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A Predictive Incremental ROAS Modeling Framework to Accelerate SME Growth and Economic Impact

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Abstract: To optimize SME advertising budget allocation and bidding strategies while enhancing campaign returns, this study employs an incremental ROAS optimization framework. Through quasi-experimental design and data analysis, it identifies incremental advertising benefits to refine budget distribution and placement strategies. Findings demonstrate that the framework significantly boosts ROAS across advertising channels, with particularly pronounced optimization effects under budget constraints. Results validate the framework's applicability across multiple advertising channels, confirming its practical value in improving campaign efficiency.

Keywords: Incremental ROAS, Advertising Budget Optimization, Quasi-Experimental Design, Advertising Effectiveness Enhancement.

Disciplines: Business. **Subjects:** Business Strategy.

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1 INTRODUCTION

In the increasingly complex landscape of digital marketing, traditional methods for evaluating advertising effectiveness no longer accurately reflect the true benefits of ad campaigns. For small and medium-sized enterprises (SMEs) with limited budgets, maximizing return on advertising investment (ROI) in a volatile market environment has become an urgent challenge. This study focuses on designing and applying an incremental ROAS optimization framework, aiming to enhance advertising performance through scientific budget allocation and bid optimization. Employing a quasi-experimental design, the study conducts incremental benefit analysis using multidimensional data to explore the framework's applicability and stability across different advertising channels. Through empirical validation, it is expected to provide SMEs with a practical advertising optimization strategy, enhancing the precision and efficiency of marketing decisions. The research will also conduct robustness tests and multiple experimental validations to ensure the framework's adaptability and stability, particularly maintaining effective performance improvements under budget fluctuations and external environmental disruptions. Furthermore, the research will explore how more refined data analysis methods can further enhance advertising ROI. In the future, the framework will integrate with real-time data to optimize budget allocation strategies, improving the responsiveness and precision of ad placements. This study not only provides practical guidance for SMEs' digital marketing but also offers new perspectives and methodologies for marketing academic research. The findings will serve as a theoretical foundation and practical guide for optimizing subsequent advertising strategies.

2 ANALYSIS OF SME MARKETING EFFECTIVENESS EVALUATION CHALLENGES

2.1 The Performance Trap of Click-Through Rate (CTR) Focus

In SME digital marketing, click-through rate (CTR) is often treated as the primary metric for evaluating ad effectiveness. Performance evaluation systems solely focused on CTR overlook actual conversions post-ad placement, leading to biased optimization decisions. A high CTR does not necessarily translate to high conversion rates. Instead, it may result in inefficient advertising expenditure, particularly when the target audience is imprecise or the ad content fails to align with user needs. Many SMEs, constrained by limited advertising budgets, overly rely on CTR as the sole metric, neglecting the optimization of conversion rates—a critical indicator [1]. The "click trap" phenomenon—where CTR diverges from the ultimate advertising goal of conversion rate—often creates the illusion of successful campaigns while delivering far lower profits and benefits than anticipated. Balancing CTR and conversion rate in marketing effectiveness evaluation, while avoiding over-reliance on a single metric, is key to improving advertising ROI. Figure 1 illustrates the relationship between a campaign's click-through rate (CTR) and conversion rate.

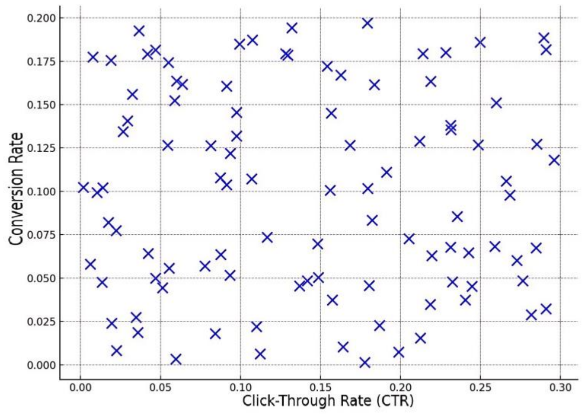

FIGURE 1: SCATTER PLOT OF CLICK-THROUGH RATE VS. CONVERSION RATE

2.2 MULTIDIMENSIONAL CAUSES OF ROAS EVALUATION BIAS

In marketing effectiveness evaluation for SMEs, ROAS (Return on Advertising Spend) is widely adopted as a core metric. ROAS assessments are frequently subject to multidimensional biases, leading to inaccurate results. Channel attribution bias is a common cause. Differences in how various advertising platforms or marketing channels measure effectiveness introduce discrepancies in evaluating ad performance. Social media platforms may tend to overestimate ad conversion effectiveness, while search engine advertising provides more direct conversion data. Exposure lag is another significant factor. The time gap between ad exposure and user conversion can cause delays in ROAS calculations, thereby affecting the timeliness of evaluations [2]. User overlap issues also impact ROAS assessment, particularly in multi-platform campaigns where repeated user actions across channels lead to over-measurement of ad effectiveness. Algorithm recommendation bias may result in excessive targeting of certain ad audiences, distorting the accuracy of ROAS.Missing values, outliers, and their handling methods during data processing may also introduce bias. For instance, improper handling of untrackable user behaviors or incompletely recorded conversions can lead to significant errors in ROAS assessment. Such biases become particularly pronounced in multi-channel campaigns, often resulting in inaccurate performance evaluations that compromise the precision of budget allocation and optimization decisions.

2.3 OPTIMIZATION CHALLENGES UNDER BUDGET CONSTRAINTS

Under budget constraints, optimization challenges for SMEs typically involve maximizing marketing effectiveness within limited resources. Linear programming models are a common technical approach for optimizing ad budget allocation. The process involves: First, defining the objective function as maximizing revenue from ad spend, formally expressed as:

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

where r_i represents the unit revenue of the i-th advertising channel, and x_i denotes the advertising expenditure for that channel. Second, the budget constraint is defined as:

$$\sum_{i=1}^{n} c_i x_i \leq B \quad (2)$$

where c_i is the unit cost of advertising channel i, and B is the company's total advertising budget. To further optimize decision-making, weight coefficients between channels and the diminishing marginal returns effect of advertising must also be considered, adjusting the model to better align with actual business scenarios. By solving the model using optimization algorithms such as gradient descent, the optimal budget allocation plan for each advertising channel is obtained.

3 DESIGN OF THE INCREMENTAL ROAS MARKETING OPTIMIZATION FRAMEWORK

3.1 CORE CONCEPTS OF THE FRAMEWORK

The core of the Incremental ROAS Marketing Optimization Framework lies in precisely evaluating and optimizing advertising returns based on "incremental effects." By integrating traditional ROAS calculation methods with quasi-experimental design, the framework identifies the actual incremental benefits of advertising campaigns rather than relying solely on linear extrapolation from historical data. The framework employs data integration technology to cleanse and fuse multi-channel, multi-dimensional advertising data, providing high-quality inputs for subsequent modeling [3]. The quasi-experimental incremental effect identification method evaluates additional conversions generated by ad placements by establishing control and treatment groups, thereby eliminating potential external interference factors. Integrated with a budget optimization model, the framework dynamically adjusts ad budget allocation strategies to maximize incremental returns with minimal investment, ensuring optimal campaign performance within budget constraints.

3.2 DATA INTEGRATION AND FEATURE ENGINEERING

Within the incremental ROAS optimization framework, data integration and feature engineering constitute the critical

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first step. Data is collected from multiple dimensions, including various advertising platforms, user behavior tracking, and marketing campaigns. Using ETL (Extract, Transform, Load) technology, data from different sources undergoes cleaning, deduplication, and standardization to ensure data quality [4]. Feature engineering is performed by applying algorithms such as PCA (Principal Component Analysis) and K-means clustering to reduce the dimensionality and cluster raw features, extracting key characteristics. For numerical features, Z-score normalization is applied using the formula:

$$x' = \frac{x-\mu}{\sigma} \quad (3)$$

where x is the raw feature value, μ is the feature mean, and σ is the standard deviation. For categorical data, one-hot encoding is applied to convert them into numerical features. After feature construction, feature selection methods (e.g., LASSO regression) are employed to identify features most influential on incremental ROAS, forming an efficient feature set. The processed data is then fed into the model for incremental effect analysis and budget optimization.

3.3 Incremental Effect Identification via Quasi-Experimental Design

The incremental ROAS optimization framework employs quasi-experimental design to precisely identify the incremental effects of advertising. This design utilizes treatment and control groups, randomly assigning user cohorts to compare intervention versus non-intervention, thereby eliminating external confounding factors [5]. Two sample groups are constructed: the treatment group receives ad exposure, while the control group receives no advertising intervention. By comparing conversion rates between the two groups, the incremental effect of ad exposure is calculated. The formula for incremental effect is:

$$\Delta ROAS = E[Y(1) - E[Y(0)]] \quad (4)$$

where Y(1) represents the conversion revenue of the treatment group, and Y(0) represents the conversion revenue of the control group. Through multiple experimental validations, factors such as seasonality and channel bias are eliminated to ensure the accuracy of incremental benefits. In practical applications, Kalman filtering is employed to dynamically adjust the experimental process, ensuring real-time performance and precision.

3.4 Budget Reallocation and Bid Optimization Model

Within the incremental ROAS optimization framework, the budget reallocation and bid optimization model maximizes incremental advertising revenue by dynamically adjusting budgets and bidding strategies. The budget reallocation problem is solved using a linear programming model, aiming to maximize the incremental return on advertising investment. The formula is:

$$\max \sum_{i=1}^{n} (\Delta r_i - \lambda c_i) x_i \quad (5)$$

Where Δr_i represents the incremental revenue of the i-th advertising channel, c_i denotes the unit cost per acquisition for channel i, λ is the weight of the budget constraint, and x_i indicates the advertising budget allocated to channel i. This formula enables the model to balance incremental benefits against costs, thereby optimizing budget allocation. Bid optimization is solved using the gradient descent method. The optimization objective is defined as:

$$\min_{b_i} \sum_{i=1}^{n} \left(\frac{\hat{y}_i - y_i}{y_i} \right)^2 \quad (6)$$

where $\hat{y}_i$ represents the model-predicted conversion effect, y_i denotes actual conversion data, and b_i is the bid strategy variable. This model iteratively adjusts bids to enhance conversion rates per click. Through joint optimization of budget and bids, it ensures efficient allocation of limited resources, ultimately achieving maximum incremental ROAS.

4 EMPIRICAL RESEARCH AND FRAMEWORK VALIDATION

4.1 Experimental Design and Data Sources

This study's experimental design adheres to principles of scientific rigor and operational feasibility to authentically reflect the incremental ROAS optimization framework's effectiveness. The experimental sample comprises advertising data from SMEs across multiple industries, including e-commerce, online education, and retail. Data sources include campaign metrics from major advertising platforms such as Google Ads, Facebook Ads, and Baidu Promotion. Raw advertising data underwent preprocessing, including removal of invalid entries and outliers, to ensure accuracy and consistency. The experimental design employed random assignment to divide participating ad campaigns into a treatment group and a control group. The treatment group implemented budget allocation and bid optimization according to the incremental ROAS optimization framework, while the control group maintained its original campaign strategy. Data collection spanned a three-month period, capturing advertising performance metrics across different time intervals. Figure 2 illustrates the experimental data sources and grouping process.

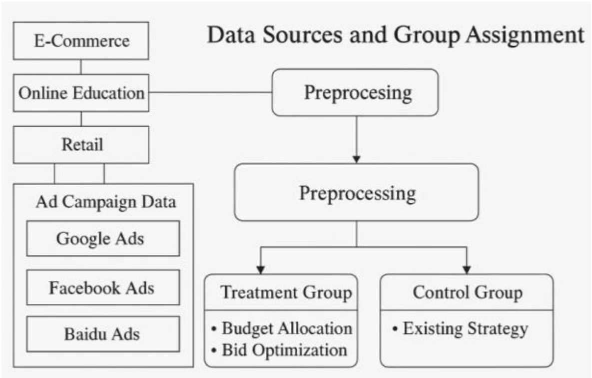

FIGURE 2: SCHEMATIC DIAGRAM OF EXPERIMENTAL DATA SOURCES AND GROUPING

4.2 ANALYSIS OF INCREMENTAL ROAS MEASUREMENT RESULTS

During incremental ROAS measurement, a quasi-experimental design was employed to compare the treatment group with the control group, thereby identifying the actual incremental benefits generated by the advertising campaigns. Incremental ROAS for each advertising channel was calculated based on conversion data from the treatment and control groups. The specific steps included: First, collecting advertising expenditure and conversion data from each channel to ensure data completeness and consistency; Second, applying smoothing techniques such as Kalman filtering to eliminate external interference; Third, using an incremental effect identification model to calculate the marginal return after advertising placement. Comparing experimental and control group results revealed that incremental ROAS significantly exceeded traditional ROAS calculations for certain advertising channels. This effect was particularly pronounced under budget allocation strategies optimized for incremental impact, where select channels demonstrated markedly enhanced returns. Figure 3 illustrates the comparative results of incremental ROAS versus traditional ROAS across different advertising channels.

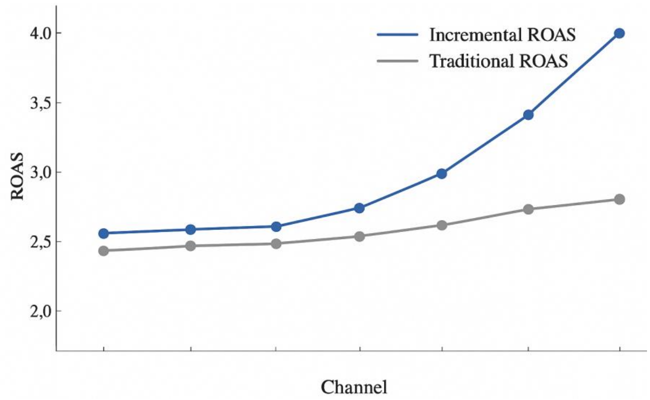

FIGURE 3: INCREMENTAL ROAS VS. TRADITIONAL ROAS COMPARISON LINE CHART

4.3 EFFECT COMPARISON BEFORE AND AFTER OPTIMIZATION FRAMEWORK

When comparing performance before and after implementing the optimization framework, key performance metrics were collected for different advertising channels. The incremental ROAS optimization framework significantly enhanced the performance of all advertising channels. Particularly under budget constraints, precise budget allocation and bid optimization effectively improved conversion rates and ROAS. Table 1 summarizes key metrics for each advertising channel before and after optimization, including click-through rate (CTR), conversion rate (CVR), and ROAS. Through comparison.

TABLE 1 COMPARISON OF KEY METRICS BEFORE AND AFTER OPTIMIZATION

Ad Channel	Pre-Optimization CTR(%)	Post-Optimization CTR(%)	Pre-Optimization CVR(%)	Post-Optimization CVR(%)	Pre-Optimization ROAS	Post-Optimization ROAS
Social Media Advertising	3.2	4.5	1.5	2.3	2.1	3.4
Search Engine Advertising	5.6	7.3	2.0	3.0	3.5	5.0
Video Ads	2.8	3.2	1.2	1.8	1.8	2.2
Display Advertising	1.9	2.4	0.8	1.2	1.3	1.7
Email advertising	4.3	5.0	1.8	2.5	2.3	3.0

Table 1 shows that optimized metrics improved across all advertising channels. Social media ads saw their CTR rise from 3.2% to 4.5%, ROAS increase from 2.1 to 3.4, and conversion rate grow by approximately 0.8 percentage points. Search engine advertising demonstrated particularly significant growth in conversion rate and ROAS, with CTR and CVR increasing by 1.7% and 1.0% respectively, while ROAS surged by 1.5 times. Adjustments made by the optimization framework to budget and bid strategies substantially enhanced advertising performance. Other advertising channels, such as video ads and display ads, also showed varying degrees of improvement, indicating the universality and practicality of the incremental ROAS optimization framework for multi-channel campaigns.

4.4 ROBUSTNESS TEST RESULTS

During robustness testing, we conducted multi-dimensional validation of the incremental ROAS optimization framework's performance across different advertising channels, budget fluctuations, and external environmental disturbances. By employing RRMSE (Relative Root Mean Square Error) and MAE (Mean Absolute Error) metrics to measure the model's error range and stability, we ensured the framework's prediction results maintained high consistency under varying test conditions. During testing, we also conducted sensitivity analyses on the performance of each advertising channel to evaluate the framework's adaptability to budget changes and advertising campaign periods. Table 2 presents the robustness test metrics under different conditions.

TABLE 2: ROBUSTNESS METRICS COMPARISON

Advertising Channel	Budget Fluctuation (%)	External Disturbance (Error)	RRMSE (%)	MAE (%)
Social Media Advertising	±10%	5%	4.2	2.1
Search Engine Advertising	±15%	3%	3.7	1.8
Video Advertising	±5%	4%	5.0	2.3
Display Ads	±12%	6%	6.5	3.1
Email advertising	±8%	2%	4.1	2.0

As shown in Table 2, across all advertising channels, both RRMSE and MAE metrics remain within reasonable ranges, indicating that the incremental ROAS optimization framework demonstrates strong stability under varying advertising channels and environmental changes. Particularly in search engine advertising and social media advertising, the errors are relatively low, demonstrating the framework's high adaptability. Although budget fluctuations and external interference have a slightly greater impact on display advertising, the overall error control remains within an acceptable range, indicating that the framework can deliver reliable optimization results under certain disturbances.

5 CONCLUSION

The incremental ROAS optimization framework significantly enhances the efficiency and returns of advertising for small and medium-sized enterprises through precise budget allocation and bid optimization. Experimental results demonstrate the framework's robust adaptability and stability across multiple advertising channels. It effectively identifies and optimizes incremental advertising benefits, achieving significant performance improvements even under tight budget constraints. Through quasi-experimental design and data-driven incremental analysis, it provides scientific grounds for marketing decisions. Future refinements could extend the framework's applicability to additional advertising platforms and dynamic market environments, further enhancing its universality and accuracy.

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Not applicable.

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REFERENCES

[1] Deldadehasl, M., Karahroodi, H. H., & Nekah, H. P. (2025). Customer clustering and marketing optimization in hospitality: A hybrid data mining and decision-making approach from an emerging economy. Tourism and Hospitality, 6(2), 80. https://doi.org/10.3390/tourhosp6020080

[2] Mardatillah, A., Angraini, M. L., & Yuliani, S. (2024). Enhancing marketing performance in batik Malay industry: Optimization of competitive advantage by leveraging augmented reality marketing. Cogent Business & Management, 11(1), 2431187. https://doi.org/10.1080/23311975.2024.2431187

[3] Ai, X. (2024). Research on optimization strategy of new

media marketing for rural tourism under the "Internet+" framework. Applied Mathematics and Nonlinear Sciences, 9(1). https://doi.org/10.2478/amns-2024-1036

[4] Sari, J., Mildawati, T., Widyawati, D., et al. (2023). Community empowerment through digital marketing optimization-based socio-preneurship training. South Asian Journal of Social Studies and Economics, 20(4), 90–102. https://doi.org/10.9734/sajsse/2023/v20i4745

[5] Computational, N. A. I. (2023). Retracted: Variational fuzzy neural network algorithm for music intelligence marketing strategy optimization. Computational Intelligence and Neuroscience, 2023, 9848521. https://doi.org/10.1155/2023/9848521