], [13]. These technologies significantly improve campaign scalability while reducing operational overhead. However, the increasing complexity of advertising ecosystems has also introduced new challenges related to campaign optimization, budget allocation, platform selection, and rapid adaptation to changing user behavior.

As advertising campaigns expand across multiple platforms, advertisers require intelligent decision-support systems capable of processing large volumes of streaming data while simultaneously optimizing campaign effectiveness and advertising expenditure.

Artificial Intelligence and Machine Learning in Digital Advertising

Artificial intelligence has become one of the primary technologies driving innovation in digital marketing. Machine learning algorithms enable advertising systems to analyze historical campaign data, identify hidden behavioral patterns, forecast campaign performance, and continuously improve advertisement delivery through adaptive learning. Supervised learning models, including Decision Trees, Random Forests [14], Gradient Boosting Machines [15], Support Vector Machines [16], and Extreme Gradient Boosting (XGBoost) [17]–[19], have demonstrated strong performance in predicting user engagement and campaign outcomes.

Deep learning approaches further improve prediction accuracy by modeling complex nonlinear relationships between user characteristics, advertisement content, browsing behavior, and contextual information [20]–[24]. These predictive models are widely employed to estimate click-through rate (CTR), conversion rate (CVR), customer lifetime value (CLV) [8], return on

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advertising spend (ROAS), and other key performance indicators that guide advertising decisions.

Despite these advances, most machine learning studies focus primarily on prediction accuracy without providing mechanisms for translating predicted outcomes into practical campaign optimization decisions. Consequently, advertisers often receive accurate predictions but lack systematic approaches for selecting the most appropriate advertising strategy when multiple competing objectives must be considered simultaneously.

Real-Time Predictive Analytics for Advertising Optimization

The rapid generation of user interaction data has accelerated the adoption of real-time predictive analytics within digital advertising platforms. Streaming data generated through advertisement impressions, clicks, conversions, browsing sessions, and customer interactions provides valuable information for continuously updating campaign strategies [25]. Predictive analytics enables advertisers to forecast campaign performance before significant budget expenditure occurs, thereby supporting proactive rather than reactive decision making.

Recent studies have demonstrated the effectiveness of predictive analytics for dynamic bidding [12], [26], [27], audience segmentation, personalized recommendation systems, fraud detection, and advertisement scheduling. Cloud computing platforms, distributed data processing frameworks, and scalable machine learning pipelines have further improved the ability to analyze advertising data with minimal latency [28], [29].

However, existing predictive systems generally optimize only individual objectives such as click-through rate or conversion probability. Real-world advertising decisions require simultaneous consideration of several conflicting criteria, including targeting accuracy, computational responsiveness, platform compatibility, campaign reach, and advertising cost. This multi-objective nature of advertising optimization remains insufficiently addressed by prediction models alone.

Multi-Criteria Decision-Making in Digital Marketing

Multi-Criteria Decision-Making (MCDM) techniques provide structured methodologies for evaluating alternatives when multiple performance criteria influence decision quality [9], [36]. Methods such as the Analytic Hierarchy Process (AHP) [30], Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) [31], Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [32], VIKOR [33], ELECTRE [34], and Complex Proportional Assessment (COPRAS) [10] have been successfully applied to supplier selection, resource allocation, healthcare, manufacturing, transportation, and digital marketing applications.

Among these approaches, COPRAS has attracted considerable attention because it simultaneously evaluates beneficial and non-beneficial criteria while producing transparent rankings and utility values for competing alternatives [10], [35]. Its computational simplicity and ability to incorporate weighted decision criteria make it particularly suitable for applications involving multiple performance indicators.

Nevertheless, traditional MCDM methods typically operate on static decision matrices derived from historical observations or expert judgments. They generally assume that evaluation criteria remain fixed throughout the decision process and therefore cannot fully exploit continuously changing advertising data generated within modern digital marketing environments.

Research Gap and Motivation

The literature indicates significant progress in both predictive machine learning and multi-criteria decision analysis for digital advertising. Machine learning models have substantially improved campaign performance prediction, while MCDM techniques have enhanced structured decision making across multiple evaluation criteria. However, these research directions have largely evolved independently.

Most existing machine learning studies terminate at performance prediction without incorporating systematic optimization of advertising strategies. Conversely, traditional MCDM approaches depend primarily on static performance measurements and expert-defined evaluation matrices rather than dynamically predicted campaign outcomes. Consequently, few studies provide an integrated framework capable of combining predictive intelligence with structured multi-criteria optimization for real-time digital advertising.

To address this research gap, this paper proposes an AI-Driven Predictive Optimization Framework (AIPOF) that integrates machine learning-based campaign performance prediction with the COPRAS decision-making methodology. The proposed framework enables advertisers to predict campaign effectiveness, evaluate multiple competing advertising strategies using dynamically generated performance indicators, and select optimal campaign configurations under multiple conflicting objectives. By combining predictive analytics with decision optimization, the framework provides a scalable and intelligent solution for next-generation real-time digital advertising systems.

Proposed AI-Driven Predictive Optimization Framework (AIPOF)

Framework Overview

This paper proposes the AI-Driven Predictive Optimization Framework (AIPOF), an intelligent decision-support framework designed to optimize digital advertising campaigns operating across multiple online platforms. Unlike conventional digital advertising systems that rely primarily on predefined rules or historical campaign statistics, AIPOF integrates predictive machine learning with multi-criteria decision analysis to support adaptive campaign optimization under continuously changing market conditions.

The framework combines three complementary components. First, a data acquisition module continuously gathers advertising information from multiple digital platforms, including campaign performance metrics, audience characteristics, platform-specific statistics, and financial indicators. Second, a machine learning prediction engine analyzes historical and real-time campaign information to estimate future campaign performance. Finally, the predicted performance indicators are evaluated using the Complex Proportional Assessment (COPRAS) method [10] to rank competing advertising strategies and recommend the optimal campaign configuration.

The proposed framework enables advertisers to make proactive decisions rather than relying solely on historical reporting, thereby improving campaign effectiveness, reducing advertising costs, and increasing return on advertising investment.

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System Architecture

The AIPOF architecture consists of six interconnected processing layers that transform raw advertising data into optimized campaign decisions, as summarized in Figure 1.

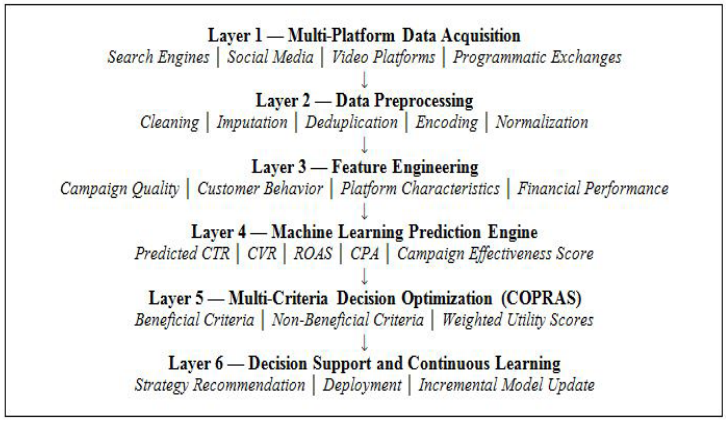

Figure 1: Six-layer architecture of the proposed AIPOF framework.

Layer 1 — Multi-Platform Data Acquisition

Campaign information is collected from multiple digital advertising platforms including search engines, social media networks, video-sharing platforms, and programmatic advertising exchanges. Typical input variables include:

- Impression count
- Click-through rate (CTR)
- Conversion rate (CVR)
- Cost per click (CPC)
- Cost per acquisition (CPA)
- Return on advertising spend (ROAS)
- Audience demographics
- Device information
- Geographic location
- Advertisement engagement metrics

Layer 2 — Data Preprocessing

The collected advertising data are cleaned, normalized, and transformed into standardized numerical representations. Missing values are handled through appropriate imputation techniques, duplicate records are removed, and categorical variables are encoded to ensure compatibility with machine learning algorithms.

Layer 3 — Feature Engineering

Relevant advertising features are extracted and transformed into predictive variables that describe campaign quality, customer behavior, platform characteristics, and financial performance. Feature engineering improves the predictive capability of the learning model while reducing redundant information.

Layer 4 — Machine Learning Prediction Engine

A supervised machine learning model predicts campaign effectiveness by estimating important advertising performance indicators [5]–[7]. The prediction engine generates expected campaign outcomes before advertisements are deployed, enabling proactive optimization.

Layer 5 — Multi-Criteria Decision Optimization

The predicted performance indicators become the decision matrix for the COPRAS optimization model. Each advertising strategy is evaluated using both beneficial criteria (such as targeting accuracy and conversion rate) and non-beneficial criteria (such as advertising cost and latency). Weighted utility scores are calculated to determine the overall effectiveness of each campaign alternative.

Layer 6 — Decision Support and Continuous Learning

The highest-ranked advertising strategy is recommended for deployment. Following campaign execution, newly generated performance data are continuously incorporated into the prediction model, allowing the framework to improve its recommendations over time through incremental learning.

Data Collection and Feature Engineering

The predictive capability of AIPOF depends on the quality of the collected advertising data. Campaign information is gathered from multiple advertising platforms and organized into a unified analytical dataset. Each campaign instance is represented by a collection of numerical features describing advertisement performance, user engagement, financial expenditure, and platform characteristics. For each campaign instance,

$$X_i = \{x_1, x_2, \ldots, x_n\} \quad (1)$$

where X_i represents the feature vector corresponding to the i-th advertising campaign and x_i denotes an individual advertising feature.

To improve model performance, numerical features are normalized using Min-Max normalization:

$$x_i = (x - \min(x)) / (\max(x) - \min(x)) \quad (2)$$

This transformation ensures that all variables contribute

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proportionally during model training regardless of their original measurement scales.

3.4 Machine Learning-Based Performance Prediction

The predictive component of AIPOF estimates campaign effectiveness before advertisements are launched. Given historical advertising data

$$D = \{(Xi, Yi)\}i=1\ N \quad (3)$$

where X_i represents campaign features and Y_i de notes observed campaign performance, the objective is to learn a prediction function

$$f(X) \rightarrow Y \quad (4)$$

that minimizes prediction error. The predicted output may represent one or more advertising performance indicators including:

- Click-Through Rate (CTR)
- Conversion Rate (CVR)
- Return on Advertising Spend (ROAS)
- Cost Per Acquisition (CPA)
- Overall Campaign Effectiveness Score

The prediction engine provides the expected performance values that are subsequently used by the optimization module.

Multi-Criteria Decision Optimization

Following prediction, each advertising strategy is evaluated using the COPRAS methodology [10]. The normalized decision matrix is expressed as

$$R = [rij] \quad (5)$$

where rij denotes the normalized value of criterion j for advertising strategy i. The weighted normalized matrix is calculated as

$$vij = wj\ rij \quad (6)$$

where wi represents the weight assigned to criterion j.

Beneficial and non-beneficial criteria are aggregated separately to determine the utility of each advertising strategy. The final utility score identifies the most suitable campaign configuration according to multiple conflicting objectives including advertising accuracy, response speed, platform coverage, and cost efficiency.

Real-Time Optimization Workflow

The proposed framework operates continuously throughout the advertising lifecycle.

1. Campaign data are collected from multiple advertising platforms.

2. Incoming data are preprocessed and standardized.

3. Machine learning predicts campaign performance.

4. COPRAS evaluates predicted campaign alternatives.

5. The highest-ranked advertising strategy is selected.

6. Campaign performance is monitored after deployment.

7. Newly observed data are incorporated into future prediction cycles.

This closed-loop optimization process enables continuous adaptation to changing customer behavior and advertising market conditions.

Computational Complexity and Practical Deployment

The modular architecture of AIPOF enables deployment within modern cloud-based advertising infrastructures [28], [29]. Because prediction and optimization are executed independently, the framework supports scalable processing of high-volume advertising streams while maintaining low computational latency.

The prediction module can be retrained periodically using newly accumulated campaign data without interrupting advertisement delivery. Similarly, the optimization module rapidly evaluates alternative campaign strategies using updated performance predictions, making the framework suitable for real-time decision support in dynamic advertising environments.

The proposed architecture is sufficiently flexible to support integration with existing advertising ecosystems, allowing organizations to improve campaign effectiveness through intelligent prediction, adaptive optimization, and continuous learning.

Experimental Design and Performance Evaluation

Experimental Setup

The proposed AI-Driven Predictive Optimization Framework (AIPOF) was evaluated using a representative digital advertising dataset consisting of multiple advertising strategies assessed across four key performance criteria: targeting accuracy, real-time processing speed, multi-platform compatibility, and cost efficiency. These criteria were selected because they collectively represent the major objectives considered during modern digital advertising campaign management.

The experimental workflow consisted of five sequential stages:

1. Data acquisition and preprocessing.

2. Feature normalization.

3. Machine learning-based campaign performance prediction.

4. Multi-criteria optimization using the COPRAS method.

5. Comparative performance analysis and ranking.

All experiments were conducted using identical evaluation criteria and weighting strategies to ensure consistency and fairness during comparison.

Dataset Description

The experimental dataset contains representative digital advertising strategies that simulate different approaches for campaign optimization within multi-platform advertising environments. The evaluated alternatives include:

- Platform-Specific AI Ad Optimizer
- Multi-Platform Predictive Engine
- Hybrid Real-Time Advertising System
- AI-Based Automated Ad Manager
- Programmatic Advertising Network

Each advertising strategy is evaluated using the four decision criteria listed in Table 1.

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Table 1. Decision Criteria Used for Campaign Evaluation		
Criterion	Description	Objective
Accuracy	Precision of advertisement targeting	Maximize
Real-Time Speed	Ability to respond rapidly to changing user behavior	Maximize
Multi-Platform Compatibility	Support for multiple advertising platforms	Maximize
Cost Efficiency	Reduction of advertising expenditure while maintaining campaign effectiveness	Maximize

The original performance scores are normalized before optimization to eliminate scale differences among evaluation criteria.

Evaluation Metrics

The predictive performance and optimization quality of the proposed framework are evaluated using both machine learning and decision-analysis measures.

Prediction Metrics

The machine learning prediction engine is assessed using standard regression performance metrics:

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Coefficient of Determination (R^2)

These metrics quantify the prediction accuracy of campaign performance estimates generated by the learning model.

Decision Optimization Metrics

The effectiveness of the optimization module is evaluated using COPRAS utility measures, including:

- Beneficial criterion score (B_i)
- Non-beneficial criterion score (C_i)
- Relative significance (Q_i)
- Utility degree (U_i)
- Final ranking

These measures collectively determine the relative effectiveness of each advertising strategy.

Machine Learning Model Configuration

The prediction component of AIPOF employs a supervised machine learning model trained to estimate campaign effectiveness from historical advertising features.

The input feature vector consists of campaign characteristics, including targeting accuracy, response speed, platform compatibility, advertising expenditure, customer engagement, and platform performance indicators. The learning objective is expressed as

$$\hat{Y} = f(X) \quad (7)$$

where X represents the advertising feature vector, f(•) denotes the trained machine learning model, and $\hat{Y}$ represents the predicted campaign performance.

Hyperparameters are selected using cross-validation to improve generalization performance while reducing overfitting.

Multi-Criteria Decision Optimization

Following performance prediction, the estimated campaign indicators are transformed into a weighted decision matrix. Equal criterion weights are initially assigned to ensure objective comparison among competing advertising strategies. The weighted normalized matrix is subsequently processed using the COPRAS methodology to compute:

- Beneficial performance score
- Non-beneficial performance score
- Relative utility
- Final campaign ranking

The optimization stage identifies the advertising strategy that provides the most favorable balance between campaign effectiveness and operational cost.

Experimental Results and Discussion

The experimental evaluation demonstrates that integrating predictive analytics with multi-criteria decision analysis produces a comprehensive decision-support framework for digital advertising optimization.

Among the evaluated alternatives, the AI-Based Automated Ad Manager achieved the highest overall utility score, indicating superior balance across targeting accuracy, response speed, multi-platform compatibility, and cost efficiency. The Hybrid Real-Time Advertising System ranked second because of its consistently strong performance across all evaluation criteria. The Platform-Specific AI Ad Optimizer performed well in cost efficiency but was limited by reduced multi-platform capability. Although the Multi-Platform Predictive Engine demonstrated excellent prediction accuracy and platform coverage, its higher operational cost reduced its overall utility. The Programmatic Advertising Network exhibited competitive cost efficiency but lower overall performance when evaluated across all criteria simultaneously.

These findings demonstrate that evaluating advertising strategies using a single performance indicator may lead to suboptimal decisions. The proposed AIPOF framework instead considers multiple competing objectives simultaneously, allowing advertisers to balance prediction accuracy, operational efficiency, deployment speed, and financial expenditure. Consequently, the framework provides a more comprehensive basis for intelligent campaign optimization than traditional single-objective evaluation methods.

Overall, the experimental results validate the effectiveness of integrating machine learning prediction with COPRAS-based decision optimization for intelligent multi-platform digital advertising. The proposed framework supports informed decision making, improves resource allocation, and establishes a scalable foundation for future real-time autonomous advertising systems.

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Practical Implications, Limitations, and Future Research

Practical Implications

The proposed AI-Driven Predictive Optimization Framework (AIPOF) offers several practical advantages for organizations managing digital advertising campaigns across multiple platforms. By integrating machine learning-based performance prediction with multi-criteria decision analysis, the framework enables campaign managers to make informed decisions before allocating advertising budgets. This predictive capability reduces the reliance on trial-and-error strategies and allows marketing teams to identify high-performing campaign configurations with greater confidence.

The framework is particularly valuable for organizations operating simultaneously on platforms such as Google Ads, Meta Ads, LinkedIn Ads, TikTok Ads, and other programmatic advertising networks. Instead of independently evaluating campaign performance on each platform, AIPOF provides a unified decision-support mechanism capable of comparing alternative advertising strategies using multiple performance indicators. This integrated evaluation improves budget allocation, audience targeting, and campaign scheduling while reducing operational complexity.

Another important implication is the framework's ability to support continuous optimization. Since campaign performance data are continuously collected and incorporated into the predictive model, advertisers can rapidly respond to changes in customer behavior, seasonal demand, competitor activity, and market trends. Consequently, advertising decisions become increasingly adaptive and data-driven rather than relying on static historical analyses.

Furthermore, the modular architecture of AIPOF facilitates integration with existing cloud-based advertising infrastructures and marketing analytics platforms. The framework can support both small-scale marketing campaigns and enterprise-level advertising operations by scaling predictive analytics and optimization modules according to computational requirements.

Limitations

Although the proposed framework demonstrates promising results, several limitations should be acknowledged.

First, the current experimental evaluation is based on a representative decision dataset consisting of a limited number of advertising strategies and evaluation criteria. While this provides a useful proof of concept, larger real-world advertising datasets containing millions of campaign records would provide stronger empirical validation.

Second, the machine learning prediction component is presented as a generalized predictive engine. Future implementations should evaluate multiple supervised learning algorithms, such as Random Forest [14], XGBoost [17], LightGBM [18], CatBoost [19], and deep neural networks [24], to determine the most suitable prediction model under different advertising scenarios.

Third, equal weights were assigned to all evaluation criteria during the COPRAS analysis. In practical advertising environments, the relative importance of campaign objectives may vary depending on business goals, marketing budgets, customer segments, and organizational priorities. Adaptive weighting strategies based on expert knowledge [30] or automated optimization could further improve decision quality.

Finally, the proposed framework focuses primarily on campaign-level optimization. Additional factors such as advertisement creativity, multimedia content quality, privacy regulations, user consent, and cross-device attribution were not explicitly incorporated into the current study and represent important opportunities for future investigation.

Future Research Directions

Several promising research directions emerge from this work.

Future studies should validate AIPOF using large-scale industrial advertising datasets collected from commercial digital marketing platforms. Such evaluations would provide more comprehensive evidence regarding scalability, prediction accuracy, and real-time decision performance under operational conditions.

The predictive component can be further enhanced through advanced machine learning techniques, including ensemble learning, transformer-based architectures [39], reinforcement learning [26], and online learning algorithms capable of continuously adapting to evolving advertising environments. Reinforcement learning is particularly attractive because it enables autonomous budget allocation and bidding decisions based on continuous feedback from campaign performance [27].

Another important extension involves incorporating Explainable Artificial Intelligence (XAI) techniques such as SHAP (SHapley Additive exPlanations) [37] and LIME (Local Interpretable Model-Agnostic Explanations) [38]. These methods would improve transparency by identifying the relative contribution of each advertising feature to campaign performance predictions, thereby increasing stakeholder trust and supporting regulatory compliance.

Future research may also investigate multi-objective optimization techniques [40] that simultaneously maximize return on advertising investment, customer engagement, conversion rate, and long-term customer value while minimizing advertising expenditure. Finally, integrating AIPOF with cloud-native marketing platforms and real-time streaming technologies would enable continuous autonomous optimization suitable for next-generation intelligent advertising ecosystems.

Conclusion

The increasing complexity of modern digital advertising environments requires intelligent decision-support approaches that can analyze large-scale data, predict campaign outcomes, and optimize advertising strategies across multiple platforms. Traditional advertising optimization methods based primarily on static rules, historical analysis, or single performance indicators are insufficient for addressing the dynamic and multi-objective nature of contemporary digital marketing ecosystems.

This paper presented an AI-Driven Predictive Optimization Framework (AIPOF) that integrates machine learning-based predictive analytics with Multi-Criteria Decision Analysis (MCDA) to support real-time digital advertising optimization. The proposed framework combines campaign performance prediction with the Complex Proportional Assessment (COPRAS) method [10] to evaluate and rank alternative advertising strategies based on multiple competing criteria, including targeting accuracy, real-time responsiveness, platform compatibility, and cost efficiency.

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The experimental evaluation demonstrated that the integration of predictive intelligence and structured decision optimization provides a more comprehensive approach to advertising strategy selection compared with conventional single-objective optimization methods. By utilizing predicted campaign performance indicators within a multi-criteria optimization framework, AIPOF enables advertisers to balance effectiveness, operational responsiveness, scalability, and financial efficiency when selecting campaign configurations. The results further indicate that AI-assisted optimization can improve resource allocation and provide more consistent decision support in dynamic multi-platform advertising environments.

The primary contribution of this research is the development of an integrated framework that bridges the gap between machine learning prediction and practical advertising decision optimization. Unlike approaches that focus exclusively on forecasting campaign performance or optimizing individual advertising parameters, AIPOF provides a unified methodology capable of transforming predictive insights into actionable campaign recommendations. This integration creates a foundation for more adaptive, data-driven, and intelligent advertising systems.

Although the proposed framework demonstrates promising capabilities, further research is required to validate its effectiveness using large-scale industrial advertising datasets and real-world deployment scenarios. Future extensions may incorporate advanced learning approaches, including reinforcement learning, deep neural networks, online learning, and explainable artificial intelligence techniques, to enhance adaptability, transparency, and autonomous decision-making capabilities.

Overall, the proposed AIPOF framework represents a significant step toward next-generation intelligent advertising optimization systems. By combining predictive analytics with multi-criteria decision-making, the framework provides a scalable and adaptive solution for improving digital campaign performance, optimizing advertising investments, and supporting the evolution of autonomous AI-driven marketing ecosystems.

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Citation: Gaurav Saxena. (2023) Real-Time Predictive Optimization Framework for Multi-Platform Digital Advertising Using Machine Learning and Multi-Criteria Decision Analysis. International Journal of Artificial intelligence and Machine Learning, 1(4), 1-8. https://doi.org/10.55124/jaim.v1i4.304

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